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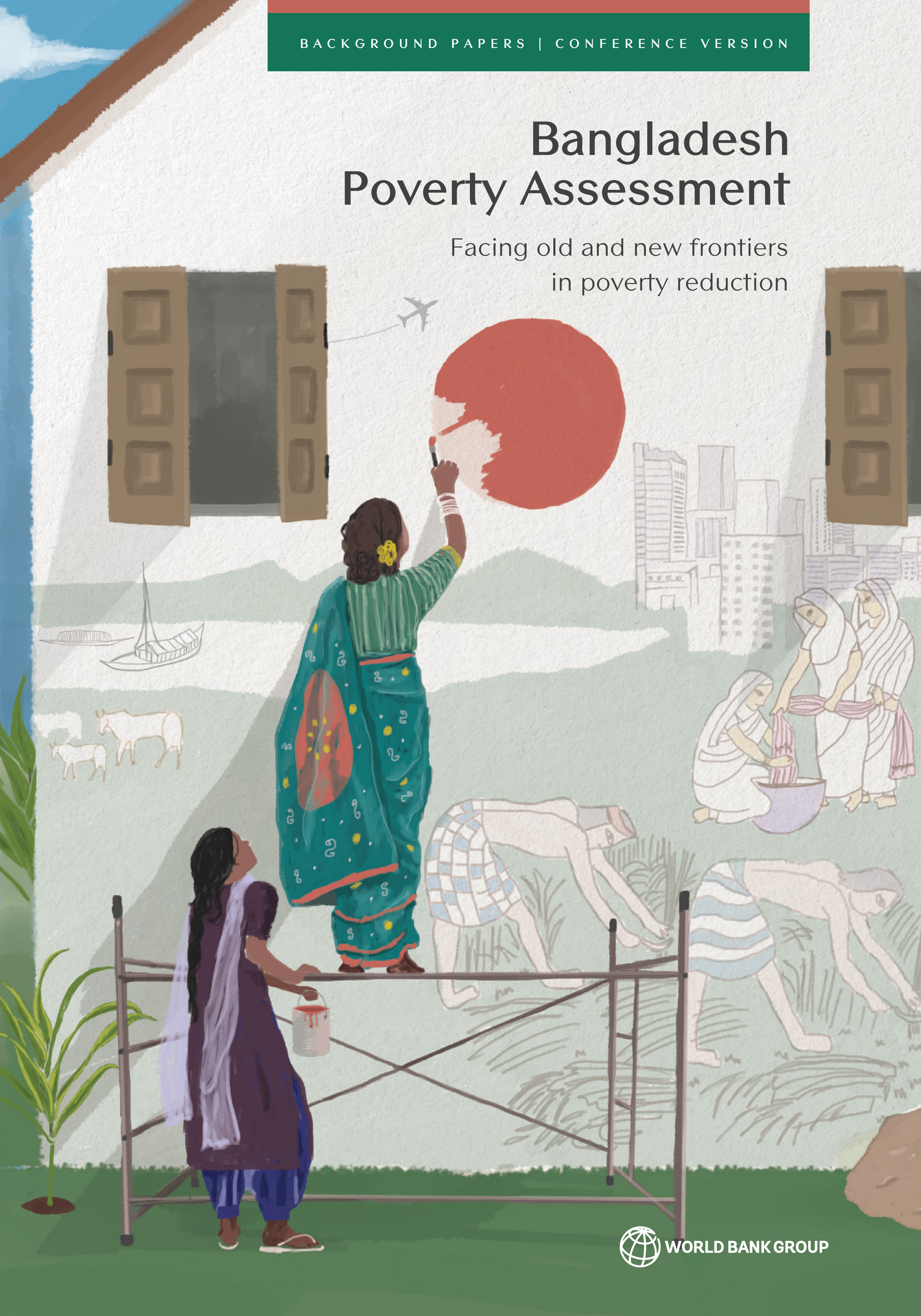

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Bangladesh Poverty Assessment

Facing old and new frontiers in poverty reduction

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List of abbreviations

ADB	Asian Development Bank
APSC	Annual Primary School Census
BANBEIS	Bangladesh Bureau of Educational Information and Statistics
BBS	Bangladesh Bureau of Statistics
BDT	Bangladesh Taka (currency)
BES	Bangladesh Enterprise Survey
BIDS	Bangladesh Institute of Development Studies
BMET	Bangladesh Bureau of Manpower, Employment and Training
BRAC	Bangladesh Rural Advancement Committee
BUISBS	Bangladesh Urban Informal Settlements Baseline Survey
CAFE	Computer-Assisted Field-Based Data Entry
CBMS	Cox's Bazar Monitoring Survey
CBN	Cost of Basic Needs
CC	City Corporation
CPI	Consumer Price Index
CRU	Climate Research Unit of the University of East Anglia
DAM	Department of Agricultural Marketing
DDS	Dietary Diversity Score
DIGNITY	Dhaka low Income area GeNder, Inclusion, and povertY survey
EA	Enumeration Area
FAO	Food and Agriculture Organization of the United Nations
FE	Fixed Effect
FGT	Foster Greer Thorbecke
FIRE	Finance, Insurance, Real Estate and Education
FLFP	Female Labor Force Participation
FSS	Food Security Sector
FY	Fiscal Year
GBV	Gender-Based Violence
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GoB	Government of Bangladesh
HCR	Headcount Rate
HDDS	Household Dietary Diversity Score
HES	Household Expenditure Survey
HIES	Household Income and Expenditure Survey
HOI	Human Opportunity Index
HSC	Higher Secondary Certificate
ILO	International Labor Organization
IMPS	Integrated Multiple-Purpose Sample
IOM	International Organization for Migration
ISCG	Inter Sector Coordinating Group
JICA	Japan International Cooperation Agency
JSC	Junior Secondary School
LFP	Labor Force Participation
LFPR	Labor Force Participation Rate
LFS	Labor Force Survey
MEB	Minimum Expenditure Basket
MFI	Microfinance Institutions
MICS	Multiple Indicator Cluster Survey
MoE	Ministry of Education

MoF	Ministry of Finance
MoPME	Ministry of Primary and Mass Education
MPC	Marginal Propensity to Consume
MPOs	Monthly Pay Orders
MTMF	Medium-Term Macroeconomic Framework
NGO	Non-Governmental Organization
NIPORT	National Institute of Population Research and Training
NPM	Needs and Population Monitoring
NU	National University
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
PAPI	Paper and Pencil
PECS	Post-Enumeration Check Survey
PESP	Primary Education Stipends Program
PG	Poverty Gap
PPP	Purchasing Power Parity
PPRC	Power and Participation Research Centre
PSU	Primary Sampling Units
QLFS	Quarterly Labor Force Survey
REVA	Rohingya Crisis Vulnerability Assessment
RIF	Recentered Influence Functions
RIVNA	Rapid Impact, Vulnerability and Needs Assessment
RMG	Ready-Made Garment
RUC	Rural/Urban/City Corporation
SAE	Small Area Estimation
SMAs	Statistical Metropolitan Areas
SPG	Squared Poverty Gap
SSC	Senior Secondary School
SVRS	Sample Vital Registration System
Tk	Taka, Bangladeshi Currency
TVET	Technical and Vocational Education and Training
UAE	United Arab Emirates
UGC	University Grants Commission
UN	United Nations
UNDESA	United Nations Department of Economic and Social Affairs
UNESCO	United Nations Educational, Scientific and Cultural Organization
VAM	Vulnerability Analysis and Mapping team
WASH	Water, Sanitation, and Hygiene
WDI	World Development Indicators
WEO	World Economic Outlook
WFP	World Food Program

CHAPTER I.

Description of the Official Methodology Used for Poverty Estimation in Bangladesh for 2016/17, through the Bangladesh Household Income and Expenditure Survey (HIES) 2016/17

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I. Bangladesh's Household Income and Expenditure Survey

The Household Income and Expenditure Survey (HIES) is a comprehensive, nationally representative survey used to measure monetary poverty in Bangladesh. The HIES 2016/17 is the fourth round in the series of HIES conducted by the Bangladesh Bureau of Statistics (BBS) in 2000, 2005, and 2010. Before 2000, BBS monitored poverty using a smaller survey, the Household Expenditure Survey (HES), which was limited to expenditure data. The World Bank provided technical assistance to the BBS in the development of the HIES 2016/17 questionnaire, sampling design, data collection protocols, and poverty estimates.

1.1 Sampling design

A stratified, two-stage sample design was adopted for the HIES 2016/17, with 2,304 Primary Sampling Units (PSU) selected from the list of the 2011 Housing and Population Census enumeration areas. Within each PSU, 20 households were selected for interviews. The final sample size was 46,080 households (Ahmed et al. 2017).

In Bangladesh, divisions are the first-level administrative geographical partitions of the country. As of 2016, the country has eight divisions: Barishal, Chattogram, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet. Each division is subsequently divided into 64 districts, or *zilas.* Each district is further subdivided into smaller geographic areas, with clear rural and urban designations. In addition, urban areas in the main divisions of Chattogram, Dhaka, Khulna, and Rajshahi are classified into City Corporations (CCs), and other urban areas.

PSUs in the HIES 2016/17 were allocated at the district level. Therefore, the sample was stratified at the district level. Since there were a total of 64 districts in Bangladesh, the sample design included a total of 132 sub-strata: 64 urban, 64 rural, and four main CCs. The sample was also implicitly stratified by month.

Table 1 presents a summary of sample design and PSU allocation.[4]

Departures from the previous HIES. The samples of the latest three rounds of the HIES were designed to provide reliable annual poverty estimates for the country's divisions by urban and rural areas separately and the Statistical Metropolitan

[4] There was a replacement strategy for households that were not found or refused to answer. However, the households that were replaced were not identified during the fieldwork.

Table 1. HIES 2016/17 summary of sampling design

Description	Number
Number of districts	64
Number of PSUs in each district	36
Number of households in each PSU	20
Total number of PSUs in sample	2,304
Total sample size	46,080
Total number of teams	128
Total number of enumerators	256

Areas (SMAs).[5] However, the HIES 2016/17 was designed to produce reliable poverty estimates at three different levels: (i) annual poverty estimates at the division level for urban and rural areas; (ii) annual poverty estimates for the country's 64 districts; and (iii) quarterly poverty estimates at the national level. This change implied quadrupling the sample size of HIES 2016/17 compared to previous rounds – from 12,240 in 2010 to 46,080 households.

The substantial increase in the sample size also required using a different sampling frame to accommodate the larger number of PSUs. The PSUs for all the previous rounds of the HIES were selected from the Integrated Multiple-Purpose Sample (IMPS) – a master sample updated after each Housing and Population Census. In the HIES 2016/17, the PSUs come from the list of Enumeration Areas (EAs) used for Bangladesh's 2011 Population and Housing Census. The IMPS could not be used because the most recent version, based on the 2011 Census, included only 2,012 EAs, an insufficient number to serve as a sampling frame for this new round of the survey. Importantly, the Bangladesh IMPS excluded some geographic areas, such as urban slums. Therefore, the HIES 2016/17 has a higher likelihood of capturing slum areas.[6]

1.2 Period of data collection

The HIES 2016/17 was in the field for an uninterrupted period of 12 months. The survey was launched on April 1, 2016, and field operations were completed on March 31, 2017. Data was collected over a year to capture seasonal variations in expenditure, expenditure patterns, and income. The one-year period was divided

[5] In 2017 the country had seven divisions: Dhaka, Chittagong, Barisal, Khulna, Sylhet, Rangpur, and Rajshahi.

[6] For details of the sampling design see Ahmed et. al (2017).

into 18 terms of 20 days. A term is the time needed for a team of two enumerators to cover the 20 households selected within a PSU.

1.3 Questionnaires

The 2016/17 HIES consisted of nine major modules, covering various aspects of household activities and characteristics (household roster, education, health, economic activities, non-agricultural enterprises, housing, agriculture, other assets and income, and consumption). The 2016/17 HIES redesigned and expanded the Social Safety Net questions. The final questionnaire reflects several technical discussions on questionnaire design and content.

1.4 Data entry and management

The data collection, entry, and transfer process for the HIES 2016/17 was conducted using Paper and Pencil (PAPI) combined with CAFE (Computer-Assisted Field-Based Data Entry). The data was collected by interviewers using PAPI and later entered or digitized using laptops while interviewers were still in the field. The data entry application was developed in CSPro and was paired with a cloud-based data transferring system, which allowed teams to transfer data to the BBS headquarters and monitor data in almost real time using a mobile internet connection. After the data was transferred to BBS headquarters, it was compiled and exported to a readable version by standard statistical software using an automatized routine.

The data entry and transfer system was combined with a data monitoring system for a selected set of variables important for poverty measurement. This data monitoring system fed from the compiled data to create a set of key indicators that were tracked on a continuous basis. The indicators that were tracked by team, term, division, and district included: number of households, household size, number of households with incomplete food and non-food consumption, number of households with incomplete durable items, number of daily food items consumed by households, number of weekly food items consumed by households, and number of non-food items and durables consumed by households. This information supported supervision of fieldwork and ensured that consumption data was complete and high quality for poverty estimation.[7]

[7] It is important to note that other variables collected were not monitored, including income-related information. Ex-post analysis of the data indicates that the data entry of income-related variables suffered weaknesses due to lack of range checks and merging issues in the CSPro data entry program.

II. Methodology to estimate poverty

2.1 Welfare aggregate

Poverty estimates in Bangladesh were based on household per capita consumption. The consumption section of the HIES questionnaire was divided into five parts:

A. Daily food consumption: Information on daily food consumption for 130 items was collected for 14 consecutive days. Interviewers registered consumption in quantities and corresponding values with sources of receipts
B. Weekly food consumption for around 19 items
C. Monthly non-food consumption for about 49 items
D. Annual non-food expenditure for more than 177 items
E. Inventory of durable goods

The consumption aggregate for the HIES 2016/17 was constructed by adding all food and non-food consumption expenditures reported by households, except for taxes and fees, lumpy-cycle expenditures such as expenses for weddings, and interest and insurance expenses. Non-food expenditures included: fuel and lighting, cosmetics and hygiene items, transport and travel, ready-made garments, clothing materials, footwear, household-use textiles, health treatment expenses, housing-related expenses, education, recreation, and leisure. The non-food expenditure component also included housing rent, imputed rent (i.e., the amount that homeowners report they would like to get if they could rent their house), or predicted rent, depending on the homeownership status of each of the households.[8] For renters, the reported rent was included as part of the non-food consumption aggregate. For homeowners, the reported imputed rent was included as part of the non-food consumption aggregate. For households that did not report rent or imputed rent, a predicted rent was estimated using a regression model on the subsample of renters and added to the non-food consumption aggregate. This regression model was estimated using the (log of) reported rent on the left-hand side and was regressed against a set of housing characteristics, including number of rooms, wall materials, access to electricity and tap water, kitchen, dining room, telephone connection, dwelling's land size, and a vector of the 16 original strata dummy variables.

The construction of the consumption aggregate followed the 2010 methodology as closely as possible. However, there was one important departure in the

[8] The rent and imputed rent variables were cross-tabulated against house ownership, and a few observations were cleaned to ensure full consistency between these two variables.

methodology related to the computation of education expenditures. Education expenditures were collected in Sections 2 and 9 of the survey. Traditionally, for the computation of the consumption aggregate, education expenditures are added using the information from Section 9. In the 2016/17 round, it was found that 5.6 percent of households had reported zero or missing education expenditures in Section 9, but had positive expenditures reported in Section 2. In 2010, this was true for only 1.2 percent of households. Therefore, the 2016/17 consumption aggregate used information from Section 2 to replace the zero and missing values in Section 9. Section 5 shows that this departure in the computation of the aggregate does not significantly change poverty estimates.

Finally, the consumption aggregate was divided by the household size to obtain a per capita measure. The HIES survey defines a household as a group of people who eat from the same pot and sleep in the same dwelling. Household members are defined as people who have eaten and slept in the dwelling for at least six months during the past 12 months (not necessarily continuous), or members who have been in the dwelling for less than six months over the past year, including any of the following: (i) the head of the household; (ii) a major provider of economic support; (iii) infants under six months old; or (iv) a new bride who joined the household less than six months ago. In addition, servants are counted as household members.

The average household size for the HIES 2016/17 was 4.06 members. This implies a significant reduction in the average household size compared to the latest HIES 2010 (average household size was 4.5), which is not explained by differences in the definition of households. Recent national representative surveys collected by BBS show consistent large reductions in household size for the past years in Bangladesh. For example, the Quarterly Labor Force Survey 2015/16 shows an average household size of 4.2. Annex 2 summarizes an analysis that compares the HIES household size estimate with other surveys and projections and concludes that the estimations from HIES 2016/17 are in line with trends in fertility and population change.

Table 2 presents the average household consumption per capita for 2010 and 2016/17.

2.2 Estimation of the poverty lines

The official methodology used in Bangladesh to estimate poverty numbers was based on the Cost of Basic Needs (CBN). The CBN method calculates the cost of obtaining a consumption bundle considered to be adequate to satisfy basic

Table 2. Household consumption per capita, HIES 2010 and 2016/17 in monthly Takas of 2016

Consumption per capita	2010		2016/17	
	Average	Standard error	Average	Standard error
Total	3431	62	3760	41
Food	1901	22	1809	13
Non-food	1536	47	1951	34

Note: All expenditures are deflated across space and expressed in 2016 prices.

consumption needs. If a person cannot afford the cost of this bundle, then this person is considered poor. Therefore, poverty lines under the CBN method represent the minimum per capita expenditure that a person needs to meet his basic needs.

The first step for computing a poverty line involved estimating the cost of a basic consumption food basket. In Bangladesh, the food basket included eleven items (coarse rice, wheat, pulses, milk, oil, meat, fish, potatoes, other vegetables, sugar, and fruits), as recommended by Ravallion and Sen (1996) following Alamgir (1974). This food bundle provided the minimal nutritional requirements corresponding to 2,122 kcal per day per person. The price for each item in the bundle was estimated using unit-values (price per unit) from the HIES. The price for each item was the median of the unit-values reported by a reference group of households calculated separately for each stratum of the survey. The food poverty line was then computed for each stratum by multiplying the estimated prices with the quantities in the food bundle.[9]

Starting in 2000, the HIES defined 16 different geographical strata that have been used since then to estimate the cost of the basic consumption bundle. The estimation of this bundle at different geographical levels allows analysts to account for cost-of-living differences across areas and therefore provides a more accurate picture of living standards after accounting for price differences across geographic areas. These 16 original strata include urban and rural areas in the six divisions that existed in 2005 (Barishal, Chattogram, Dhaka, Khulna, Rajshahi, and Sylhet)

[9] The reference groups are the households belonging to the 2nd to 6th deciles of the per capita consumption distribution that fall within the strata and reflect the median prices that are faced by households located within a reasonable range around the level of consumption where the poverty line is expected to be.

and the four main SMAs (Chattogram, Dhaka, Khulna, and Rajshahi). Out of the 16 original strata, six are classified as rural, and ten are classified as urban.[10]

Once the food poverty lines were estimated for each stratum, the second step consisted of computing non-food allowances using two different methods. In the first method, the non-food allowance was estimated by taking the median amount spent for non-food items by a reference group of households whose *total* per capita expenditure was close to the food poverty line. The non-food allowance estimated using this method is called the "lower non-food allowance." In the second method, the non-food allowance was estimated by taking the median amount spent for non-food items by a reference group of households whose *food* per capita expenditure was close to the food poverty line. The non-food allowance estimated using this method is called the "upper non-food allowance." Lastly, the food poverty lines were added to the lower and upper non-food allowances, and this yielded the official upper and lower poverty rates at the stratum level (16 upper poverty lines and 16 lower poverty lines). Table 3 shows a summary of when poverty lines were estimated for Bangladesh for the latest four rounds of the HIES. It is important to note that the update of the poverty lines across time involved a combination of re-estimation of lines in some years and inflation updates in other years.[11]

Table 3. Poverty lines in HIES

Year	2000[12]	2005	2010	2016/17
Food PL	Updated from 1991/92	Re-estimated (CBN)	Updated from 2005	Updated from 2010
Non-food PL	Updated from 1991/92	Re-estimated (CBN)	Re-estimated (CBN)	Updated from 2010

2.3 Updating the poverty lines

The 2016/17 poverty lines took the 2010 poverty lines and adjusted them by inflation to keep them in real terms. The upper and lower poverty lines for each

[10] In the HIES 2000, 2005, and 2010, the large cities were defined based on the concept of Statistical Metropolitan Areas (SMA), following the IMPS sampling frame. This concept of SMA was replaced by the concept of Rural/Urban/City Corporation (RUC) in the 2011 Census of Population and Housing. Of the 64 districts, only in three did the old SMA concept not match perfectly with the new RUC. Section 4 discusses the comparability of strata across HIES and its implications for poverty measurement.

[11] For a detailed discussion on how the lines were updated across time from 2000-2010, please refer to Jolliffe et al. (2013)

[12] The 2005 poverty lines were also back-casted to 2000.

quarter were estimated by updating the official upper and lower poverty lines available for the HIES 2010 using price indices constructed for each quarter. The annual upper and lower poverty lines were updated using a set of price indices constructed with the full HIES 2016/17.

For each quarterly and annual poverty line, a set of composite price indices was constructed for each of the 16 original strata[13] using a combination of the Törnqvist food price index and the non-food Consumer Price Index (CPI) for urban and rural areas.[14] The stratum-specific Törnqvist food price indices were constructed using a set of 13 food expenditure groups, including coarse rice, pulses, meat, potatoes, milk, fruits, sugar, fish, eggs, cooking oil, salt/spices, soft drinks, and betel/cigarette.[15] These food expenditure groups were selected because they represented some of the most frequently consumed items by households but also because they allowed minimizing the inherent issue of differences in item quality. For each of the food expenditure groups and stratum, the median unit-values were calculated, as well as the average budget shares using the 2010 and the 2016/17 data.[16]

Before calculating the median unit-values, outliers were identified and replaced.[17] An outlier was identified if the unit-value was above 2.5 standard deviations of the distribution within the strata. Those cases were replaced using median values from the lowest level (household) to the highest level (national) distribution. If the household reported more than nine observations for the item, the median of those values was used to impute the outlier at this level. If the household did not have enough observations, then the outlier was replaced by the median of the PSU, district, stratum, area (urban/rural), or national, with the condition that there were enough observations to compute the median at that level.

[13] Section 4 discusses the comparability of strata across time and the implications for poverty measurement.

[14] The Törnqvist price index was selected instead of the Laspeyres or Paasche indexes because it uses budget shares averaged between consecutive years, and therefore allows for changes in consumption patterns over time.

[15] Traditionally, the group of 13 food items used in the HIES to update the poverty lines does not perfectly overlap with the 11 food items used to estimate the poverty lines.

[16] Using the median unit-values instead of the mean unit-values for each group allows minimizing the issue of the difference in item qualities which is inherently present in the estimation of all unit values and also the effect of outliers.

[17] The replacement was done for 1.94 percent of unit values reported in the daily consumption section and 2.36 percent of unit values reported in the weekly consumption section.

The Törnqvist food price indices for each of the food expenditure groups and each stratum *k* were calculated as follows:

$$\ln P_{10}^{Tk} = \sum_{j=1}^{n} \frac{w_{1j}^{k} + w_{0j}^{k}}{2} \ln\left(\frac{p_{1j}^{k}}{p_{0j}^{k}}\right) \quad (1)$$

where P^{Tk} denotes the Törnqvist price index for region *k*, *1* and *0* denote the two years of comparison (2010 and 2016/17 in this case), w^{k}_{1j} and w^{k}_{0j} are the respective budget shares, and p^{k}_{1j} and p^{k}_{0j} are the respective prices for good *j* in the two years of comparison.

Once the HIES-based Törnqvist food price indices were computed for each stratum, a set of stratum-specific composite price indices were constructed to update the poverty lines. These composite price indices were constructed by creating a weighted average of the non-food CPI inflation rate for urban and rural areas between 2010 and 2016/17 and the Törnqvist food price indices for each stratum. The relative weights used for this calculation of the composite price index were the stratum-level average food budget shares for 2010 and 2016/17. The non-food CPI inflation rate was computed using the average CPI from February 2010-January 2011 (data collection for the HIES 2010) and the average non-food CPI for each quarter in 2016/17 (e.g., April-June 2016/17 for Q1, July-September 2016/17 for Q2, October-December 2016/17 for Q3, and January-March 2017 for Q4), separated for urban and rural areas. The annual non-food CPI for 2016/17 was computed taking the average from April 2016 to March 2017. These composite price indices are used to update the 2010 lower and upper poverty lines to 2016/17. Quarterly poverty lines are presented in Annex 1 and annual poverty lines in table 4.

Table 4. Annual poverty lines 2016/17

Stratum	HIES 2016/17	
	Lower	Upper
Barishal Rural	1778	2056
Barishal Urban	1993	2756
Chattogram Rural	2030	2439
Chattogram Urban	2135	2606
Chattogram City Corp.	2097	2660
Dhaka Rural	1835	2152
Dhaka Urban	1947	2657
Dhaka City Corp.	2020	2929
Khulna Rural	1677	2019
Khulna Urban	1817	2419
Khulna City Corp.	1942	2360
Rajshahi Rural	1716	2065
Rajshahi Urban	1864	2251
Rajshahi City Corp.	1764	2244
Sylhet Rural	1764	1865
Sylhet Urban	1911	2315

III. Poverty estimates

The latest HIES 2016/17 annual poverty estimates show that Bangladesh is continuing its remarkable progress in poverty reduction. Per the latest 2016/17 estimates, 24.3 percent of the population lived in poverty, and 12.9 percent were in extreme poverty (Table 5). This represents a 24.6 percentage point reduction in the upper poverty rate since 2000 and 7.2 percentage points since 2010. Annex 2 presents the estimated poverty rates for all analytical domains.

Importantly, the HIES design is characterized by the following: (i) sampling weights; (ii) sampling of households within clusters or PSUs; and (iii) geographic

Table 5. National poverty rates HIES 2000-2016/17

A. Upper poverty				
Year	Rate	Standard error	95% Confidence interval	
2000	0.489	0.012	0.464	0.513
2005	0.400	0.011	0.378	0.422
2010	0.315	0.010	0.296	0.334
2016/17	0.243	0.005	0.233	0.254
B. Lower poverty				
Year	Rate	Standard error	95% Confidence interval	
2000	0.343	0.012	0.319	0.367
2005	0.251	0.009	0.233	0.270
2010	0.176	0.008	0.160	0.191
2016/17	0.129	0.004	0.122	0.136

Table 6. Quarterly national poverty rates HIES 2016/17

A. Upper poverty				
Quarters	Mean	Standard error	95% Confidence interval	
Q1 (April-June 2016)	0.225	0.014	0.199	0.252
Q2 (July-September 2016)	0.230	0.012	0.206	0.253
Q3 (October-December 2016)	0.261	0.012	0.238	0.284
Q4 (January-March 2017)	0.271	0.014	0.244	0.298
B. Lower poverty				
Quarters	Mean	Standard error	95% Confidence interval	
Q1 (April-June 2016)	0.1244	0.0092	0.1064	0.1423
Q2 (July-September 2016)	0.1231	0.0092	0.1051	0.1411
Q3 (October-December 2016)	0.1345	0.0085	0.1179	0.1511
Q4 (January-March 2017)	0.1406	0.0103	0.1204	0.1607

stratification. These three elements need to be considered to compute adequate statistics using the survey. Using sampling weights (variable POPWGT) is important to calculate correct point estimates (e.g., poverty rate). In addition to the weights, the clustering (PSU variable) and stratification (ZILAID for annual estimates and STRATUM16 for quarterly estimates) of the survey design need to be considered to calculate the correct standard errors. If the analysis ignores the clustering of the survey design, it would produce standard errors that are smaller than they should be (for more details see Ahmed et al. 2017).

IV. Poverty rates using comparable strata and corrected urban classification

As previously discussed, the substantial increase in the sample size of the HIES 2016/17 required using a different sampling frame to accommodate the larger number of PSUs. The PSUs for all the previous rounds of the HIES were selected from the Integrated Multiple-Purpose Sample (IMPS) – a master sample updated after each Housing and Population Census. In the HIES 2016/17, the PSUs come from the list of Enumeration Areas (EAs) used for Bangladesh's 2011 Population and Housing Census.

The use of a different sampling frame affected the comparability of strata across HIES. In this section, we describe the adjustments that need to be made to the HIES 2016/17 microdata to create comparable strata across time. In addition, we include a fix to the urban and rural definition to ensure a comparable and consistent classification of urban areas when using HIES. Finally, we present the poverty rates estimated using the comparable strata and correct urban/rural classification.

Within urban areas the comparability across time was affected, as the concept of SMA was abandoned in the 2011 census. The concept of SMA was replaced by the concept of Rural/Urban/CC (RUC) in the 2011 Census of Population and Housing. The strata used in HIES 2000, 2005, and 2010 were the divisions separated by urban, rural, and SMAs. Instead, the strata used in HIES 2016/17 were the divisions separated by urban, rural, and CCs.

Moreover, the Post-Enumeration Check Survey (PECS) conducted after the completion of the 2011 Household and Population Census found that there was under-coverage both in urban and rural areas, but that it was more prevalent in urban areas. BBS thus used a two-step approach to adjust the 2011 census estimates. First, it reclassified urban and rural areas using the concepts of: (i) growth centers, (ii) urban agglomerations, and (iii) other urban areas. Second, it inflated all urban and rural counts from the 2011 Census of Population Areas to align with the PECS results. These two adjustments estimated the share of the urban population at 28 percent, which is the number that BBS has been using since then to produce official population projections and statistics. These adjustments (reclassification of areas and re-weighting) were also done in the HIES 2016/17 data to ensure a consistent urban share with the corrected 2011 census and with previous HIES rounds. However, 13 out of 2,304 enumeration areas in the HIES microdata were classified as rural when in fact they were urban. This classification error underestimates the urban share of the population. The urban share that is calculated directly from the HIES microdata is 27.3 percent of the population, which is actually lower than the official share for 2011. The corrected share is 29.1 percent of the population, which is more consistent with the urbanization process observed in Bangladesh in the past years.

Table 7. Poverty Rates with correct urban classification and SMA comparable with 2010

	Upper poverty			Lower poverty		
	Official	Fixing urban classification only	Fixing urban classification and SMA comparable with 2010	Official	Fixing urban classification only	Fixing urban classification and SMA comparable with 2010
	(1)	(2)	(3)	(4)	(5)	(6)
National	0.243 (0.01)	0.245 (0.01)	0.246 (0.01)	0.129 (0.00)	0.130 (0.00)	0.130 (0.00)
Rural	0.264 (0.01)	0.267 (0.01)	0.267 (0.01)	0.149 (0.00)	0.150 (0.00)	0.150 (0.00)
Urban	0.189 (0.01)	0.193 (0.01)	0.195 (0.01)	0.076 (0.01)	0.080 (0.01)	0.080 (0.01)
Poverty by division						
Barishal	0.265 (0.02)	0.264 (0.02)	0.264 (0.02)	0.145 (0.01)	0.144 (0.01)	0.144 (0.01)
Chattogram	0.184 (0.01)	0.183 (0.01)	0.186 (0.01)	0.087 (0.01)	0.090 (0.01)	0.090 (0.01)
Dhaka	0.199 (0.01)	0.205 (0.01)	0.206 (0.01)	0.096 (0.01)	0.099 (0.01)	0.099 (0.01)
Khulna	0.275 (0.01)	0.277 (0.01)	0.275 (0.01)	0.124 (0.01)	0.121 (0.01)	0.122 (0.01)
Rajshahi	0.289 (0.02)	0.290 (0.02)	0.290 (0.02)	0.142 (0.01)	0.143 (0.01)	0.143 (0.01)
Rangpur	0.472 (0.01)	0.473 (0.01)	0.473 (0.01)	0.306 (0.01)	0.306 (0.01)	0.306 (0.01)
Sylhet	0.162 (0.02)	0.162 (0.02)	0.162 (0.02)	0.115 (0.01)	0.115 (0.01)	0.115 (0.01)

Annex 4 includes a STATA code that produces a comparable strata variable (replacing STRATUM16) with the previous HIES and corrects the misclassification error in the urban/rural variable. Based on these corrections, new poverty rates were estimated and are presented in Table 7. With these adjustments, the national poverty rate is 0.3 percentage points higher. The urban poverty rate increases from 18.9 to 19.5 percent and the rural poverty rate also increases from 26.4 to 26.7 percent. The division-level poverty rates are also presented in Table 7. None of the changes are statistically different from zero.

V. Robustness checks

In this section, we investigate the sensitivity of the poverty rates to the imputation of education expenditures, correction of outliers in unit-values, and deflation within the year.

Correction of zeros and missings in education. Education expenditures were collected in Sections 2 and 9 of the survey. Traditionally, for the computation of the consumption aggregate, education expenditures are added using the information from section 9. In 2016/17, 5.6 percent of households reported missing or zero education expenditures in Section 9, but had positive values in Section 2. In 2010, this was only true for 1.2 percent of households. The current estimates for 2016/17 replace zeros and missing values in the consumption module with the information from the education section. This imputation is considered to be important for comparability with 2010.

Outlier adjustment of unit-values. When comparing the distribution of unit values between 2010 and 2016/17, it was found that the 2016/17 data had more extreme values. Table 8 presents the distribution of unit values at the national level for some key items as an example.

Two approaches to deal with unit values were compared: (i) identification of outliers using their distribution at the stratum level and imputation of unit values using median values from the lowest level possible (household) to the highest (national); (ii) identification of unit values using the distribution at the division level and imputation of median values of the division.

Quarterly inflation adjustment. Another option that was explored was to deflate the consumption aggregate within the year, to express all values to one quarter of the year. The objective of the adjustment was to test the importance of accounting for inflation within the year to calculate the 2016/17 poverty numbers.

Table 8. Right-tail distribution of unit values at the national level, HIES 2010 and 2016/17

	2010				2016/17			
Item	mean	p95	p99	max	mean	p95	p99	max
Coarse rice	3	4	4	38	3	4	5	3600
Lentil (musur)	11	12	13	24	13	16	20	1841
Puti/Big Puti/Telapia/ Nilotica	10	16	20	48	13	20	30	1400
Hen eggs	633	700	800	7000	877	1000	1050	85000
Beef	24	26	27	42	48	50	80	45000
Potato	1	2	2	14	2	3	4	3250
Liquid milk	4	5	6	12	7	8	12	9000
Sugar	5	6	6	14	8	10	25	10000
Mustard oil	13	20	20	25	16	25	50	10000
Ripe banana	5	9	10	13	17	15	500	10000
Soft drinks	5	8	9	16	14	12	50	6500
Cigarettes	149	325	600	1000	300	600	1100	35300

Note: Authors' calculations using HIES 2010 and 2016/17.

Table 9 presents the estimated upper and lower poverty rates under the different adjustments. Overall, the imputation of education expenditures, outlier corrections, or deflating expenditures within the year do not change the poverty rates in a statistically significant sense. Analysis available by request also shows limited changes to the consumption distribution. Therefore, the preferred methodology was option 3, where education expenditures were imputed, and outliers were corrected using the distribution at the stratum level. This option was considered the most comparable to the 2010 methodology.

VI. Official household income estimates

Income in Bangladesh was defined as money inflows into the household occurring during the last 12 months. Household income was computed using a set of questions from the HIES and by adding together all the sources of family income described in detail below.

A. **Labor income:** The total labor income was defined as the total amount earned or received (in-cash or in-kind) for the last 12 months from each activity by household members aged five years and above who were engaged in economic activities and were classified as day-laborer or

Table 9. National poverty rate 2016/17, different approaches

A. Upper poverty				
Options	Mean	SE	95% Confidence interval	
1. Original	0.251	0.005	0.240	0.262
2. Imputing zeros and missings in education	0.248	0.005	0.237	0.259
3. Imputing zeros and missings in education + Outlier adjustment using stratum	0.243	0.005	0.233	0.254
4. Imputing zeros and missings in education + Outlier adjustment using division	0.240	0.005	0.230	0.251
5. Imputing zeros and missings in education + Outlier adjustment using stratum + quarterly inflation adjustment	0.247	0.005	0.236	0.258
B. Lower poverty				
Options	Mean	SE	95% Confidence interval	
1. Original	0.135	0.004	0.128	0.143
2. Imputing zeros and missings in education	0.133	0.004	0.125	0.140
3. Imputing zeros and missings in education + Outlier adjustment using stratum	0.129	0.004	0.122	0.136
4. Imputing zeros and missings in education + Outlier adjustment using division	0.127	0.004	0.120	0.134
5. Imputing zeros and missings in education + Outlier adjustment using stratum + quarterly inflation adjustment	0.131	0.004	0.123	0.138

Note: Quarterly inflation adjustment means that the consumption aggregate for Q2, Q3, and Q4 was expressed in prices of Q1.

employees in agricultural and non-agricultural activities. The total labor income included other benefits that salaried workers received over the past 12 months (tips, bonuses, or transport). It was found that 7 percent of wages for day-laborers and employees were missing. This was not the case in 2010, where only 1 percent of this information was not reported. In this case, missing daily wages, net remunerations for salaried workers and other benefits were replaced by the median of the stratum and industry at the two-digit level when there were more than 30 observations. If that industry did not have enough observations at the stratum level, then the missing wage was replaced by the area (urban/rural) median—conditioned to have more than 30 observations. Otherwise, national median per industry was used.

B. **Business income:** For households owning or running businesses, net revenue over the last 12 months was calculated as the difference between total gross revenue and total expenditures. The latter were estimated by adding up expenditures on wages, rent, raw materials, kerosene, electricity, expenditure on finished goods purchased for reselling, and other operating expenses in the past 12 months. This number was multiplied by the share of the company's profit that was owned by the household. One extreme gross revenue value reported by one household was fixed because there was an additional digit compared to the number reported in the physical questionnaire.

C. **Agricultural income:** This source of income was defined as total crop production consumed and sold by the household, and was computed by multiplying crops' unit values from total production by quantities sold and consumed. In the presence of missing values for quantities consumed and sold but complete information for total production, the total value of the latter was used. In addition, outliers in unit values were identified, when the value was above 3.5 standard deviations of each crop distribution within the strata. These cases were imputed by the median at the stratum level for each crop if the number of observations exceeded 30. Otherwise, the area (urban/rural) median unit value by crop was used if there were more than 30 observations. Crops without enough observations used the national median. Total livestock and poultry sold, and the total value of livestock products, fish, and forest products sold and consumed in the last 12 months were also included in the agricultural income.
D. **Non-labor income:** The family non-labor income was the sum of rent from land, rent from other properties, other profits and dividends received as partner or shareholder, interest from banks and other sources, social incomes such as insurances, lotteries, charities, or assistance in cash or kind, and gratuities, separation payments, or retirement benefits, all of them received during the past 12 months.
E. **Other sources of income:** Other sources of income included the total amount of remittances in cash and in kind sent in the last 12 months by household members who migrated to other districts inside the country or abroad. Total payments received in cash or in kind in the last 12 months for all the household members currently enrolled in social safety nets programs, stipends for household members who were currently studying, and self-reported imputed rent were also included.

Table 10 shows the average income, expenditure, and consumption expenditure. Expenditure was defined as total consumption plus lumpy life-cycle expenditures, income tax, and interest charges. Average income was computed only for positive values. In total, 0.61 percent of the sample had a negative income, and

0.59 percent reported zero income. Negative incomes were the result of negative profits for self-employed individuals and might not reflect the permanent income of the household. Zero incomes arose when none in the household earned any income during the last 12 months, or individuals earned non-monetary income such as charities, transfers, or social assistance, but there was a misreport, and this information was not recorded (Socio-Economic Database for Latin America and the Caribbean methodological documents 2014).

Table 10. Monthly household nominal income, expenditure, and consumption, 2016

Residence	Average Monthly (Taka)		
	Income	Expenditure	Consumption expenditure
National	15,945	15,715	15,420
Rural	13,353	14,156	13,868
Urban	22,565	19,697	19,383

Note: Figures are not deflated spatially, as presented in the HIES 2016 preliminary report.

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Abbreviations

BBS – Bangladesh Bureau of Statistics
CAFE – Computer-Assisted Field-Based Data Entry
CBN – Cost of Basic Needs
CCs – City Corporation
CPI – Consumer Price Index
DHS – Demographic and Health Survey
EAs – Enumeration Areas
GPVDR – Poverty and Equity Global Practice
HES – Household Expenditure Survey
HIES – Household Income and Expenditure Survey
IMPS – Integrated Multiple-Purpose Sample
PAPI – Paper and Pencil
PSU – Primary Sampling Units
MICS – Multiple Indicator Cluster Survey
SMAs – Statistical Metropolitan Areas
QLFS – Quarterly Labor Force Survey

Annex 1. HIES 2016/17 quarterly poverty lines

stratum16	Lower poverty lines				Upper poverty lines			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Barishal Rural	1770	1802	1827	1829	2047	2085	2113	2116
Barishal Urban	1983	1977	2041	2020	2742	2733	2822	2793
Chattogram Rural	1974	2010	2087	2056	2373	2415	2508	2471
Chattogram Urban	2044	2153	2202	2193	2495	2629	2688	2677
Chattogram City Corp.	2039	2104	2172	2105	2587	2670	2756	2670
Dhaka Rural	1793	1837	1898	1882	2103	2154	2226	2208
Dhaka Urban	1894	1949	1928	1991	2584	2659	2631	2717
Dhaka City Corp.	1973	2013	2043	2032	2860	2919	2962	2946
Khulna Rural	1621	1663	1757	1703	1952	2003	2115	2051
Khulna Urban	1788	1796	1861	1836	2380	2391	2478	2444
Khulna City Corp.	1919	1913	1952	1982	2332	2325	2373	2409
Rajshahi Rural	1592	1677	1776	1740	1915	2018	2137	2094
Rajshahi Urban	1799	1834	1929	1903	2174	2216	2330	2299
Rajshahi City Corp.	1659	1767	1825	1850	2111	2248	2321	2354
Sylhet Rural	1706	1785	1826	1842	1804	1887	1931	1948
Sylhet Urban	1837	1833	1954	1952	2226	2221	2367	2365

Annex 2. HIES 2016/17 poverty estimates

2.1. National upper poverty rates by area, 2016/17

Area	Mean	Standard error	95% Confidence interval	
Rural	0.26	0.01	0.25	0.28
Urban	0.19	0.01	0.16	0.21

2.2. National lower poverty rates by area, 2016/17

Area	Mean	Standard error	95% Confidence interval	
Rural	0.15	0.00	0.14	0.16
Urban	0.08	0.01	0.06	0.09

2.3. National upper poverty rates by division, 2016/17

Division name	Mean	Standard error	95% Confidence interval	
Barishal	0.26	0.02	0.23	0.30
Chattogram	0.18	0.01	0.16	0.21
Dhaka	0.16	0.01	0.13	0.19
Khulna	0.27	0.01	0.25	0.30
Mymensingh	0.33	0.02	0.29	0.37
Rajshahi	0.29	0.02	0.26	0.32
Rangpur	0.47	0.01	0.45	0.50
Sylhet	0.16	0.02	0.13	0.20

2.4. National lower poverty rates by division, 2016/17

Division name	Mean	Standard error	95% Confidence interval	
Barishal	0.14	0.01	0.12	0.17
Chattogram	0.09	0.01	0.07	0.10
Dhaka	0.07	0.01	0.06	0.09
Khulna	0.12	0.01	0.11	0.14
Mymensingh	0.18	0.01	0.15	0.20
Rajshahi	0.14	0.01	0.12	0.16
Rangpur	0.31	0.01	0.28	0.33
Sylhet	0.11	0.01	0.09	0.14

2.5. National upper poverty rates by district, 2016/17

District name	Mean	Standard error	95% Confidence interval	
Bagerhat	0.31	0.04	0.23	0.40
Bandarban	0.63	0.08	0.48	0.78
Barguna	0.26	0.03	0.19	0.32
Barishal	0.27	0.03	0.21	0.34
Bhola	0.15	0.03	0.10	0.21
Bogura	0.27	0.04	0.20	0.34
Brahmanbaria	0.10	0.03	0.05	0.16
Chandpur	0.29	0.04	0.21	0.38
Chattogram	0.14	0.03	0.08	0.20
Chuadanga	0.32	0.03	0.26	0.37
Cumilla	0.14	0.02	0.10	0.17
Cox’s Bazar	0.17	0.04	0.09	0.25
Dhaka	0.10	0.04	0.03	0.17
Dinajpur	0.64	0.03	0.58	0.71

Division name	Mean	Standard error	95% Confidence interval	
Faridpur	0.08	0.02	0.04	0.12
Feni	0.08	0.02	0.05	0.12
Gaibandha	0.47	0.04	0.40	0.54
Gazipur	0.07	0.01	0.04	0.10
Gopalganj	0.30	0.03	0.23	0.36
Habiganj	0.13	0.03	0.08	0.19
Joypurhat	0.21	0.03	0.16	0.27
Jamalpur	0.53	0.03	0.46	0.59
Jashore	0.27	0.03	0.21	0.33
Jhalokati	0.22	0.02	0.17	0.26
Jhenaidah	0.27	0.04	0.18	0.35
Khagrachhari	0.53	0.08	0.38	0.68
Khulna	0.31	0.05	0.22	0.40
Kishoreganj	0.54	0.04	0.45	0.62
Kurigram	0.71	0.03	0.64	0.77
Kushtia	0.18	0.03	0.12	0.23
Lakshmipur	0.33	0.04	0.25	0.40
Lalmonirhat	0.42	0.05	0.33	0.51
Madaripur	0.04	0.01	0.02	0.06
Magura	0.57	0.05	0.47	0.66
Manikganj	0.31	0.04	0.24	0.38
Meherpur	0.32	0.04	0.25	0.39
Maulvibazar	0.11	0.03	0.06	0.16
Munshiganj	0.03	0.01	0.01	0.05
Mymensingh	0.22	0.04	0.15	0.29
Naogaon	0.32	0.03	0.26	0.38
Narail	0.17	0.03	0.11	0.22
Narayanganj	0.03	0.01	0.01	0.05
Narsingdi	0.10	0.03	0.05	0.16
Natore	0.24	0.03	0.17	0.30
Chapai Nababganj	0.40	0.03	0.34	0.46
Netrakona	0.34	0.04	0.27	0.41
Nilphamari	0.32	0.03	0.27	0.38
Noakhali	0.23	0.04	0.15	0.32
Pabna	0.33	0.03	0.27	0.39
Panchagarh	0.26	0.05	0.17	0.36

Division name	Mean	Standard error	95% Confidence interval	
Patuakhali	0.37	0.05	0.27	0.47
Pirojpur	0.32	0.03	0.26	0.39
Rajshahi	0.20	0.07	0.07	0.33
Rajbari	0.34	0.03	0.28	0.40
Rangamati	0.29	0.05	0.20	0.37
Rangpur	0.44	0.04	0.37	0.51
Shariatpur	0.16	0.03	0.11	0.21
Satkhira	0.19	0.03	0.12	0.25
Sirajganj	0.30	0.04	0.23	0.38
Sherpur	0.41	0.04	0.33	0.50
Sunamganj	0.26	0.05	0.17	0.35
Sylhet	0.13	0.03	0.08	0.18
Tangail	0.19	0.03	0.13	0.25
Thakurgaon	0.23	0.04	0.17	0.30

2.6. National lower poverty rates by district, 2016/17

District name	Mean	Standard error	95% Confidence interval	
Bagerhat	0.14	0.03	0.08	0.20
Bandarban	0.50	0.08	0.35	0.66
Barguna	0.12	0.03	0.07	0.17
Barishal	0.14	0.03	0.09	0.19
Bhola	0.09	0.02	0.04	0.13
Bogura	0.14	0.02	0.09	0.18
Brahmanbaria	0.05	0.02	0.02	0.08
Chandpur	0.15	0.03	0.09	0.22
Chattogram	0.04	0.02	0.00	0.07
Chuadanga	0.12	0.01	0.10	0.15
Cumilla	0.05	0.01	0.03	0.07
Cox’s Bazar	0.08	0.03	0.01	0.14
Dhaka	0.02	0.01	-0.01	0.04
Dinajpur	0.45	0.03	0.39	0.52
Faridpur	0.03	0.02	0.00	0.07
Feni	0.03	0.01	0.01	0.06
Gaibandha	0.29	0.03	0.23	0.35
Gazipur	0.02	0.01	0.00	0.04
Gopalganj	0.15	0.03	0.10	0.21

Division name	Mean	Standard error	95% Confidence interval	
Habiganj	0.10	0.03	0.05	0.15
Joypurhat	0.10	0.02	0.06	0.13
Jamalpur	0.35	0.03	0.29	0.42
Jashore	0.09	0.01	0.06	0.12
Jhalokati	0.10	0.02	0.06	0.14
Jhenaidah	0.13	0.03	0.07	0.19
Khagrachhari	0.33	0.06	0.21	0.45
Khulna	0.14	0.03	0.08	0.19
Kishoreganj	0.34	0.05	0.25	0.44
Kurigram	0.54	0.04	0.46	0.62
Kushtia	0.07	0.02	0.04	0.10
Lakshmipur	0.20	0.03	0.14	0.27
Lalmonirhat	0.23	0.04	0.16	0.30
Madaripur	0.01	0.00	0.00	0.02
Magura	0.38	0.05	0.28	0.47
Manikganj	0.16	0.03	0.11	0.21
Meherpur	0.12	0.02	0.09	0.16
Maulvibazar	0.07	0.02	0.03	0.11
Munshiganj	0.01	0.01	0.00	0.03
Mymensingh	0.10	0.02	0.05	0.14
Naogaon	0.18	0.03	0.12	0.24
Narail	0.06	0.02	0.02	0.09
Narayanganj	0.00	0.00	0.00	0.00
Narsingdi	0.05	0.02	0.00	0.09
Natore	0.13	0.02	0.08	0.17
Chapai Nababganj	0.24	0.03	0.19	0.29
Netrakona	0.16	0.02	0.11	0.20
Nilphamari	0.14	0.02	0.11	0.18
Noakhali	0.13	0.03	0.07	0.19
Pabna	0.17	0.02	0.12	0.21
Panchagarh	0.14	0.04	0.07	0.21
Patuakhali	0.24	0.04	0.17	0.32
Pirojpur	0.18	0.03	0.12	0.23
Rajshahi	0.07	0.05	-0.02	0.16
Rajbari	0.16	0.03	0.11	0.21
Rangamati	0.11	0.03	0.06	0.16

Division name	Mean	Standard error	95% Confidence interval	
Rangpur	0.27	0.03	0.22	0.32
Shariatpur	0.05	0.02	0.02	0.08
Satkhira	0.09	0.02	0.05	0.13
Sirajganj	0.12	0.02	0.08	0.16
Sherpur	0.24	0.03	0.18	0.31
Sunamganj	0.19	0.04	0.12	0.27
Sylhet	0.09	0.02	0.05	0.13
Tangail	0.09	0.02	0.04	0.13
Thakurgaon	0.15	0.03	0.10	0.21

Annex 3. Assessing consistency of household size estimates

The average household size obtained from the HIES 2016/17 was 4.06 members. This implies a significant reduction in the average household size compared to the previous HIES 2010, which is not explained by differences in the definition of households (Annex Table 3.1)

Annex Table 3.1. Average household size in HIES

HIES	Mean	Standard error	95% Confidence interval	
2000	5.18	0.04	5.10	5.26
2005	4.85	0.03	4.78	4.91
2010	4.50	0.03	4.44	4.55
2016/17	4.06	0.02	4.03	4.09

Source: HIES 2000, 2005, 2010, 2016/17.

Other recent nationally representative surveys, like the Multiple Indicator Cluster Survey (MICS 2012/13) and Demographic and Health Survey (DHS 2014), which have in principle consistent definitions of households, show a larger average household size – 4.57 and 4.69 members. However, more recent national representative surveys collected by BBS show consistent large reductions in household size. For example, the first quarter of the new Quarterly Labor Force Survey (QLFS 2015/16), collected between July and September 2015, shows an average household size of 4.2. Similarly, HIES estimates of the percentage of single-member households seems aligned with the most recent QLFS (Annex Table 3.2.)

Annex Table 3.2. Household size based on different nationally representative surveys

	HIES 2010	Population Census 2011	MICS 2012/13	LFS 2013	DHS 2014	QLFS 2015	HIES 2016/17
Average household size	4.50	4.45	4.57	4.30	4.69	4.20	4.06
Single-member households (%)	2.4	3.4	1.9	-	1.5	3.3	2.8

To assess the consistency of the average household size estimates based on the HIES 2016/17, we compared projections starting from a baseline using HIES 2000. Annex Table 3.3 compares two types of projection (linear and compound) with observed estimates from HIES and the Census. The results suggest that the reduction in household size is consistent with an expected declining trend.

Annex Table 3.3. Projections of household size

Name of survey or census	Direct estimation	Projections	
		Compound	Linear
HIES 2000	5.18	5.18	5.18
HIES 2005	4.85	4.83	4.85
HIES 2010	4.50	4.5	4.51
Population Census 2011	4.45	4.44	4.44
HIES 2016/17	4.06	4.12	4.07

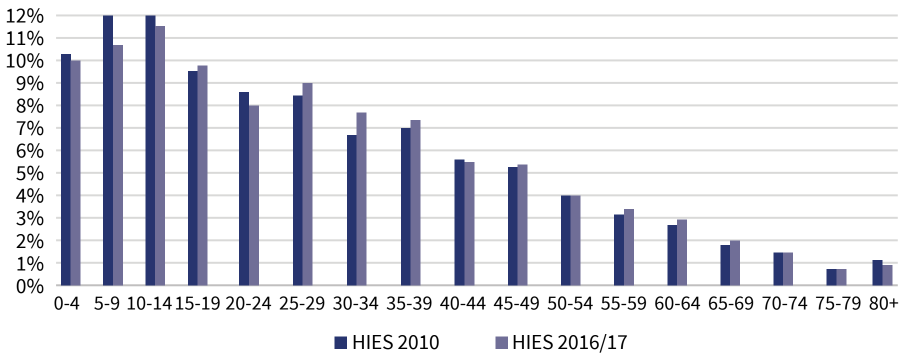
In addition, we compared the population pyramids based on the HIES 2016/17 with the ones produced using the HIES 2010 data, the official BBS population projections (BBS 2015), and the QLFS. The different population pyramids estimated are shown in Annex Figure 3.1, and none of them seem to suggest any strange pattern or important differences.

Consequently, there does not seem to be any reason to suspect that the average household size estimated based on the HIES 2016/17 round is much lower or inconsistent with what other official national representative surveys are suggesting.

Annex Figure 3.1. Population pyramids

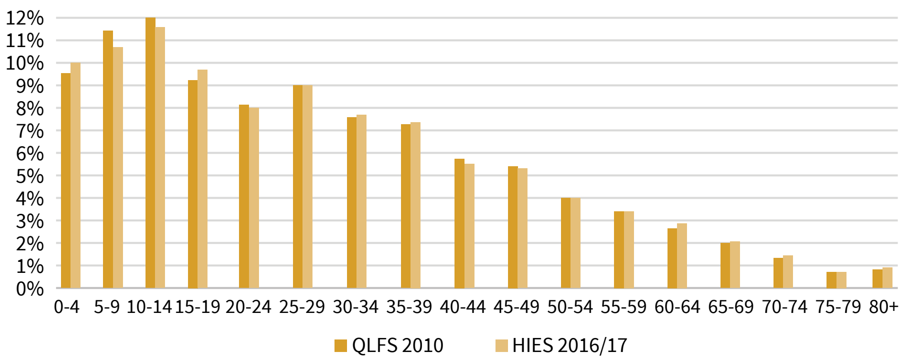
Panel A: HIES 2010 versus HIES 2016/17

Population by age group



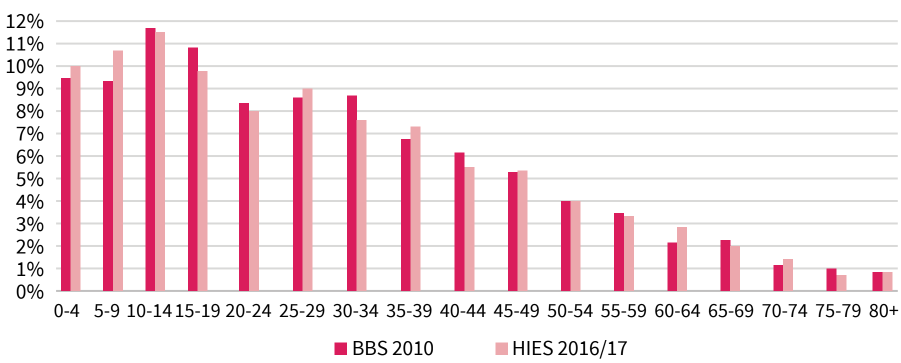
Panel B: QLFS versus HIES 2016/17

Population by age group



Panel C: BBS population projections versus HIES 2016/17

Population by age group



Note: QLFS estimates reported are based on July-September 2015. BBS population projections are based on the official publication disseminated in 2015.

Annex 4. STATA code to produce comparable strata and correct the misclassification error in the urban/rural variable

```
/*====================================================
1: Fix the Urban Rural misclassification
====================================================*/

use "$hies_raw/HH_SEC_A_Q1Q2Q3Q4",clear

gen ruc_new=ruc
*reclassify 259 households from rural to urban
#delimit
replace ruc_new=2 if inlist(psu
,222
,343
,641
,642
,705
,706
,928
,929
,1239
,1253
,1717
,1781
,1789
)
;
#d cr

compare ruc_new ruc

gen stratum16_new=stratum16

*Reclassify 40 households from Stratum Chattogram rural to
Chattogram Urban
replace stratum16_new=4 if inlist(psu,222,343)

*reclassify  120 households from Dhaka Rural to Urban stratum
replace stratum16_new=7 if inlist(psu,641,642,705,706,928,929)

*reclassify  40 households from Khulna Rural to Urban stratum
replace stratum16_new=10 if inlist(psu,1239,1253)

*reclassify  60 households from Rajshahi Rural to Urban stratum
replace stratum16_new=13 if inlist(psu,1717,1781,1789)

compare stratum16_new stratum16

keep hhold ruc_new stratum16_new psu
```

```
lab var stratum16_new "Stratum 16 urban area fix"
lab var ruc_new "Rural Urban urban area fix"


#d;
la de stratum16
1      "Barishal Rural"
2      "Barishal Urban"
3      "Chattogram Rural"
4      "Chattogram Urban"
5      "Chattogram CC"
6      "Dhaka Rural"
7      "Dhaka Urban"
8      "Dhaka CC"
9      "Khulna Rural"
10     "Khulna Urban"
11     "Khulna CC"
12     "Rajshahi Rural"
13     "Rajshahi Urban"
14     "Rajshahi CC"
15     "Sylhet Rural"
16     "Sylhet Urban"
,modify
;

la de ruc
1      "Rural"
2      "Urban"
3   "City Corporation"
;
#d cr


*rename variable
rename (stratum16_new  ruc_new) (stratum16 ruc)

*label values
la val stratum16 stratum16
la val ruc ruc


/*====================================================
 2: Generate stratum 16 comparable across time
====================================================*/

*stratum comparable from stratum 16
gen stratum16_comparable=stratum16

*gen ruc comparable
gen ruc_comparable=ruc
```

```
*from Chattogram Urban to Chittagon CC (now becoming SMA) 20
households
replace stratum16_comparable=5 if inlist(psu,343)
replace ruc_comparable=3 if inlist(psu,343)

*from Khulna Urban to Khulna CC (now becoming SMA) 40 households
replace stratum16_comparable=11 if inlist(psu,1239,1253)
replace ruc_comparable=3 if inlist(psu,1239,1253)

*from Dhaka Urban to Dhaka CC (now becoming SMA) 120 households
#delimit
replace stratum16_comparable=8 if inlist(psu
,641
,642
,705
,706
,928
,929
)
;
replace ruc_comparable=3 if inlist(psu
,641
,642
,705
,706
,928
,929
)
;
#d cr


*Var labels
#d ;
la de stratum16_comparable
1      "Barishal Rural"
2      "Barishal Urban"
3      "Chattogram Rural"
4      "Chattogram Urban"
5      "Chattogram SMA"
6      "Dhaka Rural"
7      "Dhaka Urban"
8      "Dhaka SMA"
9      "Khulna Rural"
10     "Khulna Urban"
11     "Khulna SMA"
12     "Rajshahi Rural"
13     "Rajshahi Urban"
14     "Rajshahi SMA"
15     "Sylhet Rural"
16     "Sylhet Urban"
,modify
```

```
;

la de ruc_comparable
1      “Rural”
2      “Urban”
3   “SMA”
;
#d cr


la val stratum16_comparable stratum16_comparable
la val ruc_comparable ruc_comparable

lab var stratum16_comparable “Stratum 16 Comparable acrros time
with urban area fix”
lab var ruc_comparable “1 Rural 2 Urban 3 SMA Comparable acrros
time with urban area fix”
```

CHAPTER II.

Bangladesh Poverty Trends 2010-2016/17[1]

July 2019

Abstract

This note uses the latest round of the Household Income and Expenditure Survey to provide an initial assessment of Bangladesh's poverty trends from 2010 to 2016/17. The note documents that Bangladesh has made remarkable gains in reducing poverty. However, with almost 1 in 4 people still living in poverty today, the country needs to make further progress. Economic growth has led to gains in welfare, but even though economic growth has accelerated in recent years, it has delivered less poverty reduction. Consumption has grown at a slower rate and has been less equally shared since 2010 than in the prior decade. Welfare differences between the historically poorer West and the rest of the country have re-emerged, as poverty has increased in the Northwestern division of Rangpur. The decline in urban poverty has also slowed. Slower agricultural growth, combined with slower job creation in manufacturing, could explain why growth has become less poverty reducing over time in Bangladesh.

[1] This note was prepared by Ruth Hill (Senior Economist, GPV06) and Maria Eugenia Genoni (Senior Economist, GPV06), with input from Yurani Arias Granada (Consultant, GPV06), Kelly Yelitza (Consultant, GPV06) and Joaquin Endara (Consultant).

I. Recent progress in poverty reduction

Official poverty statistics for 2016/17 show that almost 1 in 4 Bangladeshis, 24.5 percent, live on less than the national poverty line.[2, 3] These individuals cannot cover basic food and non-food needs. Half of them, 13 percent of the population, live on less than the national extreme poverty line. The international poverty line, a measure that allows the level of poverty in Bangladesh to be compared to the level of poverty in other countries, shows that the rate of poverty in Bangladesh is relatively high by regional standards.

Although poverty is still high, Bangladesh has made remarkable progress in reducing it. As recently as 2000, half of the country's population lived in poverty based on the national poverty line; by 2010, 31 percent of Bangladeshis lived in poverty. The estimates for 2016 thus represent sustained progress in reducing poverty. Measures of extreme poverty and the international poverty line show the same trend (Figure 1).

Bangladesh's continued progress in reducing poverty reflects sustained economic growth. For more than a decade, Bangladesh has experienced high and stable economic growth. Between 2000 and 2016, average GDP growth was 6 percent per year, and average GDP per capita growth was 4.4 percent per year.

However, growth has delivered less poverty reduction than in the past. Even though average annual economic growth increased from 6.1 percent between 2005 and 2010 to 6.5 percent between 2010 and 2016, the pace of poverty reduction slowed. After falling 1.7 percentage points annually from 2005 to 2010, the national poverty rate dropped 1.2 percentage points annually from 2010 to 2016. The amount of poverty reduction each percentage point of growth per capita delivers (the elasticity of poverty reduction to growth) thus fell from 0.88 to 0.73.[4]

[2] The Household Income and Expenditure Survey (HIES), used to estimate poverty in Bangladesh, is conducted over the course of one year. The HIES 2016/17 data was collected from April 2016 to March 2017. For the rest of this paper, we refer to these poverty estimates as from 2016.

[3] For a full discussion of how poverty is measured in Bangladesh and comparability across rounds of the HIES, see Paper 1 in this volume, "Description of the Official Methodology used for Poverty Estimation in Bangladesh for 2016/17." Standard errors for poverty estimates are included in graphs to indicate the precision with which poverty is measured in Bangladesh.

[4] The elasticity of poverty reduction to growth per capita is given by the percent reduction in poverty divided by GDP growth per capita. The values using the growth rate instead of growth per capita are 0.70 and 0.58, respectively. In general, the elasticity of poverty reduction to growth per capita is higher at lower levels of poverty (Ravallion 2012). This is partly for arithmetic reasons: it is easier to halve the poverty rate when going from, for example, 5 percent poverty (this requires a 2.5 percentage point reduction in poverty) than from 50 percent poverty (which would require a 25 percentage point reduction in poverty) (Cuaresma, Klasen and Wacker 2016). In order to take this into account,

Measures of the depth and severity of poverty tell the same story. While both measures fell from 2010 to 2016, the rate of progress has been slower than in previous periods. As a result, at the extreme poverty line the elasticity of poverty reduction to GDP growth per capita has fallen by a third, from 1.24 to 0.86.

Strong national poverty reduction masks differences in welfare trends between rural and urban Bangladesh. The upper poverty rate[5] fell in rural and urban Bangladesh from 2010 to 2016, but the rate of reduction was much slower in urban areas (Figure 1). There was no progress in reducing extreme poverty in urban areas: the proportion of the urban population living in extreme poverty was 7.7 percent in 2010 and 8 percent in 2016. Bangladesh continued to urbanize during this time, albeit more slowly (the urban share of the population increased from 26.3 to 29.1 percent from 2010 to 2016). Thus, there are now more people living in extreme poverty in urban Bangladesh (3.7 million) than in 2010 (3 million). Since Bangladesh will continue to urbanize, this is a worrisome trend. Interventions to strengthen urban poverty reduction will be increasingly important to achieving poverty reduction in the future.

Poverty reduction in rural Bangladesh accounts for 90 percent of all poverty reduction that occurred from 2010 to 2016. This is explained by the fact that Bangladesh is a predominantly rural country (3 in 4 Bangladeshis live in rural areas) and that the pace of poverty reduction in rural areas was faster than in urban areas.

There have also been stark differences in welfare trends across divisions. Poverty has risen in Rangpur[6] division, the historically poorer Northwest of the country; stagnated in Rajshahi and Khulna in the West; fallen moderately in Chittagong; and declined rapidly in Barisal, Dhaka, and Sylhet (Figure 2 and Table

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the semi-elasticity can also be considered, which is the percentage point reduction in poverty for each percent of GDP growth per capita. This has fallen even more substantially, from 0.35 in 2005-2010 to 0.23 in 2010-2016 (at the national poverty line).

[5] The official methodology used to estimate poverty numbers in Bangladesh was based on the Cost of Basic Needs (CBN). The CBN method calculates the cost of obtaining a consumption bundle considered to be adequate to satisfy basic consumption needs. If a person cannot afford the cost of this bundle, then this person is considered poor. The upper poverty line is the cost of a bundle that includes basic food and non-food items. The lower poverty line is the cost of a bundle that mostly includes food, along with a small share of non-food items, and aims to measure extreme poverty. For a full discussion of how poverty is measured in Bangladesh, see Paper 1 in this volume, "Description of the Official Methodology used for Poverty Estimation in Bangladesh for 2016/17."

[6] There are two new divisions in the sampling frame for HIES 2016/17, Mymensing and Rangpur. Although some trends have been presented for Rangpur since 2010, neither of these divisions were in the sampling frame until this round of HIES. In the Annex, we present the trends for the six 2000 divisions and the eight 2016 divisions, with their respective standard errors.

1). The stronger progress of poverty reduction in the Eastern regions widened a gap between Eastern and Western Bangladesh that had narrowed between 2005 and 2010 (Jolliffe et al 2013). This highlights the need for further investments to increase income growth in the West.

The HIES 2016/17 is the first survey that provides district poverty estimates.[7] Figure 3 shows that, although there are poor districts in all provinces, poor districts are much more likely to be in the periphery of the country than in the center, and are more likely to be in the Northwest.

Poverty declined in Bangladesh's largest city, Dhaka, but increased in the second largest city, Chittagong. In Chittagong Statistical Metropolitan Area (SMA), the poverty rate rose from 6.6 to 16.9 percent. Poverty fell in other urban centers, but more slowly than in rural areas (Figure 4). Although poverty rates in Dhaka SMA are low at 10.7 percent (and 9 percent in Dhaka City Corporation), parts of the city have very high poverty rates. A slum survey conducted in Dhaka City Corporation in conjunction with the first quarter of the HIES showed that poverty in slums in Dhaka was 23.3 percent – much higher than the urban average.

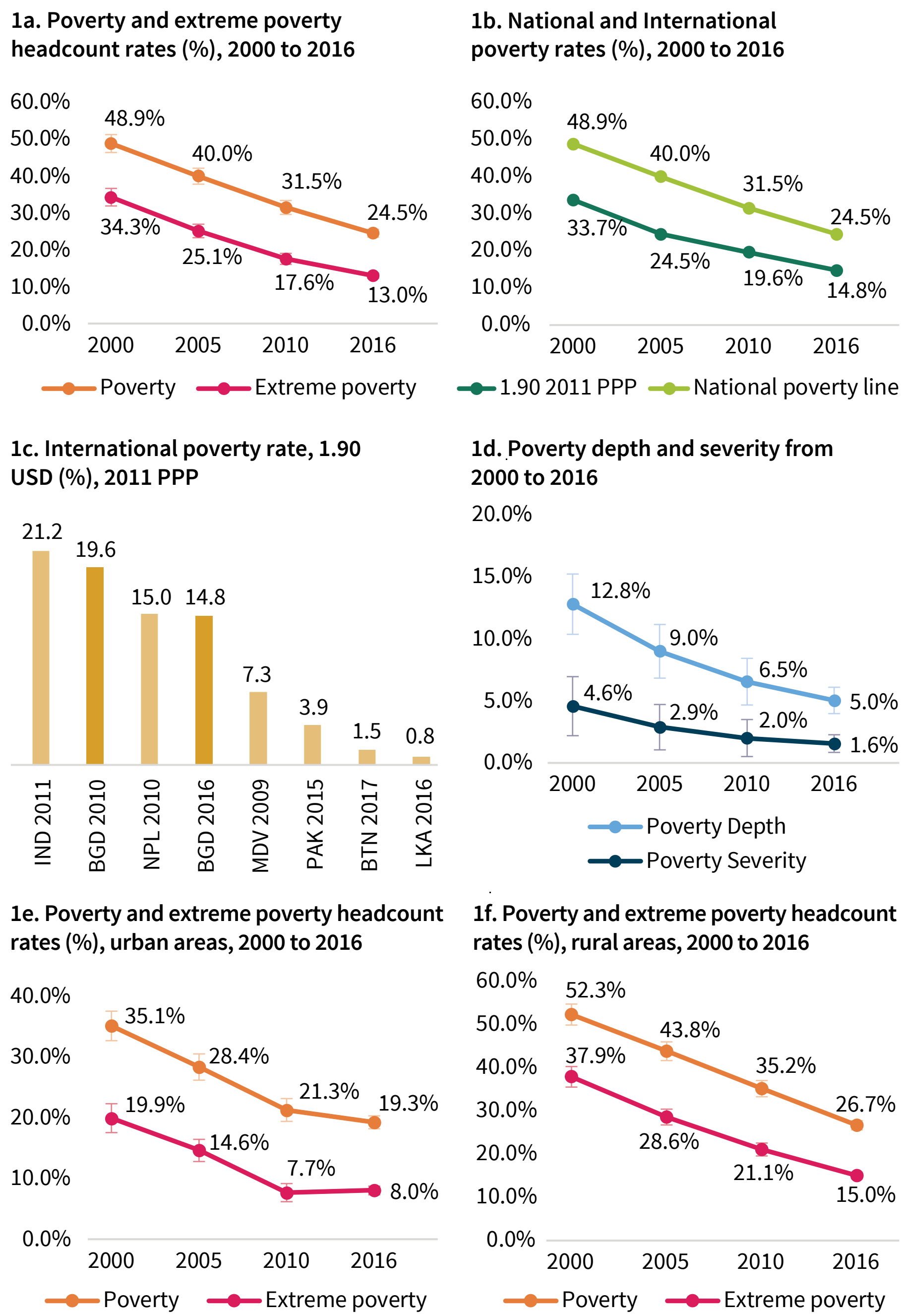
Table 1: Poverty reduction has been uneven across divisions

	Poverty rate		Extreme poverty rate	
	2010	2016	2010	2016
Barisal	39.4 (3.3)	26.4 (1.5)	26.7 (3.2)	14.4 (1.3)
Chittagong	26.2 (2)	18.3 (1.2)	13.1 (1.4)	9.0 (0.9)
Dhaka	30.5 (1.6)	20.5 (1.1)	15.6 (1.1)	9.9 (0.7)
Khulna	32.1 (2.3)	27.7 (1.3)	15.4 (1.6)	12.1 (0.8)
Rajshahi	29.7 (2.1)	29.0 (1.5)	16.0 (1.6)	14.3 (1)
Rangpur	42.3 (3.2)	47.3 (1.3)	27.7 (2.9)	30.6 (1.2)
Sylhet	28.1 (3)	16.2 (1.7)	20.7 (2.5)	11.5 (1.4)

Source: Staff calculations using HIES 2010 and 2016.
Note: Standard errors in parentheses.

[7] For a full discussion of the sampling strategy used in HIES 2016/17 and how it compares to previous years, see Ahmed et al. (2017).

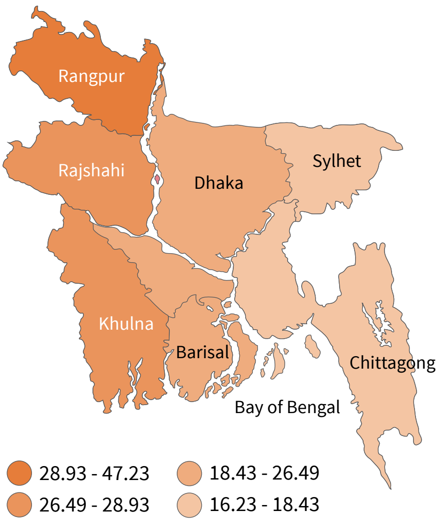
Figure 1. Bangladesh has achieved strong poverty reduction from 2010 to 2016, although the pace of reduction has slowed, particularly in urban areas



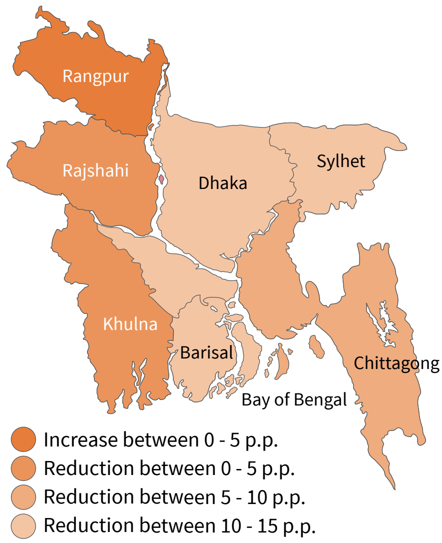
Note: PPP denotes Purchasing Power Parity. Standard error estimates presented for Figures a,d,e,f.

Figure 2. Poverty reduction has been slowest in the West, where poverty is highest

Upper poverty rate 2016 by division



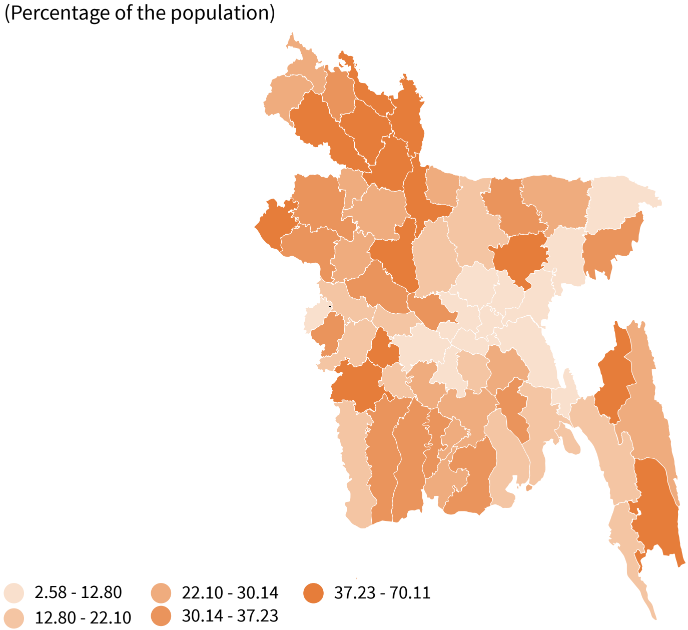
Change in upper poverty rate 2010-2016 by division (percentage points change)



Source: Staff calculations based on HIES 2010 and 2016.

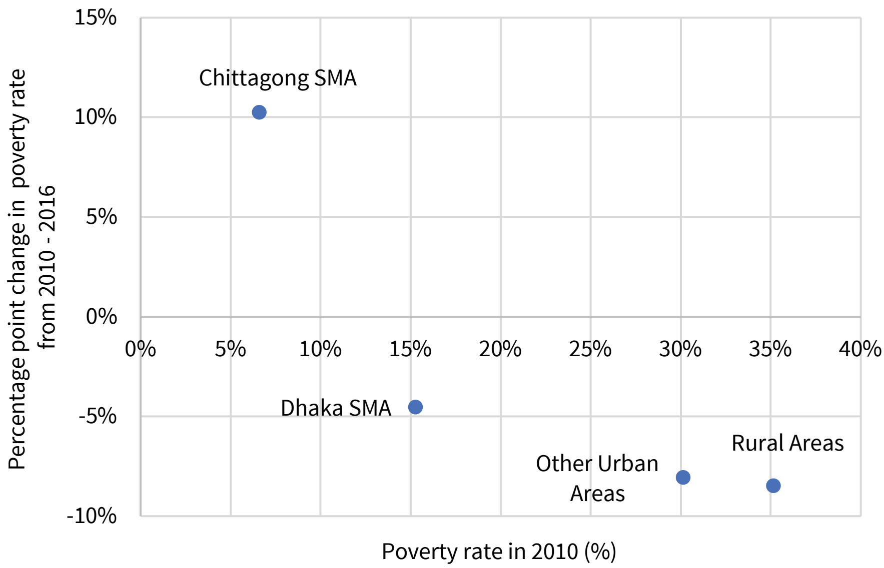
Figure 3. District upper poverty rates in 2016

(Percentage of the population)



Source: Staff calculations based on HIES 2016.

Figure 4. Poverty has increased in Chittagong but has fallen in other cities



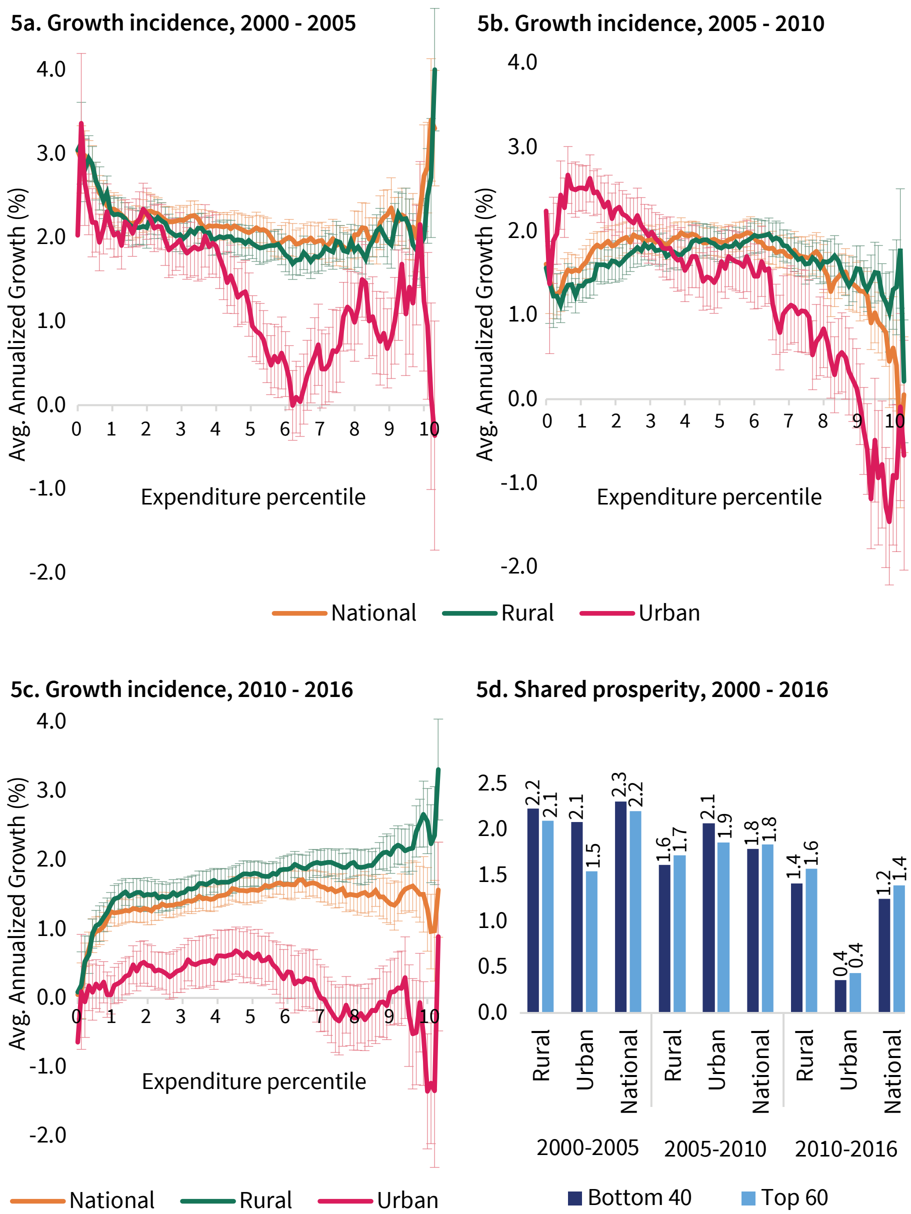
Source: Staff calculations using HIES 2010 and 2016.
Note: SMA stands for Statistical Metropolitan Area. Poverty lines for SMA areas were recalculated entirely after reassigning households to recover the SMA areas across time. For details, refer to Ahmed et al. (2019).

II. Incidence of progress and shared prosperity

Higher GDP growth has not caused faster poverty reduction, partly because average consumption growth did not keep up with GDP growth. Although GDP growth accelerated between 2010 and 2016, compared to years before 2010, household survey data show consumption growth has been slower. This reflects the declining importance of private consumption in total GDP; the share of private consumption in total GDP declined from 74 to 69 percent between 2010 and 2016, while investment increased by 3.4 percentage points. Figure 5 presents the growth incidence curve, which indicates the growth in consumption for people at each level of consumption (from the poorest on the left to the richest on the right) for 2000-2005, 2005-2010, and 2010-2016. The bottom right quadrant summarizes the average growth of the bottom 40 percent and the average growth of the top 60 percent. Average consumption growth fell from 2.2 in the period 2000 to 2005 to 1.8 in the period 2005 to 2010 and 1.4 in the period 2010 to 2016.

In addition, consumption growth has become more unequal over time. Poorer households experienced slower consumption growth (1.2 percent among the

Figure 5. Consumption growth has slowed and become more unequal



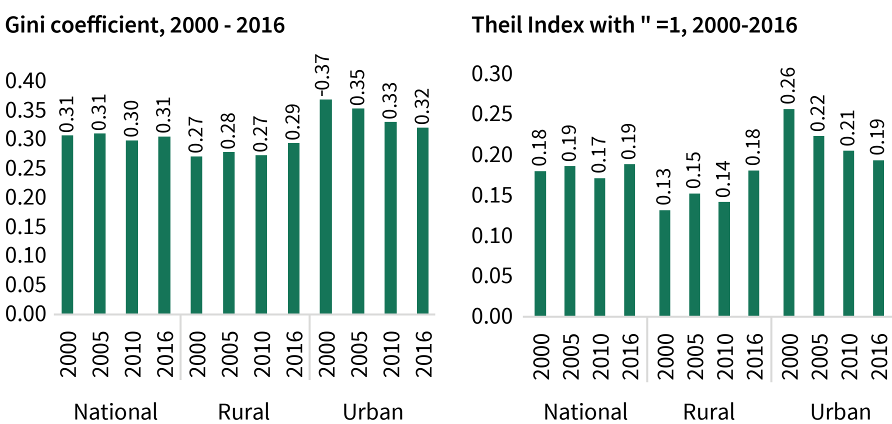
Source: Authors' calculations using HIES 2000, 2005, 2010, and 2016.
Notes: Figures a, b, and c present growth incidence curves, which indicate the growth in consumption for people at each level of consumption (from the poorest on the left to the richest on the right). Standard errors are presented in brackets. Figure d compares the annualized growth rate of the mean household per capita consumption of the poorest 40 percent of the population (bottom 40) and the richest 60 percent (top 60), where the bottom 40 and top 60 are determined by their rank in household per capita consumption.

bottom 40 percent) than richer households (1.4 percent among the top 60 percent) from 2010 to 2016; from 2000 to 2005 consumption growth had been higher among poorer households. From 2010 to 2016, consumption growth was highest for people in the 40th to 75th percentiles. It was lower for the poorest and for the richest, particularly those in the top third of the urban distribution. The richest households experienced slow consumption growth most likely because of lower consumption growth in urban areas (which tend to be richer than rural areas). Consumption growth was highest for the most well-off rural households. As a result, although Bangladesh recorded healthy consumption growth among the bottom 40 percent, it did not fare well on measures of equality and shared prosperity.

There was a slight increase in inequality from 2000 to 2016, particularly in rural areas. The Gini coefficient increased by one percentage point and the Theil index (with alpha equal to one) by two percentage points (Figure 6). It is in rural areas that inequality has particularly increased. The rural Gini increased from 0.27 to 0.29 because the bottom 10 percent of households in rural areas did not fare well, and because rich rural households experienced higher consumption growth. Inequality in urban areas fell because of the low growth of consumption at the top end of the consumption distribution.

Poverty reduction was largely driven by growth and not redistribution of consumption. Figure 7 quantifies the cost of rising inequality on poverty reduction

Figure 6. Inequality has increased because of rising inequality in rural areas; urban inequality fell

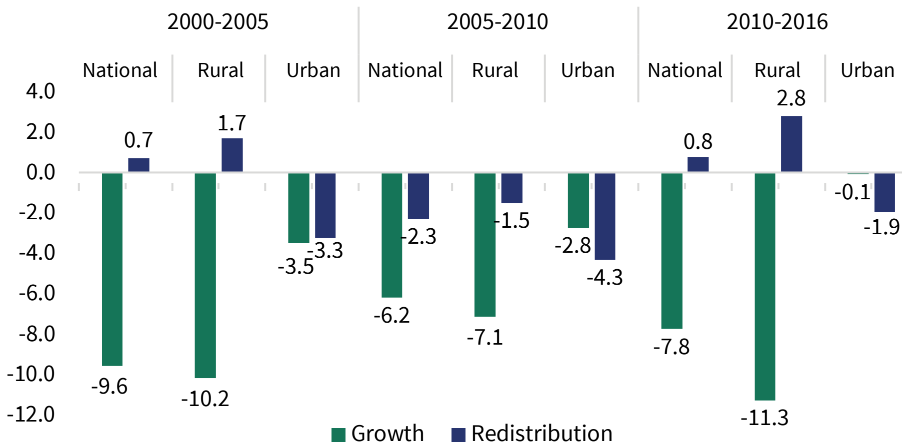


Source: Authors' calculations using HIES 2000, 2005, 2010, and 2016.

in Bangladesh. Of the 8.5 percentage points of poverty reduction from 2005 to 2010, 6.2 percentage points can be attributed to the overall growth in consumption and 2.3 percentage points can be attributed to the fact that consumption growth was equalizing (i.e., consumption grew faster among poorer households). In contrast, all of the 7.2 percentage points of poverty reduction from 2010 to 2016 can be attributed to growth in average consumption. Inequality in the growth of consumption slowed the overall rate of poverty reduction.

Figure 7. Poverty would have fallen faster had consumption growth been equally distributed

Growth and redistribution decomposition of poverty changes (%)



Source: Authors' calculations using HIES 2000, 2005, 2010 and 2016.

III. Drivers of poverty reduction: an initial assessment

The last Bangladesh Poverty Assessment showed that poverty reduction from 2005 to 2010 was driven primarily by growth in labor income (Jolliffe et al 2013). Labor income increased mainly thanks to higher agricultural incomes driven by real wage growth in agriculture. Bangladesh conforms to the international norm of poverty reduction being driven mostly by changes in labor income, with changes in transfers—be it safety net transfers or remittances—having an important but smaller impact (Azevedo et al. 2013).

An initial look at the 2016 data suggests that poverty reduction in Bangladesh has continued to be delivered by changes in labor income rather than transfers. The proportion of households receiving the main sources of transfers to households (social protection programs and international and domestic remittances) has not increased at the lower end of the consumption distribution. Indeed, the proportion of households in the bottom 40 percent receiving international remittances fell from 4.1 to 2.5 percent. The proportion of households receiving social protection transfers fell from 33.2 to 29.6 percent (Table 2).

The amount of international remittances that households report receiving has fallen quite dramatically. This is a result of a combination of factors: fewer households report having a member that migrated; fewer households report receiving remittances; and when remittances are transferred, the average value of remittances received per household is lower (Figure 9). It is not clear why the average value of remittances would have fallen so much, as the characteristics of those that migrate have not changed substantially since 2011. It could reflect households being less willing to report remittances that are being transmitted through informal channels.

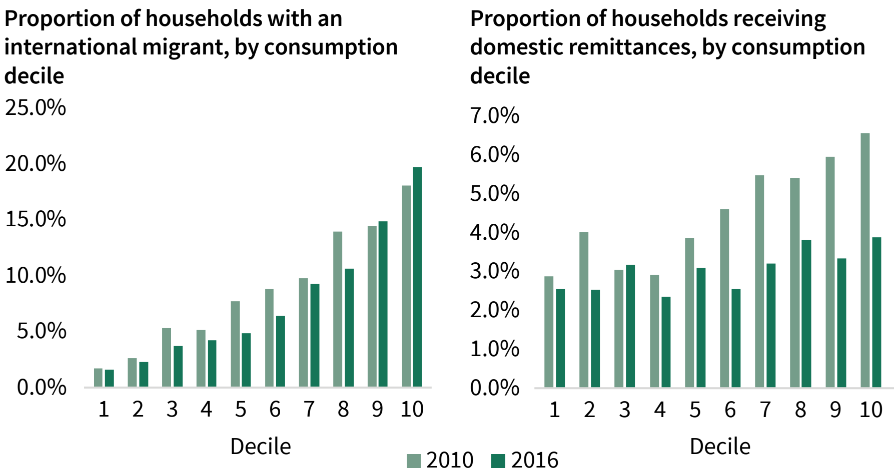
The decline in remittances observed since 2012 is unlikely to have had a large effect on national poverty rates or explain the slowdown in poverty reduction. HIES data indicates that the amount of international remittances that households report receiving has fallen significantly, confirming the trend in national accounts remittance data. However, as households at the bottom of the income distribution were less likely to have migrants and receive remittances in the first place, this reduction is unlikely to have affected overall poverty rates. Assuming that the share of households with international migrants and the size of remittances had remained at 2010 levels, the annual rate of poverty reduction would have increased only slightly, to 1.4 percentage points, between 2010 and 2016. The fall in remittances has particularly affected incomes of the top 60 percent, who are more likely to benefit from international remittances. However, the slowdown in remittances may have had some impacts at the local level, due to indirect benefits of migration. More information is needed to assess this hypothesis.

Table 2: Share of households receiving remittances and social protection transfers

	2010		2016	
	All	**Bottom 40**	**All**	**Bottom 40**
International remittances	9.59%	4.10%	5.01%	2.50%
Internal remittances	12.30%	10.54%	13.09%	11.74%
Social protection transfers	24.58%	33.20%	21.39%	29.06%

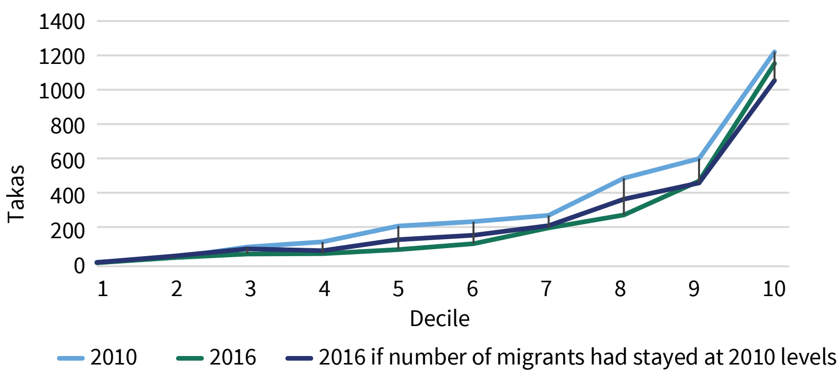
Source: Staff calculations using HIES 2010 and 2016.
Note: Bottom 40 denotes the poorest 40 percent of the per capita consumption distribution.

Figure 8. Transfers did not increase for the poorest households



Source: Staff calculations using HIES 2010 and 2016.

Figure 9. Value of remittances received (per capita), by consumption decile



Source: Staff calculation using HIES 2010 and 2016.
Note: In the lower graph, the dark blue line represents the value of international remittances per consumption decile that would have been observed, if the number of migrants per household had stayed the same as in 2010. It assumes the 2016 value of remittances per international migrant.

Labor force participation

Labor force participation increased between 2003 and 2010, driven by a 10 percentage point increase in female labor force participation (from 26 to 36 percent). This increase in labor force participation was made possible by strong job creation in the Bangladesh economy, particularly in the Ready-Made Garment (RMG) sector, which favored female employment (Farole and Cho 2017).[8]

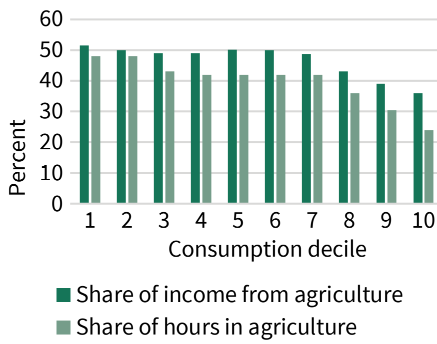
[8] Data from the Labor Force Survey 2015.

However, this trend has reversed since 2010. Job growth slowed despite accelerating GDP growth. Female labor force participation in urban areas declined by 4 percentage points, from 35 to 31 percent, between 2010 and 2016, most likely reflecting the rapid slowdown in job creation in the RMG and textiles sector (Farole and Cho 2017). Data on employment in the last seven days collected in HIES does not point to such a large drop in employment rates among household heads, and poverty reduction has occurred equally across households with employed and inactive heads.

Sectors

The pattern of growth became less favorable to the sectors poor households are more engaged in, and not enough jobs were created to increase employment in more dynamic sectors. In 2010, poorer households spent more of their time and derived more of their income from agriculture (Figure 10). Agricultural growth, if evenly distributed, would have benefited them more. However, agricultural growth slowed after 2010, while industrial growth accelerated. Between 2011 and 2016, agriculture and industry output grew 3.4 and 9.5 percent annually, respectively, in contrast to 4.5 and 7.4 percent from 2000 to 2010. The service sector grew at a uniform 6 percent across the period 2000-2016. However, accelerating growth in the industrial sector post 2010 was not matched by stronger job creation in this sector. Job creation in industry slowed sharply between 2010 and 2015 (Farole and Cho2017).

Figure 10. Agriculture is the main source of income for the poorest households

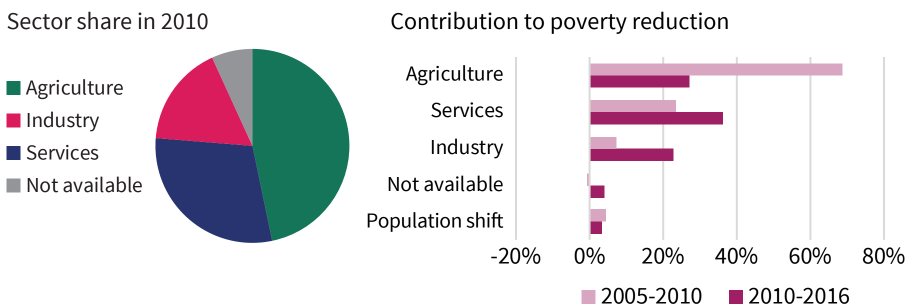


Decomposing poverty reduction by sector of employment shows that poverty did indeed fall faster among households in more dynamic sectors. Households do not tend to move in and out of sectors rapidly, so strong poverty reduction in one sector can often indicate that growth in incomes in that sector were of importance in bringing about poverty reduction. Changes in the share of the population engaged in any given sector can also be examined to assess whether there were any large structural changes in employment that may have contributed to changes in poverty.

A sectoral decomposition of poverty trends shows that although 90 percent of poverty reduction took place in rural Bangladesh, it was gains among

non-agricultural households that drove this. Although 47 percent of rural households are primarily engaged in agriculture, they accounted for 27 percent of rural poverty reduction. Most rural poverty reduction, 59 percent, occurred among the 47 percent of households whose primary sector of employment is industry or services (Figure 11). Data that follows the same households over time during this period documents the same trend: households with higher shares of non-farm income saw faster progress (Ahmed 2018). Despite strong growth in non-agricultural sectors, the share of the population in households primarily engaged in non-agricultural activities increased by only 3 percentage points. This shift contributed just 4 percent to poverty reduction.

Figure 11. Decomposing poverty trends in rural areas



Source: Staff calculations using HIES 2005, 2010, and 2016.
Notes: Results obtained from Ravallion and Huppi (1991) decompose changes in poverty over time into intra-sectoral effects, a component due to population shifts across sectors (not displayed), and an interaction (not displayed). Sector of employment defined based on reported hours of work in each sector.

In addition, agricultural growth has become less equal and less poverty reducing. Each percentage point of agricultural growth delivered less poverty reduction among agricultural households. From 2005 to 2010, one percentage point of agricultural growth was associated with a fall in poverty among agricultural households of 1.18 percent. From 2010 to 2016, the fall in poverty from each percent of agricultural growth was just 0.58 percent. Understanding why the nature of agricultural growth become less poverty reducing is important. Land ownership is highly skewed to richer households and daily wage labor in agriculture is much more important for poorer households.

In urban areas, poverty reduction was entirely driven by welfare gains among households primarily engaged in industry, and more specifically in garments. The poverty rate among households engaged primarily in manufacturing fell from 26 percent in 2010 to 19 percent in urban areas in 2016. As a result, manufacturing alone accounted for 108 percent of poverty reduction in urban areas (Figure 12a). It was households in the garment industry that contributed most to poverty reduction

(Figure 12b). Construction was also an important sector in poverty reduction. There was very little poverty reduction among urban households in the service sector. However, closer inspection reveals different trends for different service sectors. There was almost no structural shift in the main sector of employment, limiting the degree to which households could move into the more dynamic sectors and reduce poverty. The limited poverty reduction in the service sector and the lack of structural shift resulted in slower rates of poverty reduction in urban areas.

Figure 12a. Decomposing poverty trends in urban areas

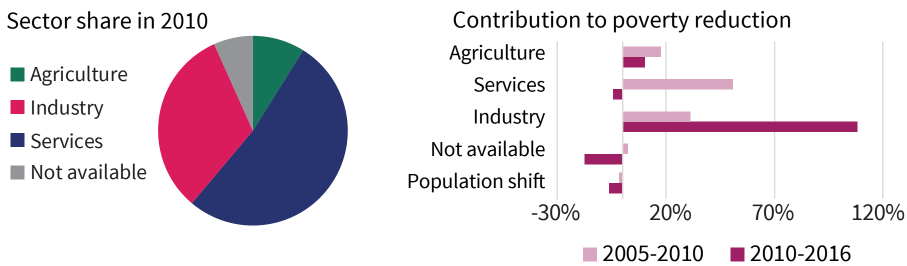
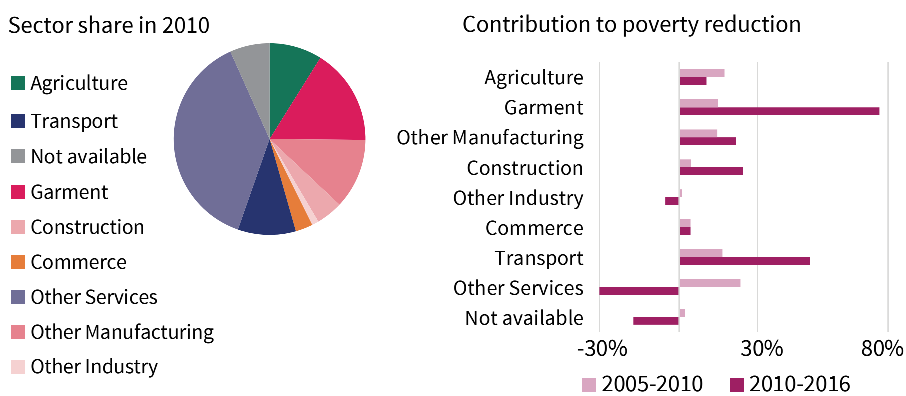


Figure 12b. Detail decomposing poverty trends in urban areas



Source: Staff calculations using HIES 2005, 2010, and 2016.
Notes: Results obtained from Ravallion and Huppi (1991) decompose changes in poverty over time into intra-sectoral effects, a component due to population shifts across sectors (not displayed), and an interaction (not displayed). Sector of employment defined based on reported hours of work in each sector.

IV. Who are the poor and poorest?

Section 1 highlighted the close relationship between poverty and geography in Bangladesh: An individual living in Rangpur division is three times more likely to be poor than one living in Sylhet division, for instance. Households in rural areas are more likely to be poor than those in urban areas.

Table 3 highlights other key characteristics of poor households compared to non-poor households, and tests whether the observed differences are large enough to be statistically significant.

Poor households are larger, so each working age adult in them has to support a larger number of non-working age members. Poor households are less likely to be headed by a female than non-poor households; this could reflect the fact that poor households are less likely to benefit from international migration and remittances, and that it is often male workers who migrate.

Poor households have just as high a share of adults who are working as non-poor households, but they work in less remunerative activities. Poor households are much more likely to be in agriculture and less likely to be in services than non-poor households; this is true even when considering only households in rural areas. In rural Bangladesh, 43 percent of poor household heads are in agriculture, compared to 28 percent of non-poor household heads.

Poorer households work in less remunerative activities because they have less access to human capital than non-poor households. This is seen starkly in measures of human capital. Literacy rates are much lower among heads of poor households (39 percent) than among heads of non-poor households (59 percent). Although these statistics do not establish causality between human capital and poverty, the large differences highlight the potential role for investing in human capital to improve the income generating abilities of poor households. Ownership of land is also lower among poor households, although the difference between poor and non-poor households is smaller than it used to be. Poor households have higher rates of access to microcredit than non-poor households (34 percent of poor compared to 29 percent of non-poor), reflecting more widespread use of microcredit services among poor urban households than non-poor urban households.

Access to social protection is higher among poor households. 32 percent of poor households have access to social protection programs, compared to 19 percent of non-poor households. This reflects the prevalence of social protection programs in rural Bangladesh. Only 18 percent of poor households in urban areas have access to social protection programs (along with 7 percent of non-poor households). These statistics indicate that there is still room to increase coverage of social protection programs, particularly in urban areas, and to improve the quality of targeting.

Table 3: Characteristics of poor and non-poor households (average)

	Non-poor	Poor	Test of difference (1)	Test of difference (2)
Demographics				
Household lives in an urban area (%)	32.13%	22.72%	***	
Household size	3.92	4.57	***	***
Household dependency ratio (3)	0.61	0.89	***	***
Age of household head	44.60	43.00	***	***
Household head is female (%)	13.88%	10.73%	***	***
Household head is married (%)	90.91%	91.24%		
Labor market				
Share of adults who are earners	0.33	0.29	***	
Share of adults in agriculture	0.10	0.13	***	
Household head in agriculture (%)	28.19%	42.54%	***	Ref. group
Household head in industry (%)	19.06%	16.13%	***	***
Household head in services (%)	31.54%	25.60%	***	***
Household member has a chronic illness/disability (%)	31.54%	24.26%	***	***
Human capital				
Household head is literate (can write a letter, %)	59.28%	38.54%	***	
Household head has no education (%)	41.47%	62.65%	***	***
Household head has some primary education (%)	8.55%	10.04%	***	***
Household head has completed primary education (%)	11.98%	10.50%	***	***
Household head has at least some secondary education (%)	37.89%	16.63%	***	Ref. group
Assets				
Household owns land (%)	35.20%	21.91%	***	***
Household owns a mobile phone (%)	93.93%	87.81%	***	***
Household has electricity (%)	80.72%	59.04%	***	***
Household has piped water (%)	13.92%	5.23%	***	***
Household has sanitary toilet (%)	28.79%	14.30%	***	***
Transfers and credit				
Household receives international remittances (%)	5.85%	2.03%	***	***
Household receives domestic remittances (%)	13.54%	11.51%	***	**
Household receives microcredit (%)	28.96%	33.56%	***	***
Household receives social protection program (%)	18.52%	31.69%	***	***

Source: Calculations using HIES 2000, 2005, 2010, and 2016. Note 1: Stars indicate whether mean for non-poor and poor is significantly different using a Wald test. Significance at the *10%, **5%, and *** 1% level. Note 2: Significance values are calculated for each year separately including division fixed effects. Significance at the *10%, **5%, and *** 1% level of probit regression correcting for the clustered nature of the errors. Note 3: Dependency ratio was calculated as the population aged zero to 14 and over the age of 65, to the total population aged 15 to 65.

V. Summary of emerging priorities

Bangladesh continues to make progress in eliminating poverty, thanks to strong growth across all sectors of the economy. Poverty has halved in 16 years, from 2000 to 2016.

However, the slower and uneven pace of progress in the last six years points to some emerging priorities to increase the pace of poverty reduction. These emerging priorities are drawn from the trends that have been documented in this note on the nature of poverty reduction in locales and sectors in Bangladesh, and differences in characteristics of the poor and non-poor. Although clear trends have emerged, further analysis is needed to identify what factors caused changes in poverty reduction in the past six years. This will allow more specific recommendations for action.

Stronger productivity growth is needed in agriculture and informal urban services and stronger job-creation in manufacturing. It is labor income growth that continues to drive poverty reduction in Bangladesh, but growth has not been high enough in the sectors in which poor people tend to be employed—agriculture and informal services in urban areas. Additionally, not enough people have been able to move into higher-productivity sectors, consistent with the finding that job creation in these sectors has slowed.

Addressing spatial inequality will require addressing constraints to income growth in Rangpur province, and in Western Bangladesh in general. The last six years of development in Bangladesh have led to the reopening of the welfare differences between East and West, and poverty rates are now much higher in the West than the rest of the country. Addressing this will likely require more than domestic migration, although this will continue to help.

Finally, there is room to examine social spending to improve coverage of social protection programs and human capital outcomes for poor households. Poor households have just as many adults engaged in work as non-poor households, but the remuneration of their work is lower, in part because of lower levels of human capital. Addressing these differences is essential to enabling poor households to gain more productive employment. Bangladesh already invests significant amounts in health and education, so further analysis is needed to understand which investments are reaching poor households and how effective districts are in securing improved outcomes given the resources committed. Similarly, social protection programs in Bangladesh are reaching poor households, but the proportion of poor households receiving social protection has fallen. There is room to increase coverage, particularly in urban areas, and to improve targeting in rural areas, to help reverse the trend of lower consumption growth among the poorest households.

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Annex

Table A1: Poverty rates by division. Using the 2000 divisions.

	Poverty Rate				Extreme Poverty Rate			
	2000	2005	2010	2016	2000	2005	2010	2016
Barisal	53.1	52.0	39.4	26.4	34.7	35.6	26.7	14.4
	(3.8)	(3.9)	(3.3)	(1.5)	(3.7)	(4.5)	(3.2)	(1.3)
Chittagong	45.7	34.0	26.2	18.3	27.5	16.1	13.1	9.0
	(2.9)	(2.7)	(2)	(1.2)	(2.9)	(1.8)	(1.4)	(0.9)
Dhaka	46.7	32.0	30.5	20.5	34.6	19.9	15.6	9.9
	(2.3)	(1.7)	(1.6)	(1.1)	(2.2)	(1.3)	(1.1)	(0.7)
Khulna	45.1	45.7	32.1	27.7	32.2	31.6	15.4	12.1
	(3.5)	(2.7)	(2.3)	(1.3)	(3.1)	(2.4)	(1.6)	(0.8)
Rajshahi	56.7	51.2	35.7	37.6	42.8	34.5	21.6	22.0
	(2.3)	(1.5)	(2)	(1)	(2.5)	(1.6)	(1.7)	(0.8)
Sylhet	42.4	33.8	28.1	16.2	26.7	20.8	20.7	11.5
	(3.3)	(5.2)	(3)	(1.7)	(3.2)	(4.1)	(2.5)	(1.4)

Source: Staff calculations using HIES 2010 and 2016.
Note: Divisions are defined in a comparable way across time. Standard errors in parentheses. These results are by design representative across time.

Table A2: Poverty rates by division. Using the 2016 divisions.

	Poverty Rate				Extreme Poverty Rate			
	2000	2005	2010	2016	2000	2005	2010	2016
Barisal	53.1	52.0	39.4	26.4	34.7	35.6	26.7	14.4
	(3.8)	(3.9)	(3.3)	(1.5)	(3.7)	(4.5)	(3.2)	(1.3)
Chittagong	45.7	34.0	26.2	18.3	27.5	16.1	13.1	9.0
	(2.9)	(2.7)	(2)	(1.2)	(2.9)	(1.8)	(1.4)	(0.9)
Dhaka	42.3	27.7	25.8	16.7	30.6	16.1	11.3	7.4
	(2.7)	(1.8)	(1.7)	(1.3)	(2.5)	(1.3)	(1.1)	(0.7)
Khulna	45.1	45.7	32.1	27.7	32.2	31.6	15.4	12.1
	(3.5)	(2.7)	(2.3)	(1.3)	(3.1)	(2.4)	(1.6)	(0.8)
Mymensingh	60.6	48.5	48.3	32.9	47.0	35.0	31.9	18.0
	(4.6)	(4.1)	(3.2)	(2)	(4.3)	(3.8)	(2.8)	(1.6)
Rajshahi	45.1	45.7	32.1	27.7	32.2	31.6	15.4	12.1
	(3.5)	(2.7)	(2.3)	(1.3)	(3.1)	(2.4)	(1.6)	(0.8)
Rangpur	60.6	48.5	48.3	32.9	47.0	35.0	31.9	18.0
	(4.6)	(4.1)	(3.2)	(2)	(4.3)	(3.8)	(2.8)	(1.6)
Sylhet	42.4	33.8	28.1	16.2	26.7	20.8	20.7	11.5
	(3.3)	(5.2)	(3)	(1.7)	(3.2)	(4.1)	(2.5)	(1.4)

Source: Staff calculations using HIES 2010 and 2016.
Note: Divisions are defined in a comparable way across time. Standard errors in parentheses. By design, only 2016 estimates are representative for Mymensingh and Rangpur.

CHAPTER III.

Understanding Poverty Trends in Bangladesh: Insights from Decomposition Analysis[1]

July 2019

Abstract

Bangladesh has continued to make remarkable progress in reducing poverty since 2010. In some regards, poverty reduction has continued in a manner consistent with the previous decade. However, important differences emerge when trends are examined more closely. Poverty rates in the poorer West and richer East converged until 2010, then diverged, as poverty reduction in the poorer Western divisions again started to lag. Poverty reduction was concentrated among those in agricultural activities until 2010, while in the more recent period it was not. This paper uses decomposition analysis to examine the changing nature of poverty reduction from 2005 to 2010 and 2010 to 2016. Why was the nature of poverty reduction so different in these two periods? Four insights emerge from the analysis:

1. Reductions in fertility and family size have been important for poverty reduction throughout the periods considered, and have been slower in the Western divisions.
2. Gains in educational attainment were key to improving household fortunes, and can help explain the divergent trajectories of the East and West.
3. Structural change is occurring, but not equally everywhere. Structural change lags in the West, where consumption remains as closely correlated

[1] This paper was produced by the Poverty and Equity Global Practice as part of the Bangladesh Programmatic Poverty and Equity Work (P165499). The team comprised Ruth Hill and Jose Joaquin Endara.

with land ownership as in the past. This is concerning, given declining land holdings in the West.

4. Special conditions were present in 2010 that increased gains to agriculture, benefiting the more agricultural West of the country and causing a temporary convergence.

I. Introduction

Since 2000, Bangladesh has made remarkable progress in reducing poverty. In 2000, half of the country's population lived in poverty, based on the national poverty line. By 2010, this figure had fallen to 31 percent. In 2016, official poverty statistics showed that the share of Bangladeshis living below the national poverty line had dropped to 24.3 percent, some 1 in 4.[2, 3] Half of these persons, 12.9 percent of the population, lived on less than the national extreme poverty line. These estimates for 2016 represent sustained progress in reducing poverty.

In some regards, poverty reduction in Bangladesh since 2010 has continued in a manner consistent with the previous decade. Poverty reduction has continued at an impressive pace (albeit somewhat more slowly). Gains have continued to be strong in rural areas. And poverty reduction continues to be driven by changes in labor income, rather than an increase in transfers received by households.

However, important differences emerge when national trends are examined more closely (World Bank 2018a). Three differences are particularly notable. First, from 2005 to 2010, poverty rates in the poorer West and richer East converged, as Western divisions experienced faster poverty reduction.[4] From 2010 to 2016, however, poverty rates between the East and West once again diverged, with the East experiencing rapid poverty reduction and poverty reduction stalling in the West. Second, while the pace of poverty reduction in rural Bangladesh was almost identical in these two periods, in the first period it was concentrated among those in agricultural activities, whereas in the second period it was concentrated among

[2] The Household Income and Expenditure Survey (HIES), used to estimate poverty in Bangladesh, is collected over a period of one year. The HIES 2016/17 data was collected from April 2016 until March 2017. The same is true for the HIES data collected in previous surveys: 2000/1, 2005/6, 2010/11. For this report we refer to these poverty estimates as from 2000, 2005, 2010, and 2016, respectively.

[3] For a full discussion of how poverty is measured in Bangladesh and comparability across rounds of the HIES, see Paper 1 in this volume: "Description of the Official Methodology Used for Poverty Estimation in Bangladesh for 2016/17." The standard errors for these poverty estimates are included in graphs to indicate the precision with which poverty is measured in Bangladesh.

[4] In this note, the West includes the divisions of Rangpur, Rajshahi, and Khulna.

those not in agriculture. Third, urban poverty reduction was much slower from 2010 to 2016 than it had been in the previous decade. In fact, the slowdown in urban poverty reduction can explain much of the observed national poverty reduction slowdown.

These trends require further examination. Why was the nature of poverty reduction so different in these two periods, when the policy environment remained little changed? Why did spatial disparities appear to lessen and then increase again?

This paper uses decomposition analysis to examine the changing nature of poverty reduction from 2005 to 2010 and 2010 to 2016. The decomposition methods used are non-parametric, to allow a focus on consumption growth across the distribution, rather than focusing on what explains changes in average consumption or changes in the poverty rate at a given poverty line. The focus is on explaining changes in consumption rather than changes in income. Given the data available for the type of analysis undertaken in this paper, the focus is on how changes in assets (a household's labor, physical assets, and access to economic services such as electricity) have been correlated with consumption growth, rather than how consumption growth has been affected by changes in how income is earned. An assessment of the role of income growth and structural change is developed in a separate paper (Hill and Endara 2018), also prepared for the Bangladesh Poverty Assessment. A further explanation of the methods used here and their rationale is presented in section 3.

Some clear insights emerge from the analysis:

- **Reductions in fertility and family size are important for poverty reduction.** The results suggest lower fertility rates will also have long-run benefits, on account of the greater investments in human capital per child that lower dependency ratios allow and the reduced pressure on agricultural land in the next generation.
- **Gains in educational attainment were likely a key component of improving household fortunes, and can help explain the divergent trajectories of the East and West.** Gains in educational attainment in rural areas in the East have outstripped educational gains in rural areas of the West, particularly since 2010, and have contributed to diverging rural poverty rates in the East and West.
- **Structural change is occurring, but not equally everywhere.** Over time, the consumption gain from agricultural land is falling, and the cost of remaining in agriculture is increasing, as employment in other sectors becomes more beneficial. Structural change lags in the West, and as a result, consumption

there is still just as closely correlated with land ownership as in the past. This is concerning, given declining land holdings in the West.

- **Special conditions were present in 2010 that increased gains to agriculture, benefiting the more agricultural West of the country.** These conditions gave the appearance of convergence between the East and West, but this was a temporary phenomenon.

II. Context

Strong national poverty reduction from 2010 to 2016 masks differences in welfare trends between rural and urban Bangladesh. The upper poverty rate[5] fell in rural and urban Bangladesh from 2010 to 2016, but the rate of reduction was much slower in urban areas (Figure 1). There was no progress in reducing extreme poverty in urban areas: the proportion of the urban population living in extreme poverty was 7.7 percent in 2010 and 7.6 percent in 2016.

There have also been stark differences in welfare trends across divisions in recent years. Poverty has risen in Rangpur division, the historically poorer Northwest of the country; stagnated in Rajshahi and Khulna in the West; fallen moderately in Chittagong; and declined rapidly in Barisal, Dhaka, and Sylhet (Figure 2 and Table 1). The stronger progress of poverty reduction in the Eastern regions widened a gap between Eastern and Western Bangladesh that had narrowed between 2005 and 2010 (World Bank 2013). In 2013, the Poverty Assessment noted that the divide between the historically richer East and the poorer West had narrowed and in fact was imperceptible from division poverty rates. However, in 2016, this divide has clearly returned, with the three poorest divisions in Bangladesh being those that lie on its Western border.

A comparison of the incidence of consumption growth across years underscores the very different experiences of households depending on their location of residence. Figure 3 shows that from 2005 to 2010 annual real per capita consumption growth averaged about 3 percent in Western divisions, while from 2010 to 2016

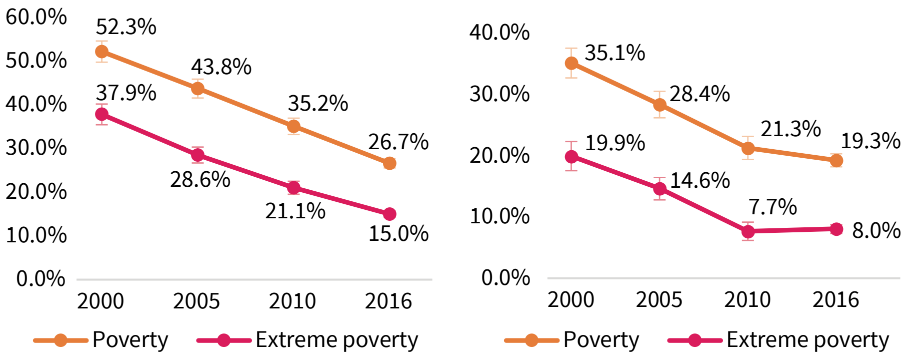
[5] The official methodology used in Bangladesh to estimate poverty numbers was based on the Cost of Basic Needs (CBN). The CBN method calculates the cost of obtaining a consumption bundle considered to be adequate to satisfy basic consumption needs. If a person cannot afford the cost of this bundle, then this person is considered poor. The upper poverty line is the cost of a bundle that includes basic food and non-food items. The lower poverty line is the cost of a bundle that mostly includes food and a small share of non-food items and aims to measure extreme poverty. For a full discussion of how poverty is measured in Bangladesh see Paper 1 in this volume, "Description of the Official Methodology used for Poverty Estimation in Bangladesh for 2016/17."

these divisions saw almost no consumption growth, on average. In contrast, average annual real per capita consumption growth was about 1 percent in Eastern divisions from 2005 to 2010 and about 2.5 percent from 2010 to 2016.

Figure 1. Continued poverty reduction from 2010 to 2016, but slower in urban areas

Poverty and extreme poverty headcount rates (%), rural areas, 2000 to 2016

Poverty and extreme poverty headcount rates (%), urban areas, 2000 to 2016

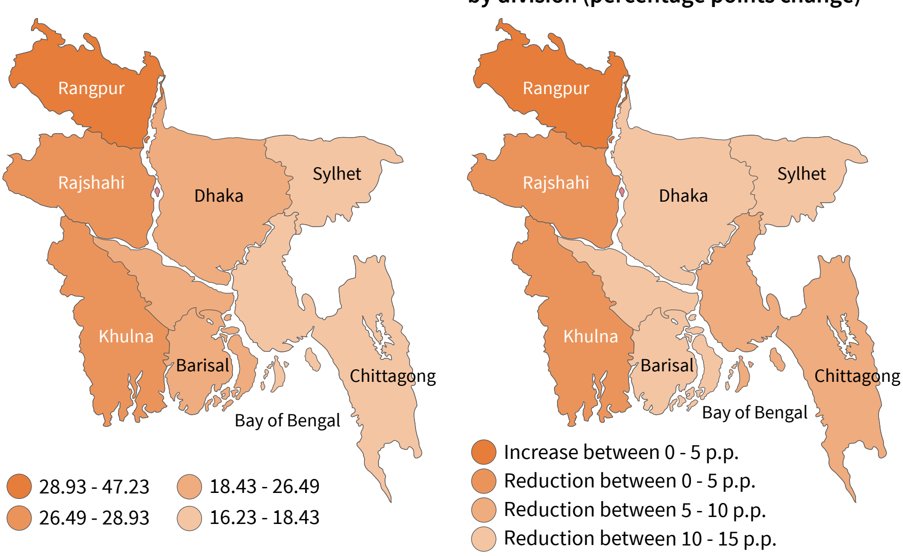


Note: PPP denotes Purchasing Power Parity.

Figure 2. Poverty reduction has been slowest in the West, where poverty is highest

Upper poverty rate 2016 by division

Change in upper poverty rate 2010-2016 by division (percentage points change)



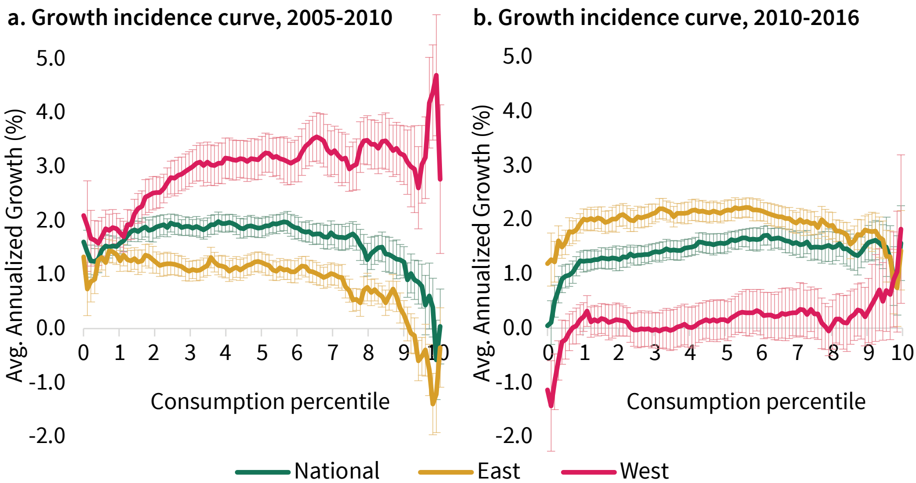
Source: Staff calculations based on HIES 2010 and 2016.

Table 1: Poverty reduction has been uneven across divisions

	Poverty rate			Extreme poverty rate		
	2005	2010	2016	2005	2010	2016
Barisal	52	39	26	36	27	14
Chittagong	34	26	18	16	13	9
Dhaka	32	31	20	20	16	10
Khulna	46	32	27	32	15	12
Rajshahi	47	30	29	28	16	14
Rangpur	42	42	47	41	28	31
Sylhet	28	28	16	21	21	11

Source: Authors' calculations using HIES 2010 and 2016.

Figure 3. Comparing the incidence of consumption growth in the East and West, 2005-2016



Source: Staff calculations using HIES 2005, 2010, and 2016.
Notes: West includes the divisions of Rangpur, Rajshahi, and Khulna. East includes the divisions of Barisal, Chittagong, Dhaka, and Sylhet. Figures present growth incidence curves, which indicate the growth in consumption for people at each level of consumption (from the poorest on the left to the richest on the right).

III. Framework, method, and data

Framework

In Bangladesh, as in many lower middle-income countries, household income is determined almost entirely by the income that is earned by household members. Public transfers and private transfers from non-household members are limited. A simple yet useful framework for thinking about important factors affecting household labor income is provided in Bussolo and Lopez-Calva (2014). A household's labor income is determined by the assets the household has—both human assets such as working-age members and skills, and physical assets such as land and location of residence—and the return that can be earned on these assets. This return is determined by a household's ability to use these assets in gainful employment and the return to these assets available in the market when they are used or invested.

In this framework, changes in labor income can be thought of as driven by changes in assets—e.g. acquiring skills, moving residence, selling or buying land—or changes in the return that an individual can earn on those assets. In this paper we explore these two possible drivers of change using decomposition methods. These methods can help identify whether the data is consistent with a story of asset accumulation having driven progress in poverty reduction, or whether the data suggests limited asset accumulation but changes in returns playing a large role.

Unlike the analysis conducted for the last Poverty Assessment (World Bank 2013), the decomposition methods do not rely on HIES income data but focus instead on household consumption growth. This is in part out of concerns regarding the quality of the income data in the HIES, as further discussed below. As a result, the variables that are included in the regression reflect labor market outcomes at the household level and do not include individual characteristics such as age and gender of the worker that would be found in a standard Mincer regression. However, information on the age and gender composition of the household is included instead.

There are many variables that can be included in an analysis like this. The focus in this analysis has been to include variables which have undergone important changes, or which the general discourse suggests have been important for poverty reduction in Bangladesh. In addition, the focus of the analysis is to look at endowments of labor and physical assets and the relationship between these endowments and consumption, rather than focusing on how these endowments are used to generate income. Another background paper for the current poverty assessment uses data on economic activity in each zone to look at how changes in income generation have driven poverty reduction over time (Hill and Endara 2019).

The concerns about income data, and the decision to focus on factors that affect income generation rather than on labor income itself, prevented some measures from being included. Among these variables are, for example, the number of hours worked and the level of participation in the labor market of particular groups, such as women. In discussing the results, we also note some variables that were included in alternate specification but were not significant, and so were not included in the final specification for reasons of parsimony. Their exclusion did not alter the other findings presented.

The decomposition methods used in this paper are non-parametric, so they allow a decomposition of consumption growth across the distribution rather than just for the average household. In this regard, the analysis departs from decomposition analysis undertaken for the last Poverty Assessment. The rest of this section outlines the methods used and the rationale for choices on the data used.

Method

The Recentered Influence Functions (RIF) approach is used to conduct the decompositions (Firpo et al. 2009). In RIF, traditional Oaxaca-Blinder decompositions are applied to each decile of the consumption distribution. A traditional Oaxaca-Blinder analysis decomposes an average outcome between two groups (for example, differences in average wages between men and women) into the difference that can be explained by differences in characteristics between these groups and the difference that arises because of a difference in the relationship between the outcome and a given characteristic (often called returns). The two regressions in equation (1) would be run separately for two different groups (in this example, men and women) where Y_i1 is the outcome of variable interest (in this example, wages) for individual i in group 1 or 2 and X is a set of characteristics of individual i in group 1 or 2 (for example, age and education).

$$Y_{i1} = \beta_0 + \beta_{X1} X_{i1} + \varepsilon_{i1} \qquad (1)$$

$$Y_{i2} = \beta_0 + \beta_{X2} X_{i2} + \varepsilon_{i2} \qquad .$$

The difference in the average outcome between the two groups ($\overline{Y_1} - \overline{Y_2}$) can be considered to be comprised of the difference in the average of the Xs evaluated at the average coefficient ($\bar{\beta}_X(\overline{X_1} - \overline{X_2})$) and the difference in the average of the coefficients evaluated at the average ($\bar{X}(\overline{\beta_{X1}} - \overline{\beta_{X2}})$), as well as an unexplained component.

In the case of welfare analysis this decomposition is done for two moments in time. The first group is the initial year and the second group is the second year. Differences in outcomes between these two years can then be decomposed according to whether there were changes in characteristics (X) between these two years or whether there was a change in the relationship between a given characteristic and the welfare outcome of interest (β) in this period.

While the Oaxaca-Blinder decomposition method focuses on differences between means, the RIF approach decomposes the difference at various points along the distribution, which allows for a more interesting analysis. The regressions in equation 1 are run for different quintiles (or quartiles or deciles) of the consumption distribution. This approach allows one to look at the covariates of poverty such as occupation, location, demography, human capital—the endowments presented in the above framework—and assess whether changes in consumption growth have been commensurate with changes in the distribution of these endowments. (This would suggest that changes in these endowments may have contributed to changes in poverty, but as this is a descriptive analysis, this is not conclusive evidence.) The analysis also allows an assessment of whether consumption growth has coincided with changes in the strength or size of the correlation between poverty and the endowment in question. Some refer to this as changes in returns to endowments. Changes in these coefficients could reflect changes in the returns, however it is also important to note that these coefficients are not true estimates of returns. They may also pick up the influence of consumption on assets (reverse causality) and the impact of other important determinants of consumption that are not included in the regression for lack of data but that are correlated with the assets that have been measured. Given that the poverty rate in Bangladesh was 35 percent in 2010, factors that seem to have been important in explaining consumption growth in the bottom three deciles are important in explaining poverty reduction from 2010 to 2016.

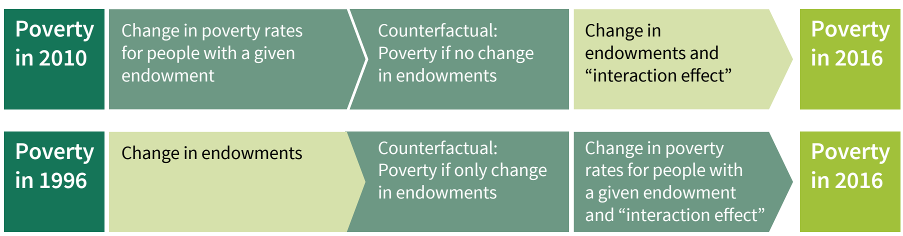
In essence, the decomposition method can be thought of as defining a counterfactual scenario (for example, that there was no change in X across time) and estimating what would have happened to consumption had the counterfactual scenario occurred. Figure 4 depicts how this can work for two different counterfactual scenarios.

The first counterfactual scenario that is considered helps assess the likely impact of endowments on consumption growth. It assumes a constant relationship between endowments and poverty in Bangladesh across the period considered, in this case by taking the relationship between endowments and consumption estimated from data at the beginning of the period. Thus, for the period 2005 to 2010 the estimates from 2005 data are used, and for the period 2010 to 2016 estimates from 2010 are used. The change in the endowment across the period is multiplied by the coefficient from the beginning of the period to assess how changes in endowments are likely to have impacted consumption growth during this time.

The second counterfactual scenario examines how much consumption grew as a result of a changing relationship between consumption and endowments. This change may reflect changes in the returns to endowments across time, but it is calculated as the change in the conditional correlation between a given endowment and consumption, so could also be driven by other factors.

In all decomposition approaches, there is an interaction effect which can be interpreted as a measure of the correlation between changes in endowments and coefficients. It is quite small in the decomposition estimates in this paper.

Figure 4. Using counterfactuals to quantify changes that have been important to poverty reduction



Data

The focus of the analysis is on examining changes in consumption per capita across three waves of HIES data: 2005/6, 2010/11, and 2016/17 (henceforth referred to as 2005, 2010, and 2016 respectively). Changes in consumption per capita are decomposed across groups defined by location, education of adult members of the household, household demographics, and land ownership. These are characteristics that tend to change slowly over time so perhaps are more likely to be determinants of changes in consumption observed, rather than the result of changes in consumption. However, it is quite possible that they are impacted by changes in consumption or that they are correlated with other factors that are important determinants or outcomes of changes in consumption, so the analysis cannot be thought of as causal. As described in the previous subsection, we are careful in this paper to be clear about what we are able to explain through this analysis.

In contrast to other decomposition methods that rely on income data to explain changes in per capita consumption (including decomposition methods used in the last poverty assessment), we do not use income data to examine changes in consumption in this paper. We do use the main sector of employment of the household, defined by the number of hours a household spends working in a given sector, but we do not look at the impact of marginal changes in income. This is in part because we expect the main sector of employment to change quite slowly, allowing us to examine something that may be somewhat exogenous to changes in consumption, but this choice was also made because of limitations in the income data collected in HIES.

It is difficult to accurately capture household income through a household survey instrument when the majority of income is earned through informal self-employment activities such as agricultural self-employment and household enterprises. This has been true for HIES in all rounds, with challenges in collecting accurate data from self-employment activities.

However, data on income is particularly poorly collected in the 2016 round of the HIES. The more complex logistics of a four-fold increase in the sample size and the move from centralized data collection to data collection in the field resulted in larger errors in some of the more complex parts of the questionnaire that were not being checked in real time. The increase in measurement error in these sections outweighs the gains in precision that come from a larger sample size. The consumption section and the demographic section were checked as data was entered in the field and feedback was provided to supervisors when problems were spotted (World Bank 2018b). However, there were no data checks on the income section, and a comparison of the income section results for 2010 and 2016 reveals higher rates of error in data collection in 2016. While there were no obvious systematic errors in the collection of income data, the high rate of error and missing values makes it more challenging to use this data in practice (see Annex 1 for more details).

IV. Understanding trends in rural and urban poverty reduction

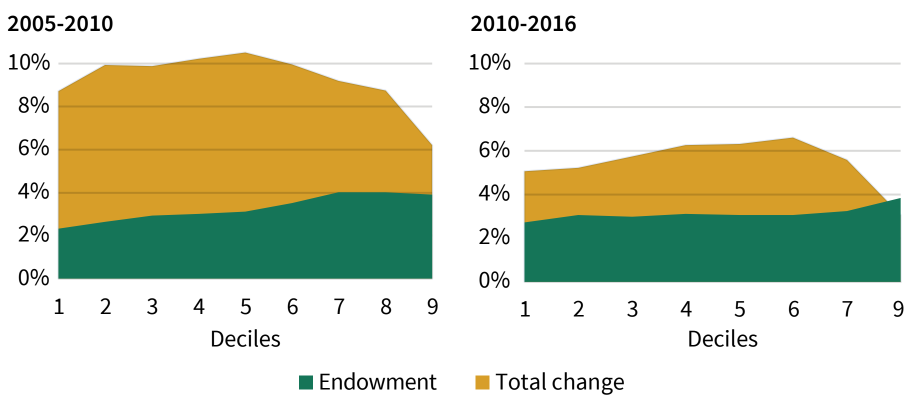
Section 4 includes two subsections. The first examines how changes in demographic characteristics (household size and structure), key assets (educational attainment and land ownership), and sectors of employment may have influenced poverty reduction. The second subsection considers how the relationship between these household characteristics and per capita consumption has changed and the likely impact of these changes on consumption growth. The full regression results are presented in Annex 2.

Endowments

From 2010 to 2016, the demographic, asset, and sectoral changes experienced by households were large enough to have contributed to consumption growth. If the relationship between these characteristics and consumption had been constant across this period, and if the estimated relationship is indicative of the true relationship between the characteristics and consumption, the changes in these factors alone could explain half of all consumption growth from 2010 to 2016 (Figure 5). The following subsection assesses whether the data supports the assumption that the relationship remained unchanged.

From 2005 to 2010, changes in these same endowments could explain a similar amount of consumption growth. However, consumption growth was higher in this period so this was a smaller share of the overall consumption growth experienced (Figure 5). The unexplained aspect of consumption growth was much larger during this period, suggesting that changes in the return to these endowments or other factors and their relationship with poverty reduction were more important.

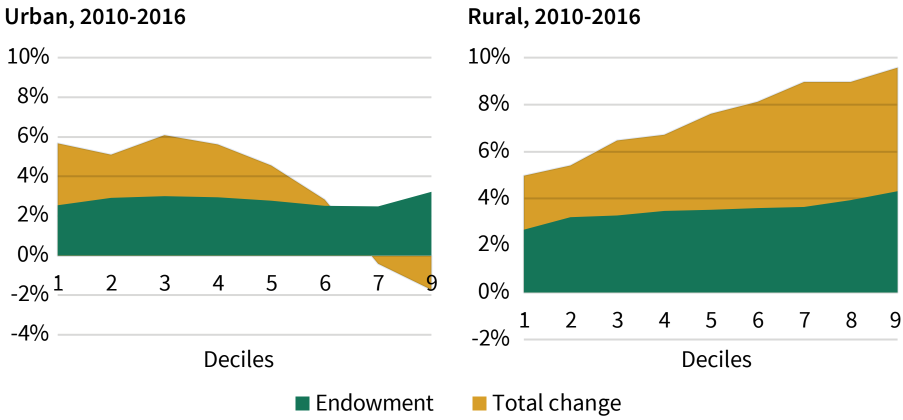
Figure 5. The role of changing endowments in total consumption growth



Note: "Endowments" refers to the estimated consumption growth from changes in household characteristics and is calculated as the sum of the change in each characteristic from 2010 to 2016 multiplied by the coefficient for that characteristic in 2010.

The slowdown in urban poverty reduction from 2010 to 2016 cannot be explained by much slower accumulation of assets in urban areas. The estimated contribution of changes in endowments to poverty reduction is slightly lower in urban areas than in rural areas. However, as Figure 6 shows, this cannot explain much of the slowdown observed. In the next section we examine whether the changing relationship between these endowments and poverty can explain the difference.

Figure 6. Can slower asset accumulation explain the slowdown in urban poverty reduction?



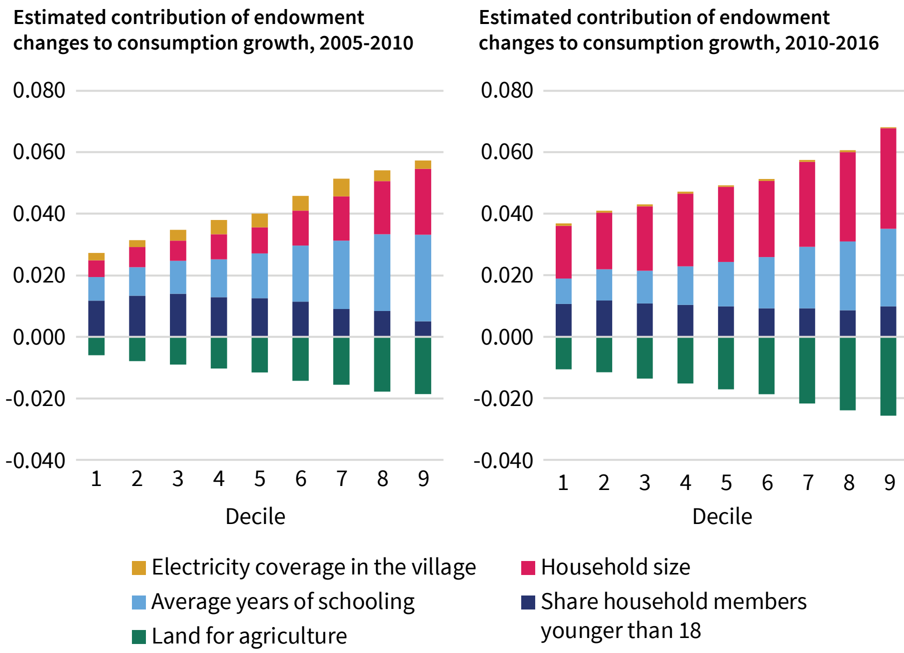
Note: "Endowments" refers to the estimated consumption growth from changes in household characteristics and is calculated as the sum of the change in each characteristic from 2010 to 2016 multiplied by the coefficient for that characteristic in 2010.

Among the assets considered, changes in the number of working age members per capita and in educational attainment were likely the largest positive contributors to consumption growth. Improvements in education and lowering fertility rates were the only factors contributing to positive changes in endowments for 2010 to 2016. From 2005 to 2010, education gains are estimated to contribute a bit more, while demographic changes contributed much less (Figure 7). It is worth noting that the large contribution of household size and structure to poverty reduction could come in part from the fact that the welfare measure used is total household consumption per capita. This measure does not account for any scale economies or for the fact that children will consume less than adults. This analysis was repeated using consumption measures that do allow for scale economies and calculate consumption per adult equivalent. Even in those cases, reductions in household size contributed significantly to poverty reduction, although to a lesser extent.

In contrast, declining land-holding sizes dragged down consumption growth, particularly from 2010. The size of land holdings continued to fall from 2010 to 2016, and this slowed poverty reduction. Reductions in the size of land holdings similarly had a negative effect from 2005 to 2010, but the impact was less substantial.

Educational attainment has been important for rural consumption growth, less so for urban consumption growth. The conditional correlation between education and consumption is higher in urban areas than in rural areas, suggesting

Figure 7. Estimated impact of changes in assets



Source: Staff calculations using HIES 2010 and 2016.
Note: Y-axis measures the predicted consumption per capita growth over the reference period from changes in household demographics and assets (i.e., location, education of adult members, household demographics, access to services, and land ownership). X-axis measures the per capita consumption decile. For more details see Hill and Endara (2019).

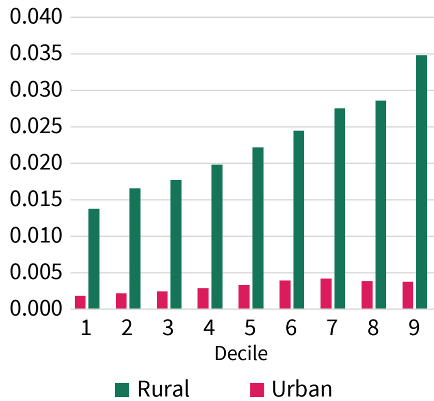
higher returns to education and therefore a larger gain to educational attainment in urban areas. However, educational attainment has increased more rapidly in rural Bangladesh than in cities. As a result, the estimated contribution of education to poverty reduction has been much higher in rural areas (Figure 8).

This analysis suggests that changes in households' main sector of employment did not play a large role in explaining poverty reduction. However, this result may be largely driven by the data available for the analysis. In the absence of income data, a measure of the "main" sector in which a household is engaged is defined for this household-level decomposition using the reported hours worked in given sectors. This results in sectoral shifts on the part of individual members of the household not being captured. Alternate sectoral breakdowns were also tried (such as whether or not a household member is engaged in the garment sector), but very little change was observed. The role of structural change is explored further using more appropriate data (See Hill and Endara 2019), and that analysis documents a significant impact of sectoral change on poverty trends.

The changing relationship between endowments and consumption

Estimating returns to assets is challenging using cross-section data. This section examines changes in the coefficient of endowments in a regression on the log of consumption across time, as a first step to looking at this question. These coefficients can be indicative of the return to a given asset. However, as section 3 noted, they can also be influenced by other relationships.

Figure 8. The contribution of increased education to consumption growth is larger in rural areas (2010-2016)

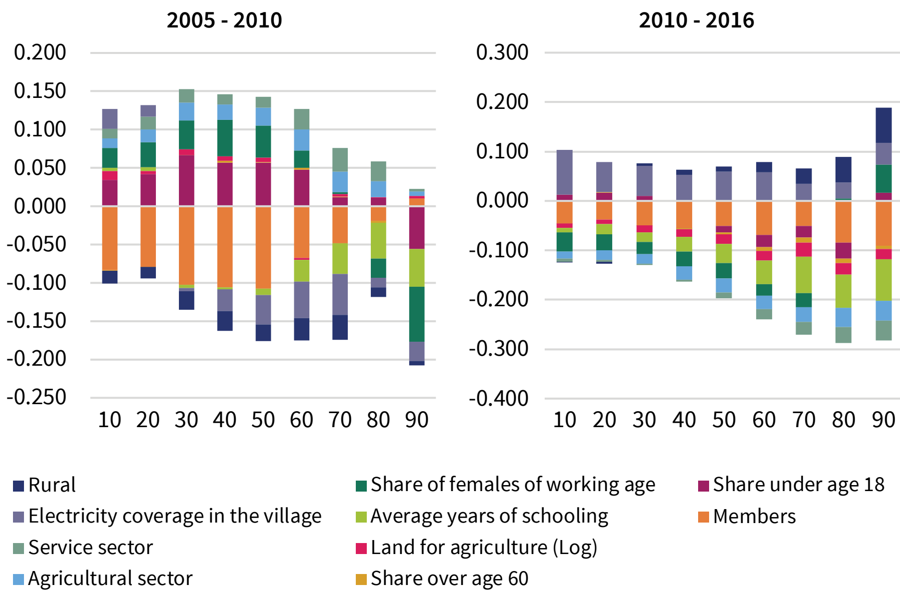


Source: Staff calculations using HIES 2000, 2005, 2010, and 2016.
Note: Average years of education calculated for adults older than 18 years. For more details see Hill and Endara (2019).

The changes in coefficients have been large enough to impact poverty reduction. The coefficients are examined fully below, but first the likely importance of changes in coefficients is assessed by multiplying the changes in coefficients by the average value of the variable at the beginning of the period. Changes in coefficients that are likely to have been more important for poverty reduction will be larger. Results are presented in Figure 9. The figure shows that, although smaller household sizes and increased educational attainment have been important for consumption growth, the coefficients on these endowments have grown smaller over time, and this change has reduced consumption growth. Figure 9 also shows that the changes in coefficients on sectoral engagement switched between 2005-2010 and 2010-2016. From 2005 to 2010, the coefficient on being engaged in the rural sector and service sector increased and was beneficial for consumption growth. From 2010 to 2016, this coefficient fell. The coefficient on land also fell from 2010 to 2016. In addition, from 2005 to 2010 the coefficient on having females of working age in the household increased for most of the distribution, whereas from 2010 to 2016 it fell. The coefficient on electricity increased from 2010 to 2016. The following paragraphs explore in more detail how coefficients have changed across time and discuss what might be driving these changes.

Larger household size has had an increasingly negative impact on consumption over time. At the same time, however, the negative consumption impact of having a larger share of the family under 18 has fallen. These changes were particularly large among poorer households from 2005 to 2010, with little change at the top of the consumption distribution (Figure 10). Taken together, the per capita consumption loss as a result of an additional child has increased. It is not clear what is behind this trend, but a shift to having more children in school and fewer children contributing to household income generation could explain it.

Figure 9. The estimated impact of changes in coefficients across periods



The tapering-off of the returns to education has resulted in consumption increasing less due to educational attainment than it otherwise would. Comparing Figure 7 and 9 shows that the estimated reduction in consumption due to this change in coefficients is large enough to more than efface the gains from educational attainment in this period. At the lower end of the distribution, this reduction in the coefficient was only present in urban areas, which may have contributed to the slowdown in urban poverty reduction.

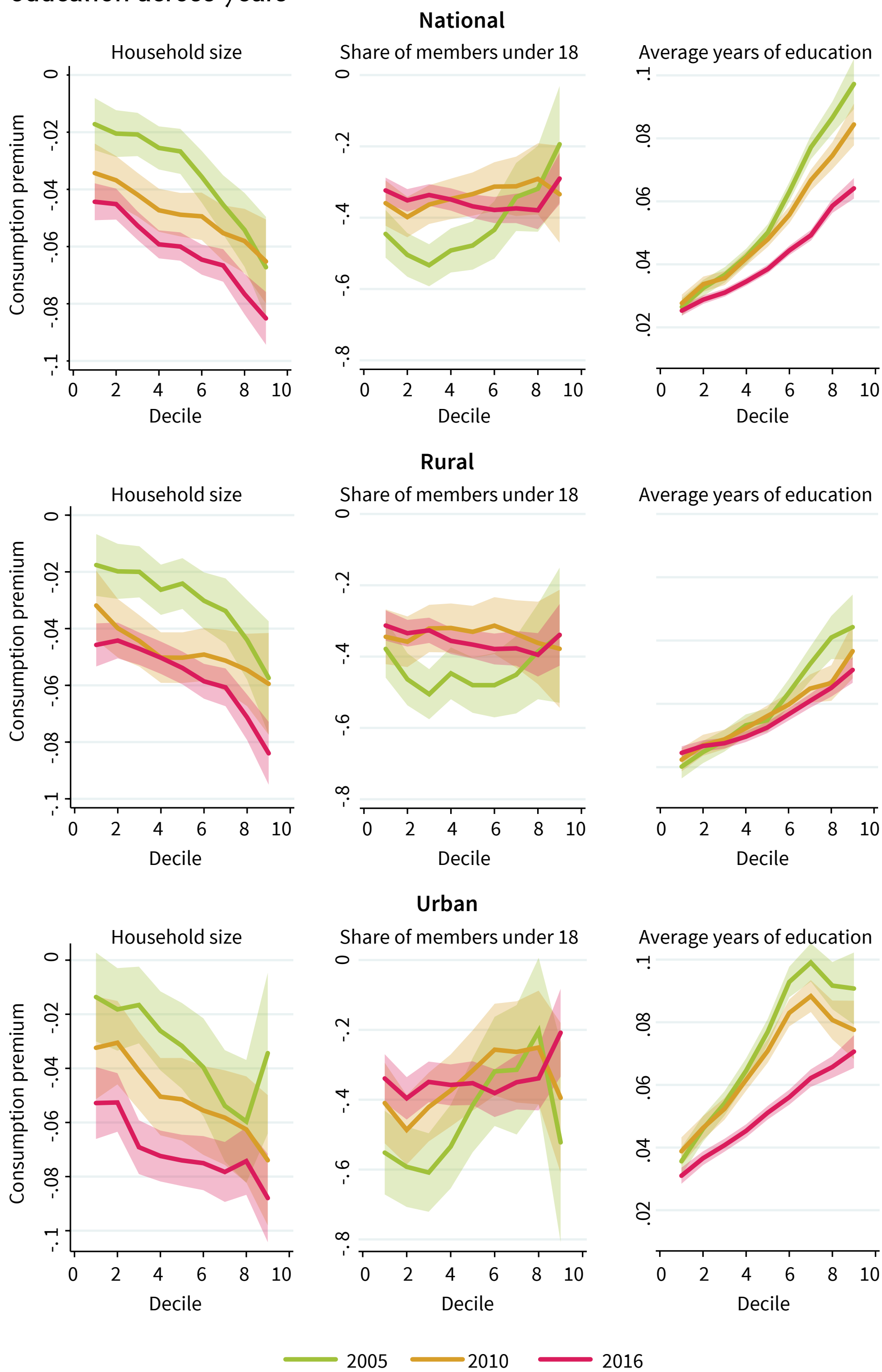
The gain in consumption observed for those with additional years of schooling has been higher for better-off households across all years (Figure 10). This most likely reflects the fact that there are higher returns to tertiary and secondary schooling (compared to primary schooling), and completion of tertiary and secondary schooling is more common among better-off households. Other analysis has documented low learning outcomes among those who completed primary school (Asadullah and Chaudhury 2013) and high private rates of return to additional years of schooling in Bangladesh, particularly in urban areas (Asadullah 2006). Returns to education and the increased educational level of women can explain a large part of the reduction in the gender wage gap that has been documented during this period (Ahmed and McGilivray 2015).

However, over the last 11 years the coefficient on education has fallen, particularly among households in the top 60 percent of the consumption distribution. As a result, there is now less difference between the return to education for richer and poorer households. In 2005, the return was four times higher in the top decile than in the bottom decile. By 2016, it was 2.5 times higher in the top decile. This likely reflects the fact that, as more people obtain secondary education, the return to having secondary education has fallen. The change has been particularly large at the top of the consumption distribution in rural areas and the middle of the consumption distribution in urban areas. This is consistent with a picture of declining returns to secondary education, while returns to tertiary education (at the top of the consumption distribution in urban areas) remain stable. The gain in consumption for those with more education is still higher in urban Bangladesh that in rural Bangladesh, but there is less of a difference now than in the past.

The strong correlation between land and consumption fell from 2010 to 2016, particularly among better-off households in rural areas. At the same time, the return to being engaged in industrial activity in rural areas has been increasing over the years. In 2016, this return was positive, in contrast to the negative impact of time spent in industrial employment in 2005. A similar pattern is observed for services (Figure 11). This suggests a structural shift occurring in rural areas over the last 11 years. Land has a weaker relationship with consumption in 2016 than in earlier periods. This is consistent with increased growth in non-farm activities reducing the importance of owning land for wealth levels. However, it could also be driven by the increased measurement error in the income data collected in 2016/17 (see Annex).

The relationship between consumption and employment in agriculture has not changed in line with these findings, with 2010 being a particularly good year for households engaged in agriculture. There was a positive increase in consumption for households that spent most of their time in agriculture from 2005 to 2010 (Figure 11). This was true across the consumption distribution. The change from 2010 to 2016 reversed this gain, such that the coefficient on agricultural employment in 2016 is not significantly different from 2005 for the bottom 60 percent. While this is surprising, it is consistent with the findings of the last Poverty Assessment (World Bank 2013), which documented substantial real wage growth

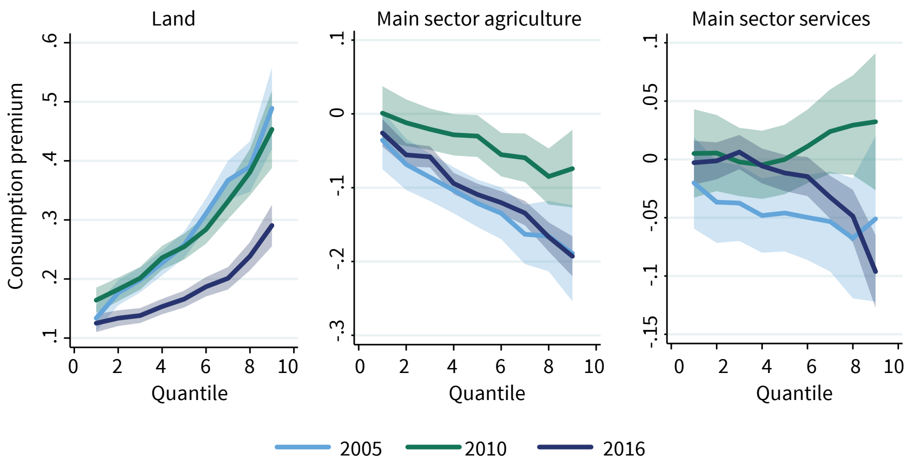
Figure 10. The relationship between consumption, demographics, and education across years



in agriculture, most likely on account of higher food prices. It is surprising to see no increase in the return to land in 2010, but the higher return to being in agriculture reflects that it was both land holders and non-land holders that benefited from the high real food prices present in 2010 (World Bank 2013).

Overall, these graphs suggest a process of structural change occurring in rural Bangladesh, but also the presence of unusual conditions in 2010 that resulted in poverty reduction from 2005 to 2010 being driven more by agriculture than appears to have been the case from 2010 to 2016.

Figure 11. **Returns to land and sectoral engagement across years, rural**

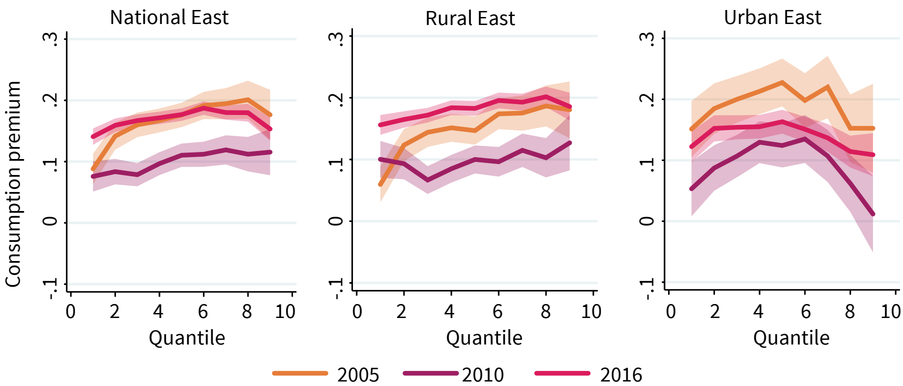


V. Understanding the changing East-West Divide

From 2010 to 2016, living in the East of the country has become much more strongly associated with higher levels of consumption, for poor and rich households alike. This calls into question the seeming end of the East-West Divide that had been documented in World Bank (2013) and Ali et al (2015). Figure 12 depicts the difference in consumption between households in the East and West across the consumption distribution after having controlled for other household endowments. The national graph shows that the gain from living in the East after controlling for endowments is the same in 2016 as it was in 2005. While that gain was also present in 2010, it was about half the size.

This trend is consistently observed across rural and urban localities, but it is particularly notable in rural areas. For poorer households in rural areas, the gain

Figure 12. The consumption premium of living in the East, controlling for differences in characteristics



from living in the East is larger in 2016 than in 2005, after controlling for observable household characteristics. In urban areas, the gain in 2016 is smaller than in 2005. The rest of this section uses decomposition analysis to examine why the divide shrank so much in 2010 and then re-emerged in 2016.

The rural West recorded slower progress on education and demographic change. As noted in the previous section, demographic change and increased educational attainment were strongly correlated with consumption growth. Household size fell more slowly in rural areas in Western divisions than in Eastern divisions, and gains in education were half of what they were in the East. The average years of education of adult household members increased by 0.77 among rural households in Eastern divisions, but by only 0.38 in rural households in Western divisions (Figure 13). As a result, the likely contribution of education to consumption growth in the West was half that in the East (Figure 14).

In urban areas in Western Bangladesh, progress on education and reducing family size was more rapid. Household size decreased more rapidly, and education attainment grew in urban areas in Western divisions (Figure 13) while education attainment fell in Eastern urban areas.[6] This more rapid progress in Western urban areas perhaps reduced the impact of any locational disadvantage in urban centers in the West.

[6] The reduction in average years of education in Eastern urban areas might be explained by two factors. The first is internal migration from less-educated rural areas towards big cities in the East (Dhaka and Chittagong), pushing average attainment levels downwards. The second factor is more methodological: in 2016, the HIES included urban slum areas in its sampling frame for the first time, which may also have contributed to lower average attainment levels.

Figure 13. Change in household size, education, and land from 2010-2016

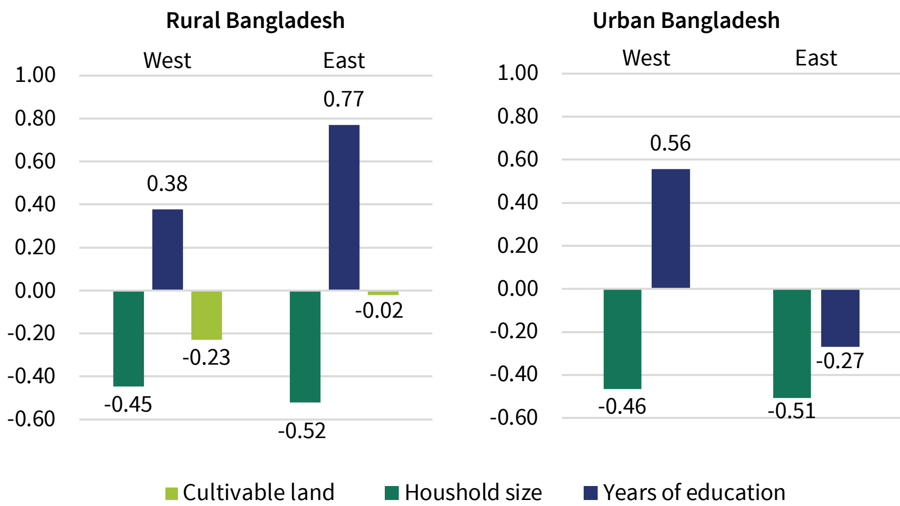
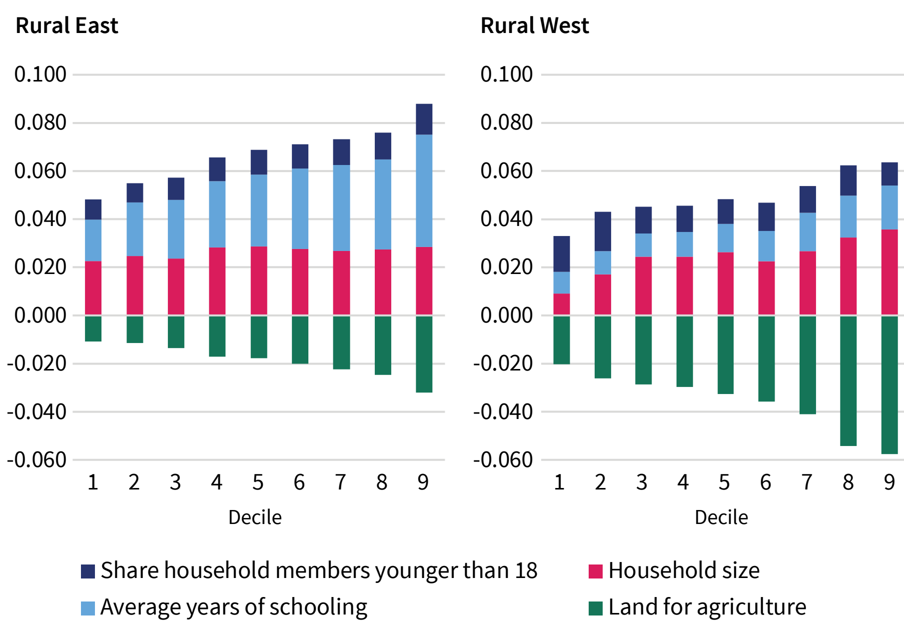


Figure 14. The impact of changing endowments on consumption growth in the East and West, 2010-16

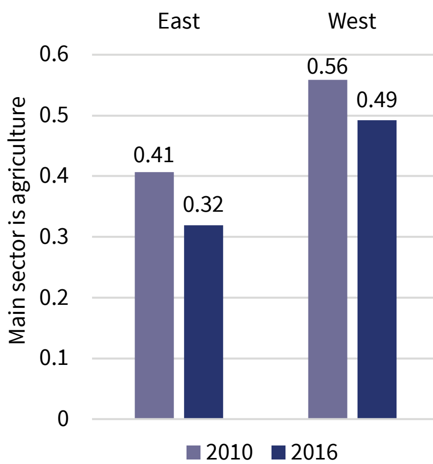


Source: Staff calculations using HIES 2010 and 2016.
Note: Y-axis measures the predicted consumption per capita growth over the reference period from changes in household demographics and assets (i.e., location, education of adult members, household demographics, access to services, and land ownership). X-axis measures the per capita consumption decile. For more details see Hill and Endara (2019).

Rural households in Western divisions also saw a more rapid decline in the average size of land holdings. Households with larger land holdings have higher consumption. As a result, the reduction in average land holdings during this period most likely contributed to a reduction in consumption growth (see previous sub-section). The fact that land-holding size fell faster in Western divisions likely caused consumption growth to decline faster than in the Eastern divisions. Land holdings are falling faster in Western regions because population growth there is more rapid.

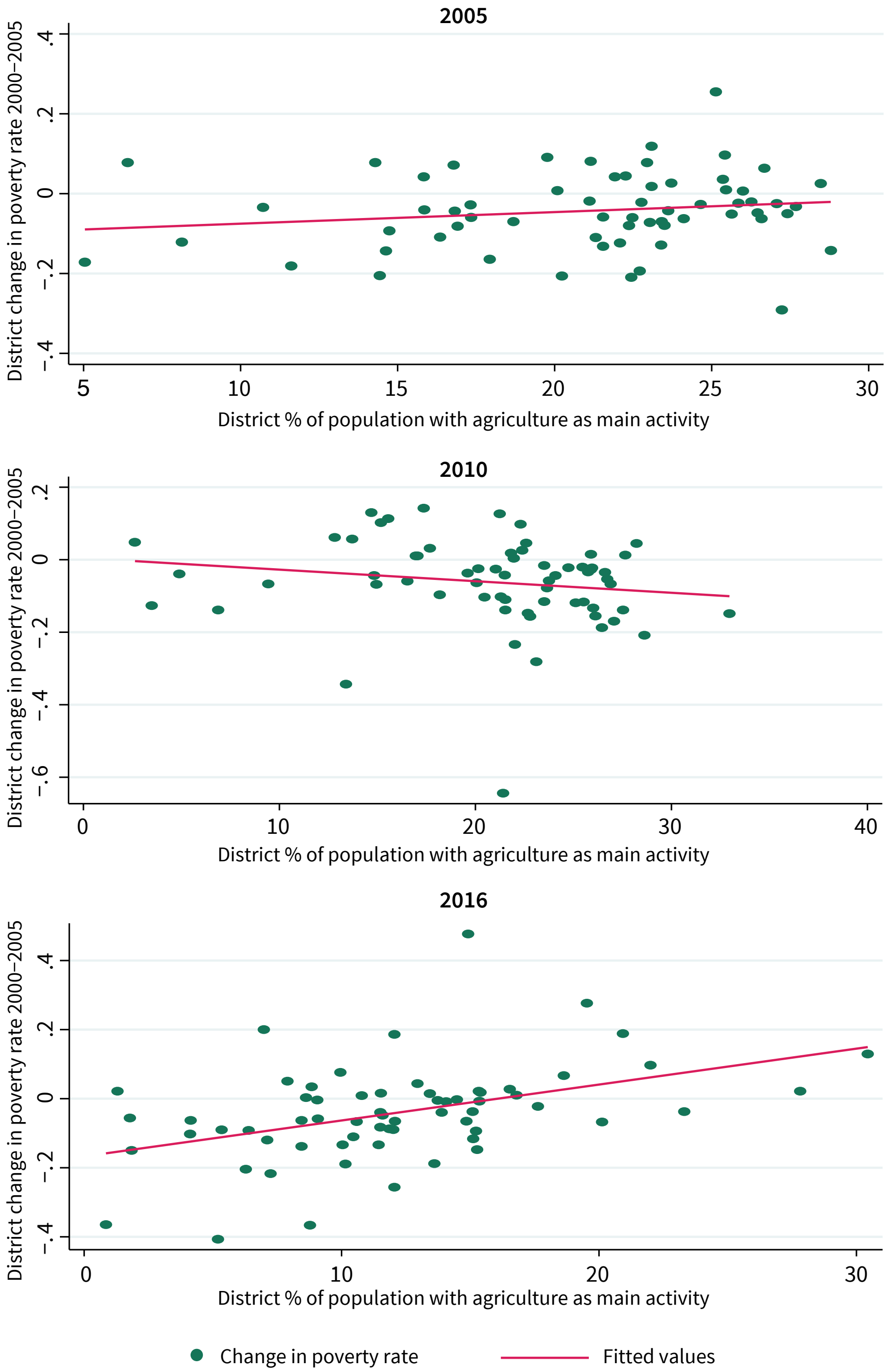
The greater prevalence of agricultural work in the West also played a role in faster consumption growth from 2005 to 2010 and slower consumption growth from 2010 to 2016. Although some of the divergence between the East and West from 2010 to 2016 can be explained by less favorable changes in assets, the difference in sectors of work also seems to have played an important role. Households in the West are more likely to report the main sector of work as agriculture. This was true in 2010 and 2016 (Figure 15). The period from 2005 to 2010 was particularly good for agricultural households, as they benefited from high food prices. This was true both for own-account workers in agriculture and those working as agricultural laborers, as agricultural wage rates increased (World Bank 2013).

Figure 15. Sector of employment



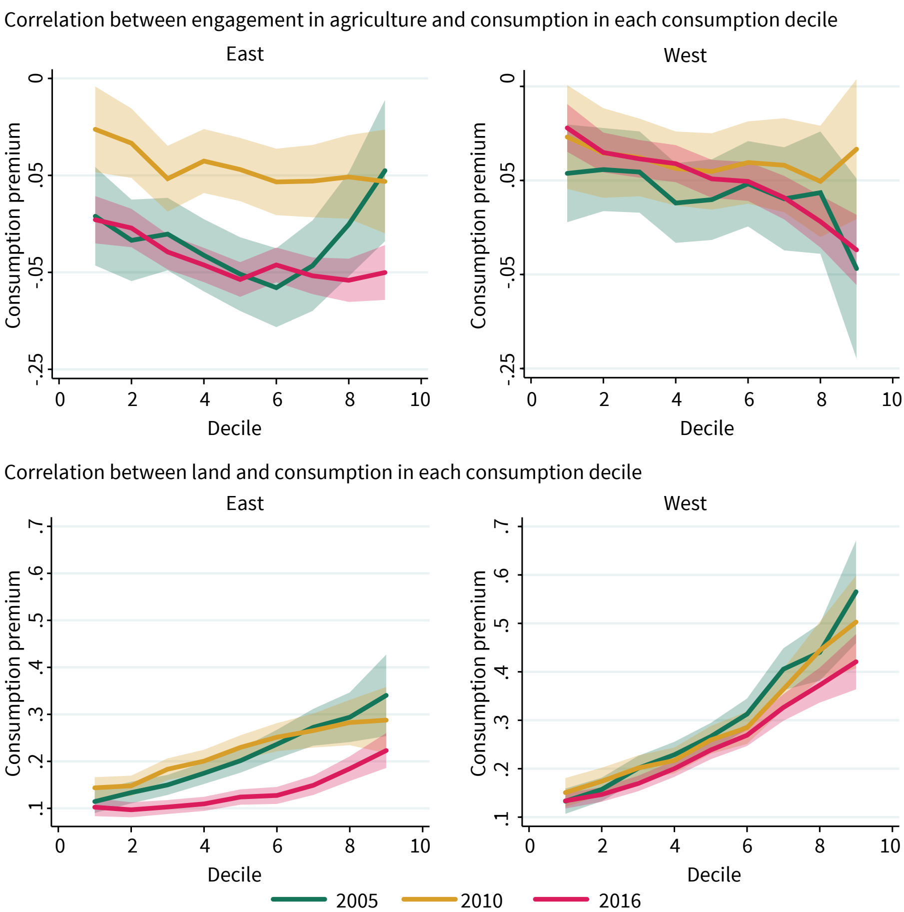
From 2005 to 2010, high rates of agricultural growth benefited areas where more households were engaged in agriculture. This pattern was reversed from 2010 to 2016. From 2010 to 2016, lower rates of agricultural growth meant that poverty reduction was stronger in places where households were more likely to be in non-agricultural sectors. This had also been true for the period from 2000 to 2005. At the district level, from 2005 to 2010, we see that poverty rates fell faster in districts in which agricultural employment was higher than in districts in which agricultural employment was lower (Figure 16). As Figure 11 shows, being in agriculture was better (or less bad) for consumption in 2010 than in 2016. As a result, the dominance of agriculture in work in the West was less detrimental in 2010 than in 2016.

Figure 16. From 2005 to 2010, poverty fell faster in areas with more people in agriculture



Structural transformation also seems to have been faster in the East than in the West, with gains for consumption growth. The shift in employment out of agriculture between 2010 and 2016 was larger in the East than in the West in both absolute and relative terms (Figure 15). The proportion of households reporting their main sector as agriculture fell by 22 percent in the East compared to 12 percent in the West. Because of more high-return economic opportunities outside of agriculture, the cost of staying in agriculture increased in the East, and the importance of owning land in determining social status fell. The correlation between land and consumption fell across the consumption distribution in the East (Figure 17). In contrast, in the West, there was little change in the opportunities outside of agriculture. This meant that the relationship between owning land and consumption did not change, despite the slowdown in returns to agriculture, and the negative correlation between consumption and being in agriculture did not increase.

Figure 17. The relationship between agriculture, land, and consumption



Conclusion

This paper has used decomposition analysis to explore some of the differences in poverty trends present in Bangladesh across time. It has focused on examining locational differences in consumption growth, specifically the slowdown of consumption growth in urban areas since 2010 and the diverging trends in consumption growth across the East and West of the country from 2005 to 2016.

The results highlight the important contribution that changes in human capital investments have made in the story of Bangladesh's progress on poverty reduction. Reductions in fertility and family size were particularly important to the stronger progress of poverty reduction in the East since 2010. Reductions in fertility have an immediate impact on consumption per capita in a household by allowing the ratio of working age members to dependents in a household to increase. In addition, in the long run, reductions in fertility allow greater human capital investments in each child in the household and less pressure on agricultural land.

Gains in educational attainment were also a key component of improving household fortunes, and can help explain the divergent trajectories of the East and West. Although starting as less poor in monetary poverty terms, rural households in the East also started as worse-off in terms of educational attainment and other human capital outcomes. However, progress in increasing educational attainment in Eastern rural areas in the last ten years, and particularly since 2010 (in Sylhet), has outstripped the progress in rural areas in the West. This has contributed to faster poverty reduction in rural areas in the East. This trend is reversed in urban areas, with urban areas in the West seeing particularly fast progress in educational outcomes. Less divergence is found between urban poverty rates in the East and West as a result. However, the analysis has also shown a tapering-off of the returns to education, which has resulted in consumption increasing less due to educational attainment than it otherwise would. This highlights the importance of increasing the demand for skilled workers in step with the rising supply of educated workers.

The results point to the importance of structural change in driving poverty reduction. Over time, the consumption gain from agricultural land is falling, and the cost of remaining in agriculture is increasing, as employment in other sectors becomes more beneficial. Average land-holding size has also been falling over time because of population growth, so in many regards this is a welcome trend. However, the results also highlight that this process has not occurred equally everywhere. Structural change lags in the West. As a result, consumption there is still just as correlated with land ownership as in the past. The benefit of being outside of agriculture in the West is no larger now than it was previously. The cost of smaller land-sizes has also been larger in the West because of faster reductions in land holdings, but also because of the lack of options outside of agriculture.

The results also point to the special conditions present in 2010 that elevated returns to agriculture and benefited the West of the country. High returns to agriculture in 2010 benefited the West more than the East, given the predominance of agricultural activities in the West. This can help explain faster consumption growth in the West from 2005 to 2010 and the slowdown in consumption growth from 2010 to 2016, as these unique conditions no longer prevailed.

These conditions gave the appearance of convergence between the East and West, but this was a temporary phenomenon. Faster progress on reducing fertility and structural change are priorities for the West. Faster progress on educational attainment is also needed, but a more urgent priority is creating non-agricultural jobs.

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Annex 1: Income data in the 2016/17 round of the HIES

This annex compares the quality of the income data collected by the HIES in 2016/17 and 2010. In summary, the annex details that, although there is no obvious systematic error that undermines the 2016/17 income data entirely, that income data is less complete and noisier than the income data collected in 2010, with coding errors also limiting the number of observations for which accurate income data is recorded. Some 2016/17 households do not have complete income data, in comparison to a smaller proportion of households in 2010. It is richer households in rural areas in self-employment activities that are more likely to be missing income data. It is important to correctly code this income data as missing and be aware of the limits of the income data in conducting analysis.

Income data is always challenging to collect, but it appears that in the 2016/17 HIES, the income data suffered from the increase in sample size and the change in the fieldwork protocols. Data-entry was undertaken in the field in the 2016/17 HIES, with a program that had few consistency checks. The income sections of the questionnaire were not checked by the World Bank team as fieldwork was ongoing (these checks focused on the consumption modules and household size). As a result, errors were not caught as survey work was ongoing.

Completeness of the data, and accurately recording under-reporting in income

Table A1 shows that 6.5% of earners are missing employment data, while 6.5% of those with employment data are missing income data for those employment sources. It is possible that the earner or employment roster is incorrect, but if not, then there are about 13% of households with incomplete income data. More households report wage employment and wage income in 2016/17 than in 2010. And more households report being engaged in daily labor income.

Table A1 also documents that 2.77% more households report no earners (and no employment data) in 2016/17, with 8.49% fewer households reporting agricultural income and employment and 7.2% reporting less non-agriculture self-employment income. These are not necessarily errors.

As a result of the increase in the proportion of households reporting no earners and increased incompleteness of the data, there are more households reporting 0 labor income and 0 hours worked (Table A2). However, these zeros really reflect missing data. Given the higher prevalence of missing data, it is important to be very clear when data is missing, rather than assuming income from a given source is 0 when it is not reported.

In 2010, it was assumed that, when a household did not fill in income data in a given section, the income for this section was zero. In 2016/17, this assumption cannot be made. The sources of income reported in 4a are used to determine whether or not income from that source should have been present, but is missing. One thing to note when using section 4a to identify a household's sources of income: across the rounds of the HIES, many households report agricultural income without reporting agricultural employment in section 4a. Self-employment in agriculture is often not counted as a source of employment by households that earn agricultural income, but are engaged in other income earning activities. These households do not report hours worked in agriculture in Section 4a, but do report the income earned in the relevant agricultural modules.

When this is done we find that:

- 2.2% of no-earner households report some labor income.
- 6.5% are missing labor income, in that they report earners in section 1 and 4a, but do not have complete income data on these earners. These households may have data recorded in some sections, but it does not appear complete.
- Missing data tends to be from the self-employed sections:

    - Data on wage income is missing for 2.3% of households (3% of households in employment).
    - Data on agricultural income is missing for 1.2% of households (6% of households that report agricultural self-employment in 4a).
    - Data on nonfarm self-employment income is missing for 2.3% of households (12% of those with non-farm self-employment).
- 7.3% have zero income. 1.3% of these are households that report earners in section 1 but do not report earners in 4a. 6.1% are households with no earners and no labor income.

To determine the type of bias the missing income data is likely to cause, we assess whether the missing data is systematic and in what ways. We find that the missing income data is systematic. Data is less likely to be missing in cities, presumably because of the greater reliance on employment rather than self-employment. Data is more likely to be missing for better-off households. Data is more likely to be missing for better-off households in rural areas. There is no relationship between missing income and consumption in urban areas (Table A3).

Quality of wages, prices, yields, hours
Wage income looks reasonable (Table A4), but daily labor income has more missing data and is quite noisy (Table A5). The hours worked look reasonable. The self-employment income and agricultural income that is collected looks reasonable. More work needs to be done to assess the quality of the crop production and income data. Yield and price data seems reasonable (Table A6). When analyzing data, it is important to address outliers to the extent possible and replace outlier prices and wages with the median value.

There are many instances of negative net income being reported. 14.3% of households reporting non-zero agricultural income have negative agricultural income. 15.1% of households reporting non-zero non-agricultural income have negative non-agricultural income. The negatives do not seem to be systematic, no relationship with consumption or location is evident.

Table A1. Completeness of the income data

All numbers are unweighted, so are percent of observations	2016	2010	Diff.
Completeness of employment roster			
Individuals that report being earners in the roster	32.10%	30.94%	1.16%
Earners that are missing in the employment roster*	7.00%	0.45%	6.55%
Households reporting no earners in roster and the employment roster	9.19%	6.42%	2.77%
Households with no earner	9.67%	6.48%	
Households with no earners but someone in employment roster	0.48%	0.06%	
Individuals in the employment roster that could not be matched to roster	0.04%	0.05%	
Individuals in employment roster that are not recorded as earners in roster	3.23%	0.88%	2.35%
Completeness of wage income data			
Individuals in employment roster that report being day laborers or employees but are missing wage income data***	4.71%	~0	4.71%
Missing for ag day labor	2.22%	~0	
Missing for ag employee	~0	~0	
Missing for nonag day labor	1.21%	~0	
Missing for nonag employee	1.21%	~0	
Completeness of ag self-employment income data			
Household reports ag self-employment and crop income	20.75%	29.24%	-8.49%
Household reports no ag self-employment and no crop income	62.93%	52.10%	10.83%
Household reports no ag self-employment but has ag income**	14.29%	17.30%	-3.01%
Household reports ag self-employment but has no ag income	2.04%	1.37%	0.67%
Completeness of non-ag self-employment income data			
Households report non-age self-employment and non-ag income	21.3%	28.5%	-7.2%
Household reports non-ag self-employment but no enterprise income	2.01%	0.77%	1.24%
Household reports no non-ag self-employment but records enterprise income	0.66%	0.46%	0.2%

*In general, the roster information is quite complete. For those that answered section 4a, in 2016 nearly all (barring about 200) gave some information on hours worked and whether rural/urban and ag/non-ag and type of contract. All earners answered this section in 2010.

** In 2016 about half of these have some engagement in agriculture, but report being daily laborers. In 2010 about a third have some engagement in agriculture, but report being daily laborers.

*** Some of this could be coding error between wage/daily employment and may not really be missing.

Table A2: Total labor income

	2010				2016			
	p10	p50	p90	mean	p10	p50	p90	Mean
Households reporting 0 labor income				4.01%				15.67%
Households reporting 0 hours worked				9.53%				12.44%
Household labor income (Taka)	1,813	7,309	21,302	10,952	0	9,000	21,900	10,368
Household labor income per capita (Taka)	492	1,723	4726	2,551	0	2,309	5,750	2,708
Hours worked	240	2,880	4320	3,333	0	2,500	5,401	2,841
Hours worked per capita	60	700	1440	778	0	648	1,440	747

Table A3: Probability of missing data

	All	Rural	Urban	SMA
Coefficient on real pce	5.39×10^{-7}	1.06×10^{-6}	-4.61×10^{-7}	8.86×10^{-7}
P-stat that coefficient is significantly different from 0	0.099	0.010	0.435	0.520

Table A4: Wage income

	2010				2016			
	p10	p50	p90	mean	p10	p50	p90	mean
Households in wage employment				26.55%				29.29%
Households reporting wage income				26.54%				27.96%
Households reporting hours but no income				0.01%				1.33%
Wage income (Taka)	1,785	6,500	19,833	9,454	4,500	12,000	30,000	16,409
Wage income per capita (Taka)	375	1,500	4,772	2,245	1,000	3,042	8,125	4,436
Hours in wage employment	1,920	2,880	6,390	3,705	1,800	3,000	6,000	3,444
Hours per capita in wage employment	357	720	1,680	894	360	750	1,680	932
Average wage rate (Taka)	7	23	72	35	19	44	129	76
Average wage rate in ag (Taka)	4	13	38	21	15	40	120	321
Average wage rate in non-ag (Taka)	8	24	74	36	19	44	130	69

Table A5: Daily labor employment

	2010				2016			
	p10	p50	p90	mean	p10	p50	p90	mean
Households in daily labor employment				37.40%				40.04%
Households reporting daily labor income				37.35%				36.85%
Households reporting hours but no income				0.05%				3.19%
Daily labor income	2,400	4,080	8,400	6,114	4,800	8,400	16,800	183,119
Daily labor income per capita	528	960	2,000	1,499	1,200	2,100	4,600	46,226
Hours in daily labor employment	1,152	2,400	4,608	2,719	960	2,304	4,032	2,447
Hours per capita in daily labor employment	240	600	1,200	666	240	576	1,188	653
Average daily labor rate	11	21	46	36	23	45	103	1,181
Average daily labor rate in agriculture	12	20	48	35	23	43	120	2,426
Average daily labor rate in non-agriculture	10	21	48	42	22	46	101	98

Table A6: Self-employment income

	2010				2016			
	p10	**p50**	**p90**	**mean**	**p10**	**p50**	**p90**	**mean**
Non-agricultural self-employment								
Non-ag enterprise income	1508	5447	18333	9153	2392	8967	24333	15120
Non-ag enterprise income per capita	333	1200	3750	2004	560	2033	5729	3470
Hours worked	1080	2880	5040	3129	1080	3000	4500	3012
Hours worked per capita	216	600	1200	688	250	672	1260	740
Agricultural self-employment								
Ag enterprise income	1706	31019	159540	70542	300	20860	138090	90714
Ag enterprise income per capita	425	7215	35000	16250	86	5117	34889	23738
Hours worked	384	1728	3600	1984	360	1440	3240	1675
Hours worked per capita	86	360	860	432	84	358	880	428
Share of crop income from rice	34.65%	89.26%	100.00%	78.70%	30.18%	98.84%	100.00%	78.37%
Average rice yield	741	1583	2500	2662	800	1825	2687	1905
Average price of rice	8	10	14	11	8	11	15	12

Annex 2: Regression results

National 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2005**	**Decile 2 2005**	**Decile 3 2005**	**Decile 4 2005**	**Decile 5 2005**	**Decile 6 2005**	**Decile 7 2005**	**Decile 8 2005**	**Decile 9 2005**
Number of members	-0.0172***	-0.0205***	-0.0208***	-0.0255***	-0.0267***	-0.0356***	-0.0454***	-0.0542***	-0.0672***
	(0.00465)	(0.00418)	(0.00386)	(0.00385)	(0.00402)	(0.00462)	(0.00527)	(0.00659)	(0.00900)
Share under age 18	-0.445***	-0.504***	-0.533***	-0.492***	-0.478***	-0.434***	-0.342***	-0.319***	-0.194**
	(0.0341)	(0.0313)	(0.0301)	(0.0316)	(0.0346)	(0.0411)	(0.0487)	(0.0615)	(0.0834)
Share over age 60	-0.0798***	-0.0930***	-0.0686**	-0.0859**	-0.0445	-0.0149	0.0580	0.121*	0.114
	(0.0307)	(0.0319)	(0.0319)	(0.0350)	(0.0382)	(0.0441)	(0.0504)	(0.0628)	(0.0787)
LN land for agriculture	0.113***	0.148***	0.168***	0.194***	0.219***	0.268***	0.293***	0.333***	0.349***
	(0.00867)	(0.00845)	(0.00843)	(0.00870)	(0.00954)	(0.0118)	(0.0150)	(0.0206)	(0.0322)
Average years of schooling	0.0265***	0.0325***	0.0367***	0.0426***	0.0502***	0.0631***	0.0772***	0.0866***	0.0973***
	(0.00143)	(0.00132)	(0.00124)	(0.00125)	(0.00134)	(0.00157)	(0.00194)	(0.00261)	(0.00407)
Share of females of working age	-0.0156	-0.0248**	-0.0272**	-0.0263**	-0.0229**	-0.0150	0.00181	0.00509	0.0107
	(0.0124)	(0.0113)	(0.0106)	(0.0106)	(0.0112)	(0.0130)	(0.0155)	(0.0200)	(0.0281)
Agricultural sector	-0.0665***	-0.0942***	-0.121***	-0.118***	-0.128***	-0.149***	-0.153***	-0.136***	-0.0800***
	(0.0177)	(0.0158)	(0.0145)	(0.0143)	(0.0147)	(0.0163)	(0.0186)	(0.0222)	(0.0275)
Service sector	-0.0313**	-0.0428***	-0.0464***	-0.0321**	-0.0231*	-0.0337**	-0.0353**	-0.0227	0.0231
	(0.0149)	(0.0135)	(0.0126)	(0.0127)	(0.0133)	(0.0153)	(0.0179)	(0.0222)	(0.0291)
Electricity coverage in the village	0.0587***	0.0545***	0.0858***	0.111***	0.111***	0.118***	0.140***	0.0853***	0.0697***
	(0.0198)	(0.0174)	(0.0156)	(0.0150)	(0.0148)	(0.0161)	(0.0174)	(0.0201)	(0.0230)
Rural	0.0628***	0.0565***	0.0508***	0.0457***	0.0308***	0.0204	-0.000146	-0.0885***	-0.147***
	(0.0143)	(0.0127)	(0.0116)	(0.0115)	(0.0119)	(0.0135)	(0.0157)	(0.0192)	(0.0251)
Constant	7.436***	7.645***	7.753***	7.813***	7.892***	7.980***	8.051***	8.311***	8.588***
	(0.0276)	(0.0260)	(0.0247)	(0.0254)	(0.0271)	(0.0314)	(0.0361)	(0.0439)	(0.0544)
Observations	10,077	10,077	10,077	10,077	10,077	10,077	10,077	10,077	10,077
R-squared	0.088	0.148	0.206	0.246	0.283	0.308	0.312	0.276	0.207

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

National 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2010**	**Decile 2 2010**	**Decile 3 2010**	**Decile 4 2010**	**Decile 5 2010**	**Decile 6 2010**	**Decile 7 2010**	**Decile 8 2010**	**Decile 9 2010**
Number of members	-0.0343***	-0.0368***	-0.0419***	-0.0473***	-0.0489***	-0.0494***	-0.0553***	-0.0581***	-0.0652***
	(0.00527)	(0.00432)	(0.00390)	(0.00384)	(0.00388)	(0.00423)	(0.00494)	(0.00574)	(0.00749)
Share under age 18	-0.359***	-0.398***	-0.363***	-0.347***	-0.334***	-0.313***	-0.312***	-0.291***	-0.334***
	(0.0324)	(0.0289)	(0.0277)	(0.0290)	(0.0310)	(0.0350)	(0.0424)	(0.0509)	(0.0694)
Share over age 60	-0.0963***	-0.0952***	-0.0670**	-0.0520*	-0.0367	0.0261	0.0748*	0.0878*	0.123*
	(0.0322)	(0.0291)	(0.0277)	(0.0289)	(0.0309)	(0.0346)	(0.0415)	(0.0497)	(0.0690)
LN land for agriculture	0.148***	0.160***	0.189***	0.211***	0.238***	0.260***	0.303***	0.334***	0.359***
	(0.00904)	(0.00862)	(0.00857)	(0.00910)	(0.00983)	(0.0113)	(0.0142)	(0.0191)	(0.0297)
Average years of schooling	0.0277***	0.0337***	0.0357***	0.0419***	0.0480***	0.0558***	0.0667***	0.0745***	0.0844***
	(0.00140)	(0.00123)	(0.00113)	(0.00114)	(0.00121)	(0.00136)	(0.00170)	(0.00219)	(0.00337)
Share of females of working age	0.00406	9.72e-05	0.00158	0.00963	0.00860	0.00189	0.00368	-0.0140	-0.0434*
	(0.0131)	(0.0109)	(0.01000)	(0.0100)	(0.0105)	(0.0116)	(0.0138)	(0.0162)	(0.0222)
Agricultural sector	-0.0320*	-0.0452***	-0.0546***	-0.0583***	-0.0617***	-0.0698***	-0.0765***	-0.0731***	-0.0637***
	(0.0169)	(0.0142)	(0.0128)	(0.0126)	(0.0127)	(0.0135)	(0.0153)	(0.0175)	(0.0227)
Service sector	-0.00102	-0.00507	-0.00340	-0.00220	0.0110	0.0292**	0.0376**	0.0371**	0.0317
	(0.0144)	(0.0124)	(0.0113)	(0.0114)	(0.0117)	(0.0128)	(0.0150)	(0.0178)	(0.0241)
Electricity coverage in the village	0.0895***	0.0726***	0.0803***	0.0784***	0.0668***	0.0617***	0.0773***	0.0703***	0.0407*
	(0.0229)	(0.0186)	(0.0164)	(0.0157)	(0.0155)	(0.0162)	(0.0181)	(0.0198)	(0.0234)
Rural	0.0362***	0.0327***	0.0136	0.00408	-0.00359	-0.0254**	-0.0520***	-0.107***	-0.156***
	(0.0139)	(0.0117)	(0.0107)	(0.0106)	(0.0109)	(0.0118)	(0.0139)	(0.0163)	(0.0219)
Constant	7.474***	7.681***	7.806***	7.904***	8.002***	8.100***	8.210***	8.426***	8.798***
	(0.0303)	(0.0261)	(0.0244)	(0.0248)	(0.0259)	(0.0283)	(0.0331)	(0.0384)	(0.0497)
Observations	12,235	12,235	12,235	12,235	12,235	12,235	12,235	12,235	12,235
R-squared	0.082	0.140	0.183	0.221	0.248	0.262	0.267	0.244	0.184

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

National 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2016	Decile 2 2016	Decile 3 2016	Decile 4 2016	Decile 5 2016	Decile 6 2016	Decile 7 2016	Decile 8 2016	Decile 9 2016
Number of members	-0.0443***	-0.0451***	-0.0527***	-0.0592***	-0.0600***	-0.0646***	-0.0666***	-0.0766***	-0.0851***
	(0.00329)	(0.00277)	(0.00254)	(0.00250)	(0.00253)	(0.00269)	(0.00291)	(0.00362)	(0.00471)
Share under age 18	-0.323***	-0.351***	-0.336***	-0.349***	-0.368***	-0.378***	-0.374***	-0.379***	-0.290***
	(0.0183)	(0.0161)	(0.0155)	(0.0160)	(0.0169)	(0.0187)	(0.0210)	(0.0271)	(0.0367)
Share over age 60	-0.0980***	-0.0875***	-0.0741***	-0.0773***	-0.0845***	-0.0733***	-0.0606***	-0.0269	0.0373
	(0.0155)	(0.0139)	(0.0135)	(0.0141)	(0.0150)	(0.0165)	(0.0183)	(0.0234)	(0.0318)
LN land for agriculture	0.118***	0.127***	0.137***	0.155***	0.167***	0.186***	0.202***	0.249***	0.284***
	(0.00638)	(0.00571)	(0.00558)	(0.00579)	(0.00638)	(0.00729)	(0.00856)	(0.0114)	(0.0162)
Average years of schooling	0.0253***	0.0288***	0.0310***	0.0346***	0.0385***	0.0444***	0.0492***	0.0586***	0.0641***
	(0.000804)	(0.000692)	(0.000647)	(0.000662)	(0.000696)	(0.000764)	(0.000866)	(0.00115)	(0.00167)
Share of females of working age	-0.0252***	-0.0242***	-0.0168***	-0.0126**	-0.0146**	-0.0155**	-0.0185**	-0.00986	0.000477
	(0.00778)	(0.00664)	(0.00618)	(0.00618)	(0.00635)	(0.00682)	(0.00753)	(0.00964)	(0.0127)
Agricultural sector	-0.0745***	-0.106***	-0.115***	-0.138***	-0.149***	-0.154***	-0.166***	-0.192***	-0.184***
	(0.00863)	(0.00736)	(0.00677)	(0.00670)	(0.00674)	(0.00708)	(0.00751)	(0.00913)	(0.0117)
Service sector	-0.0179**	-0.0150**	-0.0105*	-0.0151**	-0.0202***	-0.0242***	-0.0307***	-0.0514***	-0.0742***
	(0.00746)	(0.00643)	(0.00606)	(0.00617)	(0.00639)	(0.00689)	(0.00756)	(0.00953)	(0.0126)
Electricity coverage in the village	0.191***	0.141***	0.148***	0.138***	0.134***	0.127***	0.116***	0.106***	0.0900***
	(0.0138)	(0.0107)	(0.00939)	(0.00893)	(0.00869)	(0.00871)	(0.00883)	(0.0103)	(0.0124)
Rural	0.0333***	0.0268***	0.0213***	0.0194***	0.0117**	0.00679	-0.00281	-0.0259***	-0.0470***
	(0.00720)	(0.00615)	(0.00573)	(0.00579)	(0.00596)	(0.00640)	(0.00698)	(0.00879)	(0.0116)
Constant	7.510***	7.744***	7.880***	8.026***	8.151***	8.281***	8.425***	8.619***	8.876***
	(0.0179)	(0.0150)	(0.0139)	(0.0139)	(0.0143)	(0.0152)	(0.0164)	(0.0206)	(0.0266)
Observations	45,784	45,784	45,784	45,784	45,784	45,784	45,784	45,784	45,784
R-squared	0.070	0.107	0.138	0.162	0.176	0.185	0.183	0.164	0.114

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Urban 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2005	Decile 2 2005	Decile 3 2005	Decile 4 2005	Decile 5 2005	Decile 6 2005	Decile 7 2005	Decile 8 2005	Decile 9 2005
Number of members	-0.0160*	-0.0211***	-0.0197***	-0.0295***	-0.0352***	-0.0427***	-0.0573***	-0.0620***	-0.0368**
	(0.00838)	(0.00777)	(0.00717)	(0.00736)	(0.00797)	(0.00920)	(0.0104)	(0.0115)	(0.0152)
Share under age 18	-0.564***	-0.607***	-0.624***	-0.551***	-0.434***	-0.335***	-0.332***	-0.216**	-0.534***
	(0.0615)	(0.0585)	(0.0564)	(0.0596)	(0.0673)	(0.0788)	(0.0932)	(0.107)	(0.146)
Share over age 60	-0.0769	-0.123	-0.129	-0.124	-0.00643	0.0195	0.114	0.103	0.217
	(0.0778)	(0.0833)	(0.0794)	(0.0802)	(0.0847)	(0.0912)	(0.108)	(0.110)	(0.173)
LN land for agriculture	0.0790***	0.112***	0.137***	0.146***	0.177***	0.230***	0.275***	0.302***	0.336***
	(0.0127)	(0.0134)	(0.0138)	(0.0151)	(0.0182)	(0.0236)	(0.0311)	(0.0395)	(0.0629)
Average years of schooling	0.0339***	0.0439***	0.0518***	0.0621***	0.0743***	0.0906***	0.0966***	0.0900***	0.0890***
	(0.00223)	(0.00210)	(0.00200)	(0.00203)	(0.00213)	(0.00251)	(0.00312)	(0.00383)	(0.00585)
Share of females of working age	-0.0221	-0.0310	-0.0238	0.00534	0.0208	0.0329	0.0332	0.0585*	-0.0614
	(0.0218)	(0.0200)	(0.0181)	(0.0185)	(0.0204)	(0.0248)	(0.0303)	(0.0348)	(0.0462)
Agricultural sector	-0.161***	-0.142***	-0.129***	-0.133***	-0.143***	-0.146***	-0.114***	-0.103***	-0.0707
	(0.0447)	(0.0386)	(0.0342)	(0.0320)	(0.0319)	(0.0343)	(0.0382)	(0.0385)	(0.0509)
Service sector	-0.0416*	-0.0161	-0.00405	0.0292	0.0275	0.0210	0.0318	0.0474	0.00998
	(0.0232)	(0.0222)	(0.0212)	(0.0214)	(0.0224)	(0.0260)	(0.0301)	(0.0325)	(0.0429)
Electricity coverage in the village	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
East	0.151***	0.185***	0.200***	0.213***	0.228***	0.198***	0.220***	0.152***	0.152***
	(0.0234)	(0.0211)	(0.0195)	(0.0192)	(0.0200)	(0.0228)	(0.0261)	(0.0283)	(0.0372)
Constant	7.442***	7.580***	7.650***	7.679***	7.693***	7.748***	7.936***	8.176***	8.653***
	(0.0338)	(0.0361)	(0.0359)	(0.0379)	(0.0420)	(0.0489)	(0.0565)	(0.0622)	(0.0818)
Observations	3,679	3,679	3,679	3,679	3,679	3,679	3,679	3,679	3,679
R-squared	0.135	0.216	0.288	0.346	0.379	0.384	0.345	0.278	0.181

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Urban 2010

VARIABLES	(1) Decile 1 2010	(2) Decile 2 2010	(3) Decile 3 2010	(4) Decile 4 2010	(5) Decile 5 2010	(6) Decile 6 2010	(7) Decile 7 2010	(8) Decile 8 2010	(9) Decile 9 2010
Number of members	-0.0329***	-0.0314***	-0.0419***	-0.0518***	-0.0527***	-0.0569***	-0.0593***	-0.0632***	-0.0741***
	(0.00967)	(0.00786)	(0.00735)	(0.00722)	(0.00772)	(0.00832)	(0.00890)	(0.0100)	(0.0123)
Share under age 18	-0.417***	-0.499***	-0.436***	-0.392***	-0.334***	-0.276***	-0.278***	-0.259***	-0.396***
	(0.0589)	(0.0507)	(0.0501)	(0.0521)	(0.0582)	(0.0667)	(0.0740)	(0.0831)	(0.110)
Share over age 60	-0.111	-0.0578	-0.00164	0.00494	0.134*	0.228***	0.178**	0.177**	0.120
	(0.0718)	(0.0638)	(0.0610)	(0.0642)	(0.0698)	(0.0775)	(0.0814)	(0.0863)	(0.123)
LN land for agriculture	0.0949***	0.107***	0.135***	0.169***	0.210***	0.260***	0.311***	0.345***	0.399***
	(0.0149)	(0.0160)	(0.0167)	(0.0179)	(0.0201)	(0.0243)	(0.0291)	(0.0375)	(0.0604)
Average years of schooling	0.0384***	0.0456***	0.0515***	0.0606***	0.0699***	0.0819***	0.0875***	0.0802***	0.0775***
	(0.00226)	(0.00192)	(0.00178)	(0.00178)	(0.00195)	(0.00220)	(0.00260)	(0.00318)	(0.00476)
Share of females of working age	-0.00178	-0.0254	-0.00639	0.00527	-0.00161	0.0130	0.00169	0.0289	-0.00280
	(0.0238)	(0.0191)	(0.0178)	(0.0178)	(0.0195)	(0.0219)	(0.0236)	(0.0269)	(0.0361)
Agricultural sector	-0.0603	-0.0944***	-0.104***	-0.0758**	-0.0998***	-0.0653**	-0.0838***	-0.0463	-0.0294
	(0.0433)	(0.0351)	(0.0313)	(0.0298)	(0.0292)	(0.0310)	(0.0321)	(0.0340)	(0.0454)
Service sector	-0.00577	0.0143	0.0115	0.0400**	0.0479**	0.0736***	0.0518**	0.0480*	0.0254
	(0.0233)	(0.0198)	(0.0187)	(0.0188)	(0.0201)	(0.0220)	(0.0239)	(0.0260)	(0.0342)
Electricity coverage in the village	-0.128	-0.235*	-0.227*	0.0264	0.0827	0.0194	0.125	0.0913	-0.103
	(0.167)	(0.124)	(0.121)	(0.146)	(0.144)	(0.157)	(0.129)	(0.117)	(0.185)
East	0.0531**	0.0873***	0.107***	0.130***	0.124***	0.135***	0.107***	0.0620***	0.0117
	(0.0230)	(0.0191)	(0.0177)	(0.0175)	(0.0184)	(0.0201)	(0.0218)	(0.0238)	(0.0321)
Constant	7.637***	7.924***	8.002***	7.803***	7.808***	7.892***	7.986***	8.254***	8.916***
	(0.172)	(0.130)	(0.126)	(0.151)	(0.150)	(0.164)	(0.139)	(0.130)	(0.200)
Observations	4,398	4,398	4,398	4,398	4,398	4,398	4,398	4,398	4,398
R-squared	0.105	0.190	0.247	0.303	0.326	0.342	0.331	0.267	0.176

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Urban 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2016**	**Decile 2 2016**	**Decile 3 2016**	**Decile 4 2016**	**Decile 5 2016**	**Decile 6 2016**	**Decile 7 2016**	**Decile 8 2016**	**Decile 9 2016**
Number of members	-0.0555***	-0.0559***	-0.0725***	-0.0758***	-0.0776***	-0.0783***	-0.0813***	-0.0768***	-0.0903***
	(0.00676)	(0.00549)	(0.00505)	(0.00478)	(0.00481)	(0.00508)	(0.00565)	(0.00636)	(0.00834)
Share under age 18	-0.348***	-0.407***	-0.360***	-0.369***	-0.364***	-0.392***	-0.360***	-0.347***	-0.216***
	(0.0354)	(0.0308)	(0.0295)	(0.0297)	(0.0316)	(0.0346)	(0.0396)	(0.0467)	(0.0641)
Share over age 60	-0.182***	-0.166***	-0.121***	-0.132***	-0.0621**	-0.0577*	0.0273	0.0435	0.190***
	(0.0367)	(0.0321)	(0.0298)	(0.0300)	(0.0311)	(0.0330)	(0.0373)	(0.0435)	(0.0630)
LN land for agriculture	0.0855***	0.106***	0.130***	0.155***	0.179***	0.208***	0.257***	0.273***	0.305***
	(0.0106)	(0.0108)	(0.0109)	(0.0118)	(0.0128)	(0.0161)	(0.0190)	(0.0246)	(0.0372)
Average years of schooling	0.0311***	0.0368***	0.0409***	0.0455***	0.0513***	0.0562***	0.0623***	0.0658***	0.0708***
	(0.00131)	(0.00113)	(0.00105)	(0.00106)	(0.00111)	(0.00122)	(0.00143)	(0.00176)	(0.00266)
Share of females of working age	-0.0351**	-0.0278**	-0.00522	-0.00977	-0.00732	-0.0130	-0.0110	-0.00735	0.00718
	(0.0155)	(0.0127)	(0.0118)	(0.0117)	(0.0121)	(0.0129)	(0.0145)	(0.0170)	(0.0220)
Agricultural sector	-0.131***	-0.137***	-0.131***	-0.138***	-0.127***	-0.136***	-0.137***	-0.136***	-0.104***
	(0.0254)	(0.0205)	(0.0181)	(0.0169)	(0.0164)	(0.0163)	(0.0171)	(0.0182)	(0.0233)
Service sector	-0.00821	-0.00151	0.0122	0.00750	0.00353	0.0108	0.0123	-0.00336	-0.0112
	(0.0129)	(0.0111)	(0.0105)	(0.0104)	(0.0106)	(0.0113)	(0.0126)	(0.0143)	(0.0193)
Electricity coverage in the village	0.639***	0.467***	0.448***	0.409***	0.380***	0.318***	0.266***	0.174***	0.162***
	(0.110)	(0.0771)	(0.0618)	(0.0505)	(0.0424)	(0.0381)	(0.0372)	(0.0406)	(0.0346)
East	0.122***	0.152***	0.154***	0.155***	0.163***	0.151***	0.137***	0.114***	0.109***
	(0.0129)	(0.0110)	(0.0101)	(0.00984)	(0.00998)	(0.0105)	(0.0116)	(0.0133)	(0.0180)
Constant	7.034***	7.355***	7.504***	7.668***	7.777***	7.964***	8.123***	8.371***	8.615***
	(0.113)	(0.0801)	(0.0654)	(0.0547)	(0.0477)	(0.0446)	(0.0454)	(0.0507)	(0.0524)
Observations	13,903	13,903	13,903	13,903	13,903	13,903	13,903	13,903	13,903
R-squared	0.097	0.152	0.196	0.226	0.244	0.250	0.238	0.199	0.130

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Rural 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2005	Decile 2 2005	Decile 3 2005	Decile 4 2005	Decile 5 2005	Decile 6 2005	Decile 7 2005	Decile 8 2005	Decile 9 2005
Number of members	-0.0193***	-0.0233***	-0.0241***	-0.0306***	-0.0283***	-0.0351***	-0.0388***	-0.0493***	-0.0626***
	(0.00554)	(0.00492)	(0.00459)	(0.00446)	(0.00453)	(0.00505)	(0.00582)	(0.00712)	(0.0102)
Share under age 18	-0.386***	-0.480***	-0.525***	-0.467***	-0.500***	-0.503***	-0.474***	-0.411***	-0.364***
	(0.0414)	(0.0370)	(0.0355)	(0.0367)	(0.0390)	(0.0451)	(0.0544)	(0.0674)	(0.0962)
Share over age 60	-0.0873**	-0.130***	-0.105***	-0.0968***	-0.102***	-0.0986**	-0.0666	-0.0291	-0.00684
	(0.0340)	(0.0344)	(0.0340)	(0.0356)	(0.0390)	(0.0452)	(0.0527)	(0.0638)	(0.0899)
LN land for agriculture	0.134***	0.177***	0.198***	0.227***	0.258***	0.311***	0.367***	0.390***	0.489***
	(0.0113)	(0.0108)	(0.0107)	(0.0107)	(0.0114)	(0.0131)	(0.0168)	(0.0218)	(0.0353)
Average years of schooling	0.0197***	0.0239***	0.0273***	0.0321***	0.0338***	0.0421***	0.0513***	0.0596***	0.0629***
	(0.00189)	(0.00178)	(0.00175)	(0.00176)	(0.00187)	(0.00217)	(0.00271)	(0.00345)	(0.00522)
Share of females of working age	-0.0103	-0.0276**	-0.0333**	-0.0362***	-0.0414***	-0.0443***	-0.0515***	-0.0412*	-0.0416
	(0.0153)	(0.0139)	(0.0130)	(0.0129)	(0.0133)	(0.0149)	(0.0175)	(0.0215)	(0.0308)
Agricultural sector	-0.0357*	-0.0685***	-0.0859***	-0.103***	-0.121***	-0.135***	-0.163***	-0.166***	-0.189***
	(0.0200)	(0.0177)	(0.0164)	(0.0159)	(0.0164)	(0.0179)	(0.0206)	(0.0244)	(0.0332)
Service sector	-0.0201	-0.0367**	-0.0375**	-0.0482***	-0.0460***	-0.0498***	-0.0533**	-0.0676**	-0.0510
	(0.0200)	(0.0178)	(0.0166)	(0.0163)	(0.0168)	(0.0186)	(0.0219)	(0.0263)	(0.0362)
Electricity coverage in the village	0.0644***	0.0646***	0.0943***	0.121***	0.127***	0.133***	0.158***	0.160***	0.151***
	(0.0184)	(0.0160)	(0.0145)	(0.0137)	(0.0135)	(0.0145)	(0.0162)	(0.0184)	(0.0244)
East	0.0595***	0.123***	0.144***	0.151***	0.147***	0.174***	0.175***	0.187***	0.180***
	(0.0148)	(0.0133)	(0.0121)	(0.0116)	(0.0116)	(0.0126)	(0.0146)	(0.0170)	(0.0234)
Constant	7.435***	7.634***	7.735***	7.813***	7.916***	8.002***	8.100***	8.238***	8.506***
	(0.0293)	(0.0271)	(0.0260)	(0.0265)	(0.0279)	(0.0318)	(0.0374)	(0.0446)	(0.0608)
Observations	6,398	6,398	6,398	6,398	6,398	6,398	6,398	6,398	6,398
R-squared	0.072	0.137	0.194	0.235	0.256	0.283	0.280	0.249	0.183

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2010**	**Decile 2 2010**	**Decile 3 2010**	**Decile 4 2010**	**Decile 5 2010**	**Decile 6 2010**	**Decile 7 2010**	**Decile 8 2010**	**Decile 9 2010**
Number of members	-0.0363***	-0.0439***	-0.0473***	-0.0539***	-0.0546***	-0.0534***	-0.0563***	-0.0591***	-0.0651***
	(0.00621)	(0.00524)	(0.00463)	(0.00456)	(0.00457)	(0.00479)	(0.00555)	(0.00659)	(0.00926)
Share under age 18	-0.359***	-0.372***	-0.331***	-0.332***	-0.345***	-0.327***	-0.353***	-0.376***	-0.396***
	(0.0391)	(0.0362)	(0.0338)	(0.0349)	(0.0370)	(0.0405)	(0.0480)	(0.0589)	(0.0844)
Share over age 60	-0.107***	-0.127***	-0.0863***	-0.126***	-0.113***	-0.0670*	-0.0785*	-0.0577	-0.0480
	(0.0351)	(0.0324)	(0.0304)	(0.0320)	(0.0339)	(0.0368)	(0.0436)	(0.0541)	(0.0797)
LN land for agriculture	0.164***	0.182***	0.201***	0.236***	0.255***	0.284***	0.331***	0.381***	0.453***
	(0.0108)	(0.0102)	(0.00982)	(0.0104)	(0.0111)	(0.0123)	(0.0153)	(0.0201)	(0.0333)
Average years of schooling	0.0225***	0.0270***	0.0289***	0.0324***	0.0362***	0.0399***	0.0449***	0.0467***	0.0568***
	(0.00188)	(0.00170)	(0.00157)	(0.00160)	(0.00169)	(0.00188)	(0.00227)	(0.00287)	(0.00438)
Share of females of working age	0.00707	0.0120	0.0138	0.0153	0.0172	0.00175	0.00540	-0.0168	-0.0386
	(0.0155)	(0.0133)	(0.0120)	(0.0122)	(0.0126)	(0.0136)	(0.0158)	(0.0186)	(0.0271)
Agricultural sector	0.000973	-0.0120	-0.0208	-0.0283**	-0.0301**	-0.0552***	-0.0594***	-0.0848***	-0.0742***
	(0.0186)	(0.0162)	(0.0143)	(0.0143)	(0.0144)	(0.0150)	(0.0168)	(0.0194)	(0.0268)
Service sector	0.00508	0.00543	-0.00221	-0.00468	-4.47e-05	0.0111	0.0239	0.0293	0.0323
	(0.0193)	(0.0167)	(0.0149)	(0.0149)	(0.0152)	(0.0161)	(0.0184)	(0.0218)	(0.0300)
Electricity coverage in the village	0.103***	0.0986***	0.0917***	0.101***	0.0897***	0.0782***	0.0989***	0.128***	0.103***
	(0.0217)	(0.0178)	(0.0154)	(0.0148)	(0.0147)	(0.0149)	(0.0164)	(0.0186)	(0.0257)
East	0.100***	0.0932***	0.0667***	0.0850***	0.100***	0.0963***	0.115***	0.103***	0.127***
	(0.0152)	(0.0129)	(0.0115)	(0.0115)	(0.0116)	(0.0122)	(0.0138)	(0.0163)	(0.0228)
Constant	7.439***	7.642***	7.773***	7.878***	7.969***	8.083***	8.165***	8.347***	8.608***
	(0.0321)	(0.0284)	(0.0260)	(0.0266)	(0.0279)	(0.0298)	(0.0342)	(0.0404)	(0.0572)
Observations	7,837	7,837	7,837	7,837	7,837	7,837	7,837	7,837	7,837
R-squared	0.078	0.126	0.161	0.194	0.211	0.217	0.216	0.193	0.141

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2016**	**Decile 2 2016**	**Decile 3 2016**	**Decile 4 2016**	**Decile 5 2016**	**Decile 6 2016**	**Decile 7 2016**	**Decile 8 2016**	**Decile 9 2016**
Number of members	-0.0528***	-0.0516***	-0.0548***	-0.0585***	-0.0621***	-0.0674***	-0.0694***	-0.0804***	-0.0923***
	(0.00386)	(0.00319)	(0.00288)	(0.00288)	(0.00293)	(0.00311)	(0.00338)	(0.00410)	(0.00569)
Share under age 18	-0.340***	-0.363***	-0.356***	-0.388***	-0.398***	-0.412***	-0.410***	-0.430***	-0.371***
	(0.0217)	(0.0190)	(0.0179)	(0.0186)	(0.0197)	(0.0217)	(0.0244)	(0.0307)	(0.0439)
Share of over age 60	-0.101***	-0.0852***	-0.0723***	-0.0848***	-0.0929***	-0.0958***	-0.0906***	-0.0964***	-0.0249
	(0.0174)	(0.0153)	(0.0147)	(0.0156)	(0.0166)	(0.0184)	(0.0206)	(0.0257)	(0.0375)
LN land for agriculture	0.125***	0.134***	0.138***	0.153***	0.166***	0.187***	0.201***	0.239***	0.291***
	(0.00769)	(0.00680)	(0.00644)	(0.00668)	(0.00728)	(0.00839)	(0.00969)	(0.0122)	(0.0179)
Average years of schooling	0.0240***	0.0262***	0.0270***	0.0290***	0.0319***	0.0361***	0.0403***	0.0444***	0.0501***
	(0.00106)	(0.000912)	(0.000841)	(0.000860)	(0.000902)	(0.000992)	(0.00111)	(0.00141)	(0.00207)
Share of females of working age	-0.0203**	-0.0170**	-0.0156**	-0.0174**	-0.0175**	-0.0151*	-0.0170*	-0.00457	0.00380
	(0.00924)	(0.00778)	(0.00714)	(0.00721)	(0.00739)	(0.00795)	(0.00876)	(0.0108)	(0.0154)
Agricultural sector	-0.0258***	-0.0556***	-0.0582***	-0.0943***	-0.109***	-0.120***	-0.134***	-0.167***	-0.193***
	(0.00953)	(0.00804)	(0.00734)	(0.00735)	(0.00747)	(0.00789)	(0.00844)	(0.0101)	(0.0138)
Service sector	-0.00282	-0.00125	0.00628	-0.00566	-0.0116	-0.0147*	-0.0325***	-0.0487***	-0.0962***
	(0.00956)	(0.00808)	(0.00749)	(0.00763)	(0.00792)	(0.00856)	(0.00939)	(0.0115)	(0.0160)
Electricity coverage in the village	0.210***	0.169***	0.173***	0.175***	0.174***	0.176***	0.165***	0.156***	0.153***
	(0.0135)	(0.0104)	(0.00909)	(0.00883)	(0.00870)	(0.00889)	(0.00925)	(0.0107)	(0.0138)
East	0.156***	0.165***	0.172***	0.184***	0.183***	0.196***	0.193***	0.202***	0.186***
	(0.00819)	(0.00675)	(0.00608)	(0.00605)	(0.00615)	(0.00649)	(0.00699)	(0.00844)	(0.0115)
Constant	7.449***	7.656***	7.784***	7.924***	8.053***	8.169***	8.315***	8.510***	8.785***
	(0.0190)	(0.0159)	(0.0146)	(0.0148)	(0.0153)	(0.0164)	(0.0179)	(0.0219)	(0.0300)
Observations	31,881	31,881	31,881	31,881	31,881	31,881	31,881	31,881	31,881
R-squared	0.077	0.113	0.140	0.161	0.171	0.177	0.170	0.148	0.100

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural East 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2005**	**Decile 2 2005**	**Decile 3 2005**	**Decile 4 2005**	**Decile 5 2005**	**Decile 6 2005**	**Decile 7 2005**	**Decile 8 2005**	**Decile 9 2005**
Number of members	-0.0352***	-0.0296***	-0.0309***	-0.0332***	-0.0310***	-0.0415***	-0.0439***	-0.0433***	-0.0613***
	(0.00766)	(0.00647)	(0.00574)	(0.00557)	(0.00582)	(0.00650)	(0.00727)	(0.00895)	(0.0133)
Share under age 18	-0.296***	-0.478***	-0.458***	-0.404***	-0.489***	-0.464***	-0.454***	-0.452***	-0.439***
	(0.0588)	(0.0503)	(0.0468)	(0.0480)	(0.0520)	(0.0609)	(0.0719)	(0.0890)	(0.132)
Share over age 60	-0.0419	-0.0882*	-0.0457	-0.0425	-0.0612	-0.00168	0.0266	0.0438	0.0490
	(0.0498)	(0.0461)	(0.0453)	(0.0495)	(0.0549)	(0.0639)	(0.0762)	(0.0929)	(0.137)
LN land for agriculture	0.129***	0.148***	0.160***	0.187***	0.211***	0.258***	0.277***	0.316***	0.425***
	(0.0166)	(0.0151)	(0.0141)	(0.0141)	(0.0153)	(0.0186)	(0.0224)	(0.0287)	(0.0468)
Average years of schooling	0.0184***	0.0266***	0.0278***	0.0314***	0.0395***	0.0486***	0.0588***	0.0622***	0.0693***
	(0.00288)	(0.00251)	(0.00234)	(0.00233)	(0.00249)	(0.00292)	(0.00347)	(0.00438)	(0.00691)
Share of females of working age	0.0271	-0.00677	-0.00675	-0.0202	-0.0220	-0.0244	-0.0233	-0.0417	-0.0467
	(0.0211)	(0.0184)	(0.0166)	(0.0163)	(0.0172)	(0.0194)	(0.0224)	(0.0267)	(0.0408)
Agricultural sector	-0.0605**	-0.108***	-0.116***	-0.119***	-0.142***	-0.189***	-0.204***	-0.180***	-0.161***
	(0.0281)	(0.0238)	(0.0211)	(0.0207)	(0.0214)	(0.0237)	(0.0267)	(0.0311)	(0.0435)
Service sector	-0.00603	-0.0405*	-0.0418**	-0.0350*	-0.0439**	-0.0831***	-0.0860***	-0.0924***	-0.0600
	(0.0271)	(0.0235)	(0.0210)	(0.0207)	(0.0217)	(0.0247)	(0.0283)	(0.0334)	(0.0466)
Electricity coverage in the village	0.108***	0.0990***	0.139***	0.166***	0.147***	0.141***	0.161***	0.148***	0.152***
	(0.0276)	(0.0223)	(0.0190)	(0.0178)	(0.0179)	(0.0193)	(0.0207)	(0.0236)	(0.0327)
Constant	7.468***	7.753***	7.842***	7.913***	8.034***	8.187***	8.287***	8.449***	8.712***
	(0.0418)	(0.0352)	(0.0331)	(0.0336)	(0.0364)	(0.0420)	(0.0487)	(0.0586)	(0.0843)
Observations	3,818	3,818	3,818	3,818	3,818	3,818	3,818	3,818	3,818
R-squared	0.066	0.133	0.183	0.215	0.252	0.272	0.272	0.229	0.168

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural East 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2010	Decile 2 2010	Decile 3 2010	Decile 4 2010	Decile 5 2010	Decile 6 2010	Decile 7 2010	Decile 8 2010	Decile 9 2010
Number of members	-0.0433***	-0.0473***	-0.0452***	-0.0540***	-0.0549***	-0.0530***	-0.0513***	-0.0524***	-0.0543***
	(0.00707)	(0.00587)	(0.00543)	(0.00550)	(0.00551)	(0.00573)	(0.00649)	(0.00763)	(0.0109)
Share under age 18	-0.289***	-0.272***	-0.312***	-0.335***	-0.343***	-0.342***	-0.362***	-0.375***	-0.432***
	(0.0477)	(0.0432)	(0.0420)	(0.0451)	(0.0472)	(0.0512)	(0.0597)	(0.0726)	(0.107)
Share over age 60	-0.0480	-0.0342	-0.0381	-0.0450	-0.0696	-0.0396	-0.0390	0.00937	0.0477
	(0.0422)	(0.0386)	(0.0391)	(0.0421)	(0.0443)	(0.0477)	(0.0555)	(0.0691)	(0.108)
LN land for agriculture	0.148***	0.156***	0.184***	0.234***	0.241***	0.274***	0.306***	0.336***	0.437***
	(0.0127)	(0.0122)	(0.0124)	(0.0136)	(0.0146)	(0.0160)	(0.0196)	(0.0253)	(0.0429)
Average years of schooling	0.0221***	0.0288***	0.0316***	0.0356***	0.0387***	0.0432***	0.0462***	0.0486***	0.0606***
	(0.00236)	(0.00205)	(0.00198)	(0.00209)	(0.00218)	(0.00239)	(0.00284)	(0.00356)	(0.00565)
Share of females of working age	0.0430**	0.0355**	0.0181	0.0223	0.0224	0.00178	-0.000551	-0.0166	-0.0524
	(0.0176)	(0.0151)	(0.0144)	(0.0152)	(0.0155)	(0.0165)	(0.0188)	(0.0220)	(0.0331)
Agricultural sector	0.0287	0.00390	-0.0164	-0.0263	-0.0196	-0.0622***	-0.0697***	-0.108***	-0.115***
	(0.0226)	(0.0191)	(0.0178)	(0.0182)	(0.0181)	(0.0186)	(0.0205)	(0.0234)	(0.0338)
Service sector	-0.00339	-0.00599	-0.00790	-0.00705	0.00853	-0.000855	0.0107	-0.00667	-0.0415
	(0.0233)	(0.0194)	(0.0181)	(0.0187)	(0.0187)	(0.0197)	(0.0221)	(0.0259)	(0.0368)
Electricity coverage in the village	0.0643***	0.0395**	0.0426**	0.0661***	0.0633***	0.0511***	0.0682***	0.0918***	0.0780**
	(0.0246)	(0.0200)	(0.0185)	(0.0186)	(0.0182)	(0.0186)	(0.0203)	(0.0227)	(0.0325)
Constant	7.518***	7.721***	7.848***	7.967***	8.070***	8.202***	8.298***	8.467***	8.754***
	(0.0345)	(0.0307)	(0.0302)	(0.0325)	(0.0338)	(0.0364)	(0.0422)	(0.0494)	(0.0734)
Observations	4,858	4,858	4,858	4,858	4,858	4,858	4,858	4,858	4,858
R-squared	0.076	0.122	0.157	0.194	0.207	0.220	0.207	0.183	0.138

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Rural East 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2016	Decile 2 2016	Decile 3 2016	Decile 4 2016	Decile 5 2016	Decile 6 2016	Decile 7 2016	Decile 8 2016	Decile 9 2016
Number of members	-0.0535***	-0.0486***	-0.0511***	-0.0570***	-0.0608***	-0.0653***	-0.0700***	-0.0802***	-0.0859***
	(0.00482)	(0.00392)	(0.00361)	(0.00352)	(0.00363)	(0.00383)	(0.00412)	(0.00504)	(0.00658)
Share under age 18	-0.293***	-0.292***	-0.303***	-0.326***	-0.345***	-0.338***	-0.339***	-0.358***	-0.298***
	(0.0283)	(0.0243)	(0.0234)	(0.0238)	(0.0258)	(0.0282)	(0.0318)	(0.0404)	(0.0553)
Share over age 60	-0.0615**	-0.0210	-0.0285	-0.0290	-0.0341	-0.0288	-0.0396	-0.0200	0.0476
	(0.0239)	(0.0205)	(0.0202)	(0.0211)	(0.0233)	(0.0257)	(0.0288)	(0.0370)	(0.0515)
LN land for agriculture	0.100***	0.0937***	0.0963***	0.0980***	0.110***	0.113***	0.135***	0.171***	0.216***
	(0.0112)	(0.00906)	(0.00846)	(0.00840)	(0.00913)	(0.0103)	(0.0115)	(0.0146)	(0.0205)
Average years of schooling	0.0262***	0.0279***	0.0298***	0.0330***	0.0359***	0.0402***	0.0407***	0.0448***	0.0488***
	(0.00144)	(0.00120)	(0.00112)	(0.00113)	(0.00121)	(0.00130)	(0.00146)	(0.00186)	(0.00262)
Share of females of working age	0.00901	-0.00793	-0.0150*	-0.0102	-0.00871	-0.00801	0.000929	0.00525	0.0114
	(0.0116)	(0.00969)	(0.00906)	(0.00892)	(0.00935)	(0.00990)	(0.0109)	(0.0136)	(0.0182)
Agricultural sector	-0.0828***	-0.0925***	-0.112***	-0.132***	-0.150***	-0.153***	-0.166***	-0.193***	-0.193***
	(0.0131)	(0.0108)	(0.00995)	(0.00977)	(0.0101)	(0.0104)	(0.0110)	(0.0132)	(0.0172)
Service sector	-0.0287**	-0.00497	-0.0188*	-0.0226**	-0.0327***	-0.0375***	-0.0614***	-0.0870***	-0.131***
	(0.0121)	(0.0101)	(0.00963)	(0.00969)	(0.0103)	(0.0109)	(0.0119)	(0.0146)	(0.0191)
Electricity coverage in the village	0.236***	0.192***	0.202***	0.193***	0.187***	0.181***	0.186***	0.175***	0.155***
	(0.0170)	(0.0128)	(0.0113)	(0.0106)	(0.0105)	(0.0104)	(0.0106)	(0.0122)	(0.0153)
Constant	7.557***	7.768***	7.917***	8.067***	8.203***	8.329***	8.474***	8.683***	8.928***
	(0.0234)	(0.0193)	(0.0182)	(0.0181)	(0.0191)	(0.0203)	(0.0222)	(0.0278)	(0.0372)
Observations	18,633	18,633	18,633	18,633	18,633	18,633	18,633	18,633	18,633
R-squared	0.079	0.109	0.139	0.162	0.168	0.171	0.159	0.136	0.091

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural West 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2005	Decile 2 2005	Decile 3 2005	Decile 4 2005	Decile 5 2005	Decile 6 2005	Decile 7 2005	Decile 8 2005	Decile 9 2005
Number of members	-0.00807	-0.0203**	-0.0214***	-0.0209***	-0.0286***	-0.0343***	-0.0363***	-0.0523***	-0.0703***
	(0.00901)	(0.00793)	(0.00751)	(0.00763)	(0.00750)	(0.00777)	(0.00920)	(0.0109)	(0.0175)
Share under age 18	-0.498***	-0.479***	-0.561***	-0.632***	-0.582***	-0.533***	-0.509***	-0.357***	-0.286*
	(0.0612)	(0.0542)	(0.0531)	(0.0554)	(0.0595)	(0.0654)	(0.0798)	(0.0969)	(0.154)
Share over age 60	-0.156***	-0.168***	-0.188***	-0.207***	-0.234***	-0.174***	-0.208***	-0.127	-0.00441
	(0.0459)	(0.0465)	(0.0487)	(0.0521)	(0.0557)	(0.0616)	(0.0715)	(0.0800)	(0.132)
LN land for agriculture	0.160***	0.200***	0.252***	0.270***	0.319***	0.375***	0.477***	0.516***	0.679***
	(0.0165)	(0.0153)	(0.0157)	(0.0166)	(0.0173)	(0.0188)	(0.0237)	(0.0318)	(0.0595)
Average years of schooling	0.0195***	0.0194***	0.0209***	0.0281***	0.0322***	0.0304***	0.0397***	0.0475***	0.0591***
	(0.00249)	(0.00246)	(0.00255)	(0.00265)	(0.00287)	(0.00322)	(0.00412)	(0.00536)	(0.00914)
Share of females of working age	-0.0686***	-0.0423*	-0.0606***	-0.0732***	-0.0856***	-0.0740***	-0.105***	-0.0722**	-0.0294
	(0.0246)	(0.0216)	(0.0205)	(0.0212)	(0.0215)	(0.0224)	(0.0265)	(0.0321)	(0.0540)
Agricultural sector	-0.0178	-0.0441*	-0.0536**	-0.0813***	-0.0983***	-0.0886***	-0.0731**	-0.0964***	-0.172***
	(0.0307)	(0.0264)	(0.0256)	(0.0256)	(0.0261)	(0.0272)	(0.0311)	(0.0365)	(0.0567)
Service sector	-0.0168	-0.0303	-0.0303	-0.0466*	-0.0647**	-0.0268	-0.000801	-0.0148	-0.0274
	(0.0319)	(0.0276)	(0.0268)	(0.0268)	(0.0275)	(0.0287)	(0.0328)	(0.0389)	(0.0604)
Electricity coverage in the village	0.0214	0.0333	0.0214	0.0397*	0.0555***	0.0795***	0.115***	0.139***	0.170***
	(0.0261)	(0.0228)	(0.0218)	(0.0214)	(0.0214)	(0.0212)	(0.0247)	(0.0285)	(0.0414)
Constant	7.521***	7.660***	7.816***	7.940***	8.040***	8.080***	8.131***	8.220***	8.393***
	(0.0385)	(0.0361)	(0.0361)	(0.0375)	(0.0403)	(0.0439)	(0.0544)	(0.0651)	(0.0994)
Observations	2,580	2,580	2,580	2,580	2,580	2,580	2,580	2,580	2,580
R-squared	0.095	0.145	0.200	0.247	0.278	0.292	0.307	0.273	0.205

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Rural West 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2010**	**Decile 2 2010**	**Decile 3 2010**	**Decile 4 2010**	**Decile 5 2010**	**Decile 6 2010**	**Decile 7 2010**	**Decile 8 2010**	**Decile 9 2010**
Number of members	-0.0201	-0.0381***	-0.0544***	-0.0543***	-0.0584***	-0.0500***	-0.0596***	-0.0721***	-0.0798***
	(0.0128)	(0.0107)	(0.00922)	(0.00860)	(0.00897)	(0.00904)	(0.0104)	(0.0129)	(0.0169)
Share under age 18	-0.472***	-0.519***	-0.359***	-0.341***	-0.325***	-0.375***	-0.352***	-0.398***	-0.310**
	(0.0728)	(0.0650)	(0.0599)	(0.0575)	(0.0619)	(0.0672)	(0.0802)	(0.104)	(0.135)
Share over age 60	-0.154**	-0.237***	-0.165***	-0.240***	-0.181***	-0.139**	-0.114	-0.131	-0.120
	(0.0633)	(0.0560)	(0.0493)	(0.0495)	(0.0525)	(0.0578)	(0.0695)	(0.0899)	(0.117)
LN land for agriculture	0.168***	0.217***	0.236***	0.247***	0.271***	0.297***	0.339***	0.449***	0.476***
	(0.0194)	(0.0182)	(0.0168)	(0.0165)	(0.0176)	(0.0199)	(0.0243)	(0.0338)	(0.0519)
Average years of schooling	0.0244***	0.0257***	0.0255***	0.0279***	0.0318***	0.0339***	0.0427***	0.0466***	0.0486***
	(0.00321)	(0.00293)	(0.00264)	(0.00256)	(0.00271)	(0.00307)	(0.00370)	(0.00500)	(0.00680)
Share of females of working age	-0.0476	-0.0354	0.00302	-0.00183	0.0192	-0.00483	0.0101	-0.0148	-0.00426
	(0.0318)	(0.0260)	(0.0223)	(0.0215)	(0.0225)	(0.0243)	(0.0288)	(0.0353)	(0.0466)
Agricultural sector	-0.00687	-0.0321	-0.0488*	-0.0437*	-0.0613**	-0.0584**	-0.0403	-0.0454	0.0173
	(0.0353)	(0.0305)	(0.0258)	(0.0243)	(0.0251)	(0.0264)	(0.0295)	(0.0355)	(0.0421)
Service sector	0.0455	0.0310	-0.00576	-0.00845	-0.0255	0.0112	0.0694**	0.111***	0.172***
	(0.0372)	(0.0325)	(0.0279)	(0.0263)	(0.0271)	(0.0289)	(0.0329)	(0.0409)	(0.0494)
Electricity coverage in the village	0.241***	0.223***	0.191***	0.168***	0.157***	0.154***	0.162***	0.192***	0.174***
	(0.0458)	(0.0352)	(0.0283)	(0.0251)	(0.0248)	(0.0253)	(0.0275)	(0.0324)	(0.0394)
Constant	7.346***	7.622***	7.762***	7.876***	7.960***	8.047***	8.104***	8.290***	8.474***
	(0.0609)	(0.0511)	(0.0440)	(0.0420)	(0.0445)	(0.0475)	(0.0536)	(0.0684)	(0.0868)
Observations	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979
R-squared	0.088	0.146	0.178	0.201	0.218	0.217	0.227	0.216	0.150

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Rural West 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2016	Decile 2 2016	Decile 3 2016	Decile 4 2016	Decile 5 2016	Decile 6 2016	Decile 7 2016	Decile 8 2016	Decile 9 2016
Number of members	-0.0626***	-0.0582***	-0.0639***	-0.0677***	-0.0736***	-0.0717***	-0.0676***	-0.0669***	-0.0782***
	(0.00709)	(0.00547)	(0.00505)	(0.00483)	(0.00503)	(0.00520)	(0.00567)	(0.00656)	(0.0104)
Share under age 18	-0.354***	-0.414***	-0.419***	-0.430***	-0.444***	-0.473***	-0.554***	-0.561***	-0.626***
	(0.0360)	(0.0298)	(0.0287)	(0.0287)	(0.0313)	(0.0335)	(0.0377)	(0.0456)	(0.0732)
Share over age 60	-0.124***	-0.125***	-0.125***	-0.140***	-0.154***	-0.173***	-0.209***	-0.224***	-0.192***
	(0.0243)	(0.0210)	(0.0212)	(0.0217)	(0.0240)	(0.0258)	(0.0293)	(0.0349)	(0.0558)
LN land for agriculture	0.158***	0.165***	0.188***	0.217***	0.271***	0.296***	0.337***	0.388***	0.509***
	(0.0104)	(0.00930)	(0.00984)	(0.0102)	(0.0117)	(0.0138)	(0.0166)	(0.0209)	(0.0362)
Average years of schooling	0.0219***	0.0221***	0.0251***	0.0242***	0.0252***	0.0278***	0.0316***	0.0376***	0.0529***
	(0.00159)	(0.00133)	(0.00128)	(0.00127)	(0.00140)	(0.00150)	(0.00171)	(0.00211)	(0.00356)
Share of females of working age	-0.0417**	-0.0374***	-0.0248**	-0.0250**	-0.0225*	-0.0283**	-0.0476***	-0.0580***	-0.0578**
	(0.0163)	(0.0130)	(0.0121)	(0.0118)	(0.0124)	(0.0128)	(0.0143)	(0.0168)	(0.0279)
Agricultural sector	0.0173	-0.00170	-0.0221**	-0.0251**	-0.0487***	-0.0528***	-0.0549***	-0.0934***	-0.147***
	(0.0146)	(0.0119)	(0.0111)	(0.0109)	(0.0114)	(0.0118)	(0.0129)	(0.0150)	(0.0234)
Service sector	0.0317*	0.0283**	0.0157	0.0340***	0.0284**	0.0353***	0.0430***	0.0382**	0.0217
	(0.0163)	(0.0132)	(0.0125)	(0.0121)	(0.0129)	(0.0134)	(0.0148)	(0.0176)	(0.0281)
Electricity coverage in the village	0.157***	0.142***	0.103***	0.0940***	0.0939***	0.0818***	0.0585***	0.0205	0.0304
	(0.0249)	(0.0186)	(0.0164)	(0.0152)	(0.0156)	(0.0157)	(0.0168)	(0.0194)	(0.0287)
Constant	7.541***	7.727***	7.895***	8.027***	8.156***	8.275***	8.434***	8.627***	8.882***
	(0.0317)	(0.0248)	(0.0229)	(0.0222)	(0.0237)	(0.0248)	(0.0277)	(0.0334)	(0.0538)
Observations	13,248	13,248	13,248	13,248	13,248	13,248	13,248	13,248	13,248
R-squared	0.074	0.111	0.137	0.156	0.168	0.175	0.175	0.162	0.117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Urban East 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2005**	**Decile 2 2005**	**Decile 3 2005**	**Decile 4 2005**	**Decile 5 2005**	**Decile 6 2005**	**Decile 7 2005**	**Decile 8 2005**	**Decile 9 2005**
Number of members	-0.0153	-0.0250**	-0.0318***	-0.0338***	-0.0403***	-0.0519***	-0.0702***	-0.0658***	-0.0473**
	(0.0116)	(0.00975)	(0.00942)	(0.00945)	(0.00989)	(0.0112)	(0.0119)	(0.0135)	(0.0187)
Share under age 18	-0.521***	-0.660***	-0.633***	-0.509***	-0.396***	-0.321***	-0.165	-0.127	-0.319*
	(0.0869)	(0.0727)	(0.0732)	(0.0779)	(0.0873)	(0.102)	(0.113)	(0.128)	(0.192)
Share over age 60	-0.214	-0.303***	-0.159	-0.0437	-0.0133	0.154	0.388***	0.307**	0.476*
	(0.132)	(0.115)	(0.110)	(0.109)	(0.112)	(0.131)	(0.139)	(0.149)	(0.275)
LN land for agriculture	0.0880***	0.115***	0.112***	0.127***	0.189***	0.252***	0.212***	0.271***	0.308***
	(0.0153)	(0.0164)	(0.0182)	(0.0207)	(0.0242)	(0.0322)	(0.0396)	(0.0486)	(0.0825)
Average years of schooling	0.0369***	0.0466***	0.0574***	0.0678***	0.0757***	0.0889***	0.0902***	0.0811***	0.0842***
	(0.00308)	(0.00269)	(0.00260)	(0.00250)	(0.00271)	(0.00319)	(0.00358)	(0.00445)	(0.00728)
Share of females of working age	-0.0261	-0.0147	0.0124	0.00884	0.0297	0.0329	0.0778**	0.0558	-0.0435
	(0.0305)	(0.0245)	(0.0233)	(0.0239)	(0.0255)	(0.0316)	(0.0350)	(0.0398)	(0.0559)
Agricultural sector	-0.278***	-0.183***	-0.147***	-0.152***	-0.154***	-0.115**	-0.0928**	-0.0392	-0.0646
	(0.0697)	(0.0531)	(0.0478)	(0.0431)	(0.0418)	(0.0455)	(0.0453)	(0.0460)	(0.0652)
Service sector	-0.0302	-0.0288	0.0194	0.0202	0.00459	0.00444	0.00494	0.0302	-0.0240
	(0.0316)	(0.0283)	(0.0277)	(0.0267)	(0.0288)	(0.0334)	(0.0352)	(0.0381)	(0.0554)
Electricity coverage in the village	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	7.577***	7.797***	7.831***	7.870***	7.907***	7.996***	8.136***	8.358***	8.785***
	(0.0450)	(0.0426)	(0.0452)	(0.0488)	(0.0546)	(0.0631)	(0.0671)	(0.0704)	(0.102)
Observations	2,279	2,279	2,279	2,279	2,279	2,279	2,279	2,279	2,279
R-squared	0.130	0.225	0.300	0.353	0.364	0.364	0.326	0.257	0.153

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Urban East 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2010	Decile 2 2010	Decile 3 2010	Decile 4 2010	Decile 5 2010	Decile 6 2010	Decile 7 2010	Decile 8 2010	Decile 9 2010
Number of members	-0.0414***	-0.0410***	-0.0539***	-0.0526***	-0.0580***	-0.0562***	-0.0608***	-0.0630***	-0.0614***
	(0.0125)	(0.0101)	(0.00911)	(0.00931)	(0.00978)	(0.0100)	(0.0104)	(0.0118)	(0.0154)
Share under age 18	-0.374***	-0.388***	-0.304***	-0.273***	-0.250***	-0.248***	-0.259***	-0.210**	-0.372***
	(0.0737)	(0.0642)	(0.0629)	(0.0683)	(0.0752)	(0.0821)	(0.0870)	(0.0988)	(0.134)
Share over age 60	-0.0496	-0.0220	0.0975	0.180**	0.247***	0.321***	0.224**	0.258**	0.227
	(0.106)	(0.0910)	(0.0850)	(0.0881)	(0.0950)	(0.0996)	(0.101)	(0.111)	(0.159)
LN land for agriculture	0.105***	0.0938***	0.0991***	0.135***	0.155***	0.144***	0.196***	0.217***	0.287***
	(0.0214)	(0.0233)	(0.0236)	(0.0250)	(0.0280)	(0.0339)	(0.0378)	(0.0464)	(0.0749)
Average years of schooling	0.0429***	0.0517***	0.0582***	0.0650***	0.0742***	0.0801***	0.0772***	0.0718***	0.0672***
	(0.00310)	(0.00254)	(0.00230)	(0.00232)	(0.00245)	(0.00268)	(0.00308)	(0.00378)	(0.00558)
Share of females of working age	0.0356	0.0183	0.0361*	0.0420*	0.0300	0.0438*	0.0294	0.0455	0.0204
	(0.0301)	(0.0238)	(0.0219)	(0.0227)	(0.0243)	(0.0266)	(0.0278)	(0.0325)	(0.0450)
Agricultural sector	-0.233***	-0.182***	-0.172***	-0.146***	-0.117***	-0.0406	-0.0932**	-0.0887**	-0.0427
	(0.0716)	(0.0528)	(0.0454)	(0.0413)	(0.0402)	(0.0422)	(0.0411)	(0.0432)	(0.0595)
Service sector	-0.00351	-0.00834	0.00826	0.0345	0.0415	0.0519*	0.0230	0.00872	-0.00224
	(0.0310)	(0.0257)	(0.0243)	(0.0247)	(0.0260)	(0.0275)	(0.0285)	(0.0318)	(0.0429)
Electricity coverage in the village	-0.183	-0.281**	-0.138	0.0530	0.116	0.0722	0.0955	0.0875	-0.0601
	(0.179)	(0.130)	(0.151)	(0.158)	(0.143)	(0.144)	(0.118)	(0.109)	(0.177)
Constant	7.707***	7.985***	7.939***	7.792***	7.833***	7.948***	8.177***	8.375***	8.887***
	(0.187)	(0.137)	(0.156)	(0.165)	(0.152)	(0.155)	(0.132)	(0.127)	(0.198)
Observations	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719	2,719
R-squared	0.120	0.202	0.261	0.292	0.318	0.307	0.288	0.224	0.137

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Urban East 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**Decile 1 2016**	**Decile 2 2016**	**Decile 3 2016**	**Decile 4 2016**	**Decile 5 2016**	**Decile 6 2016**	**Decile 7 2016**	**Decile 8 2016**	**Decile 9 2016**
Number of members	-0.0702***	-0.0723***	-0.0838***	-0.0803***	-0.0801***	-0.0779***	-0.0781***	-0.0741***	-0.0866***
	(0.00900)	(0.00685)	(0.00615)	(0.00590)	(0.00576)	(0.00599)	(0.00668)	(0.00774)	(0.0102)
Share under age 18	-0.276***	-0.288***	-0.278***	-0.349***	-0.336***	-0.339***	-0.347***	-0.357***	-0.177**
	(0.0462)	(0.0380)	(0.0363)	(0.0373)	(0.0386)	(0.0420)	(0.0485)	(0.0588)	(0.0785)
Share over age 60	-0.212***	-0.154***	-0.157***	-0.156***	-0.0934**	-0.0492	0.0156	0.0705	0.295***
	(0.0534)	(0.0420)	(0.0399)	(0.0410)	(0.0409)	(0.0432)	(0.0496)	(0.0600)	(0.0868)
LN land for agriculture	0.0963***	0.108***	0.125***	0.159***	0.175***	0.168***	0.210***	0.262***	0.310***
	(0.0161)	(0.0152)	(0.0160)	(0.0167)	(0.0174)	(0.0221)	(0.0263)	(0.0338)	(0.0500)
Average years of schooling	0.0339***	0.0370***	0.0405***	0.0466***	0.0507***	0.0538***	0.0597***	0.0627***	0.0661***
	(0.00180)	(0.00143)	(0.00134)	(0.00137)	(0.00138)	(0.00150)	(0.00177)	(0.00224)	(0.00328)
Share of females of working age	-0.0198	-0.00974	0.00327	-0.00913	-0.0187	-0.0277*	-0.0184	-0.0227	-0.00319
	(0.0205)	(0.0158)	(0.0146)	(0.0144)	(0.0141)	(0.0146)	(0.0165)	(0.0196)	(0.0269)
Agricultural sector	-0.161***	-0.177***	-0.158***	-0.186***	-0.154***	-0.145***	-0.145***	-0.125***	-0.0904***
	(0.0382)	(0.0285)	(0.0249)	(0.0231)	(0.0217)	(0.0211)	(0.0225)	(0.0248)	(0.0303)
Service sector	-0.0323*	-0.0301**	-0.0198	-0.0271**	-0.0238*	-0.0115	-0.0270*	-0.0238	-0.0253
	(0.0168)	(0.0136)	(0.0129)	(0.0130)	(0.0130)	(0.0135)	(0.0152)	(0.0178)	(0.0232)
Electricity coverage in the village	0.708***	0.531***	0.441***	0.374***	0.341***	0.276***	0.227***	0.179***	0.150***
	(0.120)	(0.0771)	(0.0601)	(0.0503)	(0.0401)	(0.0359)	(0.0358)	(0.0365)	(0.0337)
Constant	7.110***	7.464***	7.693***	7.883***	8.016***	8.184***	8.331***	8.519***	8.742***
	(0.123)	(0.0805)	(0.0642)	(0.0551)	(0.0464)	(0.0434)	(0.0459)	(0.0503)	(0.0547)
Observations	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548
R-squared	0.103	0.159	0.197	0.230	0.244	0.240	0.224	0.185	0.124

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Urban West 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2005	Decile 2 2005	Decile 3 2005	Decile 4 2005	Decile 5 2005	Decile 6 2005	Decile 7 2005	Decile 8 2005	Decile 9 2005
Number of members	-0.0109	-0.0211*	-0.0132	-0.0154	-0.0253**	-0.0379***	-0.0472***	-0.0580***	-0.0381*
	(0.0142)	(0.0123)	(0.0119)	(0.0117)	(0.0118)	(0.0138)	(0.0181)	(0.0217)	(0.0229)
Share under age 18	-0.685***	-0.608***	-0.601***	-0.616***	-0.521***	-0.442***	-0.441***	-0.298	-0.556***
	(0.0949)	(0.0864)	(0.0873)	(0.0888)	(0.0956)	(0.115)	(0.148)	(0.186)	(0.209)
Share over age 60	-0.0180	0.0393	0.000152	-0.0859	-0.0216	0.0151	-0.162	-0.0376	-0.220
	(0.0851)	(0.103)	(0.105)	(0.109)	(0.116)	(0.133)	(0.150)	(0.198)	(0.175)
LN land for agriculture	0.0693***	0.0884***	0.123***	0.160***	0.195***	0.228***	0.278***	0.391***	0.336***
	(0.0221)	(0.0211)	(0.0218)	(0.0231)	(0.0252)	(0.0326)	(0.0451)	(0.0661)	(0.0886)
Average years of schooling	0.0374***	0.0448***	0.0489***	0.0542***	0.0631***	0.0809***	0.100***	0.115***	0.0905***
	(0.00366)	(0.00319)	(0.00307)	(0.00305)	(0.00327)	(0.00381)	(0.00522)	(0.00741)	(0.00929)
Share of females of working age	-0.0541	-0.0313	-0.0540*	-0.0384	-0.0172	0.00623	0.0495	0.0265	-0.0713
	(0.0348)	(0.0310)	(0.0303)	(0.0292)	(0.0298)	(0.0357)	(0.0466)	(0.0658)	(0.0690)
Agricultural sector	-0.0757	-0.0841	-0.110**	-0.105**	-0.124***	-0.109**	-0.142**	-0.154**	-0.101
	(0.0589)	(0.0521)	(0.0488)	(0.0466)	(0.0452)	(0.0498)	(0.0593)	(0.0725)	(0.0769)
Service sector	-0.0719*	-0.0331	0.000461	0.0163	0.0365	0.0618	0.0935*	0.103*	0.0609
	(0.0368)	(0.0338)	(0.0331)	(0.0329)	(0.0338)	(0.0389)	(0.0487)	(0.0612)	(0.0656)
Electricity coverage in the village	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	7.496***	7.590***	7.685***	7.754***	7.787***	7.804***	7.867***	8.006***	8.648***
	(0.0421)	(0.0476)	(0.0495)	(0.0527)	(0.0570)	(0.0702)	(0.0886)	(0.109)	(0.122)
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.139	0.202	0.245	0.296	0.337	0.362	0.352	0.306	0.199

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Urban West 2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2010	Decile 2 2010	Decile 3 2010	Decile 4 2010	Decile 5 2010	Decile 6 2010	Decile 7 2010	Decile 8 2010	Decile 9 2010
Number of members	-0.0224	-0.00923	-0.0286**	-0.0330***	-0.0410***	-0.0436***	-0.0471***	-0.0589***	-0.113***
	(0.0157)	(0.0128)	(0.0123)	(0.0125)	(0.0123)	(0.0136)	(0.0164)	(0.0187)	(0.0209)
Share under age 18	-0.478***	-0.652***	-0.604***	-0.607***	-0.537***	-0.412***	-0.383***	-0.368**	-0.510**
	(0.0983)	(0.0856)	(0.0824)	(0.0865)	(0.0913)	(0.105)	(0.133)	(0.152)	(0.204)
Share over age 60	-0.233**	-0.128	-0.0784	-0.0516	-0.0987	0.0932	0.0325	0.0768	-0.0951
	(0.0935)	(0.0855)	(0.0847)	(0.0900)	(0.0991)	(0.114)	(0.133)	(0.144)	(0.211)
LN land for agriculture	0.0687***	0.0974***	0.140***	0.189***	0.228***	0.320***	0.437***	0.597***	0.590***
	(0.0207)	(0.0214)	(0.0219)	(0.0238)	(0.0266)	(0.0316)	(0.0408)	(0.0594)	(0.104)
Average years of schooling	0.0306***	0.0395***	0.0432***	0.0511***	0.0624***	0.0774***	0.0983***	0.104***	0.103***
	(0.00321)	(0.00297)	(0.00283)	(0.00287)	(0.00301)	(0.00350)	(0.00464)	(0.00596)	(0.00923)
Share of females of working age	-0.0597	-0.107***	-0.0766**	-0.0601**	-0.0459	-0.0512	-0.0735*	-0.0629	-0.0267
	(0.0396)	(0.0331)	(0.0308)	(0.0305)	(0.0316)	(0.0355)	(0.0439)	(0.0471)	(0.0615)
Agricultural sector	0.0400	-0.0142	-0.0139	-0.0431	-0.0240	-0.0449	-0.0598	-0.0334	-0.0335
	(0.0500)	(0.0461)	(0.0427)	(0.0413)	(0.0421)	(0.0453)	(0.0532)	(0.0587)	(0.0764)
Service sector	0.0193	0.0498	0.0803***	0.0601**	0.0650**	0.0900***	0.106**	0.0728	0.0625
	(0.0348)	(0.0316)	(0.0299)	(0.0300)	(0.0311)	(0.0343)	(0.0416)	(0.0465)	(0.0597)
Electricity coverage in the village	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	7.597***	7.760***	7.875***	7.961***	7.996***	7.996***	8.070***	8.301***	8.866***
	(0.0509)	(0.0493)	(0.0483)	(0.0512)	(0.0562)	(0.0646)	(0.0777)	(0.0877)	(0.115)
Observations	1,679	1,679	1,679	1,679	1,679	1,679	1,679	1,679	1,679
R-squared	0.092	0.170	0.224	0.277	0.319	0.360	0.373	0.357	0.254

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Urban West 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Decile 1 2016	Decile 2 2016	Decile 3 2016	Decile 4 2016	Decile 5 2016	Decile 6 2016	Decile 7 2016	Decile 8 2016	Decile 9 2016
Number of members	-0.0326***	-0.0437***	-0.0635***	-0.0671***	-0.0618***	-0.0750***	-0.0837***	-0.0877***	-0.100***
	(0.00995)	(0.00884)	(0.00868)	(0.00814)	(0.00814)	(0.00890)	(0.0103)	(0.0117)	(0.0142)
Share under age 18	-0.422***	-0.517***	-0.494***	-0.442***	-0.440***	-0.465***	-0.408***	-0.294***	-0.192*
	(0.0544)	(0.0499)	(0.0503)	(0.0499)	(0.0521)	(0.0585)	(0.0689)	(0.0797)	(0.109)
Share over age 60	-0.159***	-0.180***	-0.152***	-0.118***	-0.0695	-0.0365	0.0682	0.0839	0.0654
	(0.0490)	(0.0462)	(0.0460)	(0.0454)	(0.0460)	(0.0511)	(0.0589)	(0.0673)	(0.0932)
LN land for agriculture	0.0746***	0.0994***	0.129***	0.161***	0.181***	0.241***	0.307***	0.338***	0.327***
	(0.0124)	(0.0126)	(0.0147)	(0.0147)	(0.0174)	(0.0207)	(0.0268)	(0.0375)	(0.0573)
Average years of schooling	0.0285***	0.0337***	0.0406***	0.0447***	0.0501***	0.0576***	0.0670***	0.0735***	0.0780***
	(0.00189)	(0.00172)	(0.00170)	(0.00169)	(0.00176)	(0.00202)	(0.00244)	(0.00299)	(0.00453)
Share of females of working age	-0.0517**	-0.0405**	-0.0210	-0.0190	-0.00855	0.0123	0.0131	0.0401	0.0111
	(0.0231)	(0.0206)	(0.0203)	(0.0198)	(0.0203)	(0.0227)	(0.0272)	(0.0322)	(0.0388)
Agricultural sector	-0.0957***	-0.113***	-0.0829***	-0.0902***	-0.0567**	-0.0844***	-0.107***	-0.125***	-0.135***
	(0.0324)	(0.0285)	(0.0269)	(0.0250)	(0.0244)	(0.0257)	(0.0275)	(0.0291)	(0.0377)
Service sector	0.00944	0.0228	0.0589***	0.0581***	0.0613***	0.0620***	0.0947***	0.0624**	0.0205
	(0.0202)	(0.0185)	(0.0184)	(0.0177)	(0.0179)	(0.0196)	(0.0222)	(0.0251)	(0.0343)
Electricity coverage in the village	0	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Constant	7.640***	7.836***	7.951***	8.047***	8.089***	8.196***	8.284***	8.408***	8.749***
	(0.0304)	(0.0290)	(0.0307)	(0.0312)	(0.0325)	(0.0364)	(0.0420)	(0.0482)	(0.0630)
Observations	5,355	5,355	5,355	5,355	5,355	5,355	5,355	5,355	5,355
R-squared	0.082	0.138	0.184	0.213	0.230	0.253	0.255	0.226	0.141

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

CHAPTER IV.

Assessing the Role of Spatial and Structural Changes in Poverty Reduction in Bangladesh from 2000 to 2016[1]

Abstract

Bangladesh has documented consistent reductions in poverty since 2000 and has also seen considerable transformation in the sector and location of economic activities. This paper exploits variation in sectoral growth and migration across districts and time to examine whether spatial variation in sectoral growth patterns—growth in agriculture, industry, or services—can explain spatial variation in poverty reduction, and what the role of migration was. We control for district fixed effects and instrument growth in agriculture and international migration to explore causal effects. We find that reductions in poverty were largest in places where agricultural output growth was highest and where industrial growth was highest. Poverty reduction was greater in districts which were sending larger numbers of international migrants. The relationship between agricultural growth and poverty reduction holds when instrumenting agricultural growth with rainfall data, and manufacturing growth has a significant impact on poverty reduction when proxied by a Bartik-style instrument, indicating that some of these findings are causal.

[1] This paper was prepared as a background paper for the Bangladesh Poverty Assessment by Ruth Hill and Joaquin Endara.

I. Introduction

Bangladesh has secured remarkable progress in reducing poverty since 2000. From 2000 to 2016, the proportion of the population living on less than the official upper poverty line has halved, falling from 49 to 24 percent.[2] Education, health, and nutrition outcomes similarly saw substantial improvement.

Bangladesh has experienced high and consistent economic growth during this time, recording annual average per capita growth rates of 4.4 percent from 2000 to 2016,[3] driven largely by growth in industry. Growth in services has also been high, but growth in agriculture has been variable across this period.

Bangladesh has also seen the structure of its economy transform. In 2000, the share of the workforce that reported their main sector as agriculture was 64.8 percent. By 2016, this had fallen to 41.1 percent (International Labor Organization estimates). The share of workers in industry doubled from 10.7 percent in 2000 to 20.8 percent in 2016, and the share of workers in services also grew, from 24.5 to 38 percent. In addition to sectoral shifts, other large changes were occurring in the labor force during this time. Bangladesh urbanized from 20.3 percent in 2000 to 28.1 percent in 2016. And there has also been significant growth in the number of workers migrating internationally to work. In 2000, 223,000 Bangladeshis migrated internationally to work, and this figure had grown to over 1 million by 2017 (Bureau of Manpower Employment and Training). Most migrants go to the Gulf countries, with Saudi Arabia and the United Arab Emirates (UAE) receiving an important share. As migration increased, so did remittances, from almost USD 2 billion in 2000 to USD 9 billion in 2016 (at 2000 prices, Bangladesh Bank).

This paper examines poverty reduction in Bangladesh to understand what aspects of the growth process during 2000 to 2016 drove the gains secured. In particular, the paper examines spatial variation in the sectoral nature of growth and how it impacted spatial differences in poverty reduction. It also examines the contribution of migration, both domestic and international, to reductions in poverty at the district level. The analysis in this paper exploits variation in poverty reduction, sectoral output growth, and migration across districts and time to examine what type of growth—output growth in agriculture, industry, or services—was more effective at reducing poverty.

[2] Official poverty estimates produced by the Bangladesh Bureau of Statistics (BBS) using the Household Income and Expenditure Surveys (HIES).
[3] World Development Indicators.

The findings show that poverty fell fastest in places and periods when agricultural growth was strong and when manufacturing growth was high. Poverty reduction would have been much slower without either one of these engines of growth. Although the calculated elasticity of poverty to service sector growth is very similar to that for manufacturing growth, spatial variation in service sector growth does not explain differences in district poverty reduction. This could be because service sector growth tends to accompany growth in the other two sectors (agriculture and manufacturing). This would be consistent with Shilpi and Emran (2016), who find that productivity shocks to agriculture also spur formalization of the service sector.

These results reflect a causal relationship. Finding that poverty has fallen faster in places and times where agricultural growth has been stronger does not necessarily allow one to deduce that agricultural growth causes poverty reduction. Following Hill and Tsehaye (2018), we use weather data for each district in each year to instrument agricultural growth and try and identify whether the observed relationship between growth in agriculture and poverty reduction is causal. Results suggest it is. Additionally, when manufacturing growth is proxied by a Bartik instrument (Bartik 1991), it is significant.[4]

We also find that international migration provided opportunities for poverty reduction, with districts sending more migrants internationally seeing higher poverty reduction. It is hard to determine in what direction causality flows, as migration could be easier from districts that are more connected and better off. Equally, migration can reduce poverty by generating remittance flows and tightening rural labor markets. Efforts to disentangle these two effects were inconclusive.

Population growth net of in-migration is associated with faster poverty reduction, and in-migration is not correlated with poverty reduction. The positive correlation between population growth and poverty reduction could reflect the benefits of agglomeration, but equally it could reflect the fact that life expectancy increases at the same time as better levels of material wellbeing. The lack of beneficial effects from in-migration could reflect any benefits of agglomeration being outweighed by the fact that international migration often involves the movement

[4] District manufacturing growth is given by the share of workers in the district in each subsector multiplied by the national growth rate in that sub-sector. District level poverty reduction is unlikely to influence national sub-sector growth rates, allowing this measure to reflect an exogenous source of growth to manufacturing in a district.

of poorer individuals to wealthier places. Indeed, rates of internal migration are higher to better-off districts.

These findings fit into a literature that shows that growth in sectors from which poor households derive a considerable share of their income are more poverty reducing than growth in other sectors (Loayza and Raddatz 2010). Agricultural growth has been shown to be associated with stronger poverty reduction at the country level, followed by growth in services (Christiaensen, Demery and Kuhl 2011). Analysis of sub-national sectoral growth and poverty rates in China, Ethiopia, and India has documented that poverty has fallen faster in states and periods of high agricultural growth (Ravallion and Datt 1996; Hill and Tsehaye 2018; Montalvo and Ravallion 2009). In Brazil, similar analysis showed poverty reduction was faster in regions and periods where service sector growth was higher (Ferreira, Leite and Ravallion 2010). In Bangladesh, poor households are engaged in both agriculture and manufacturing through employment in labor-intensive light manufacturing. In addition, cross-country studies point out that international migration and remittances help to reduce poverty in countries that send migrants (Adams and Page 2005; Gupta, Pattillo and Wagh 2009).

The findings are consistent with the extant literature on Bangladesh that has explored the determinants of poverty reduction and structural change over time. Previous poverty assessments documented the importance of growth in agriculture and manufacturing in driving poverty reduction (World Bank 2008, 2013). The important role of agricultural productivity growth in driving poverty reduction over the last two decades is also underscored by Gautam and Faruqee (2016), while Sen et al. (2014) show that differential rates of urbanization and international migration can help explain the spatial pattern of poverty reduction across districts in Bangladesh. It is important to note that this literature also highlights the role that agriculture can play in spurring growth in other sectors. Gautam and Faruqee (2016) find that a 10 percent increase in farm incomes generates an increase of 6 percent in nonfarm incomes. Shilpi and Emran (2016) highlight the role of positive agricultural productivity shocks (driven by weather) in driving an increase in wages, as well as increased informal manufacturing and a formalization of the service sector. The causal role that growth in one sector plays in spurring growth in other sectors is not considered in this paper.

In the next section, we discuss the data used in this report. In section 3, we summarize trends in poverty reduction. Section 4 outlines the empirical methodology used, and section 5 presents the main results. Section 6 concludes.

II. Data

Information on poverty, employment, agricultural growth, and migration was combined to build a district-level panel for the years 2000, 2005, 2010, and 2016. Bangladesh is divided into eight divisions, while each division is divided further into 64 districts (*zilas*), and each district is divided into sub-districts (*upazilas*). The panel was built at the district level, as this was the lowest level at which data on poverty, employment, and agricultural output could be disaggregated at multiple points in time for the period under consideration. The different sources of data used in the analysis are described next.

2.1 Poverty estimates

The Household Income and Expenditure Survey (HIES) is a comprehensive, nationally representative survey used to measure monetary poverty in Bangladesh. The HIES 2016/17 is the fourth round in the series of HIES conducted by BBS in 2000, 2005, and 2010. Before 2000, BBS monitored poverty using a smaller survey that only collected data on expenditure, known as the Household Expenditure Survey (HES). Poverty estimates are based on total consumption per capita, which is generated from this data. The HIES was fielded during 2000, 2005, 2010, and from April 2016 to March 2017. (The latest HIES round will hereafter simply be referred to as 2016.)

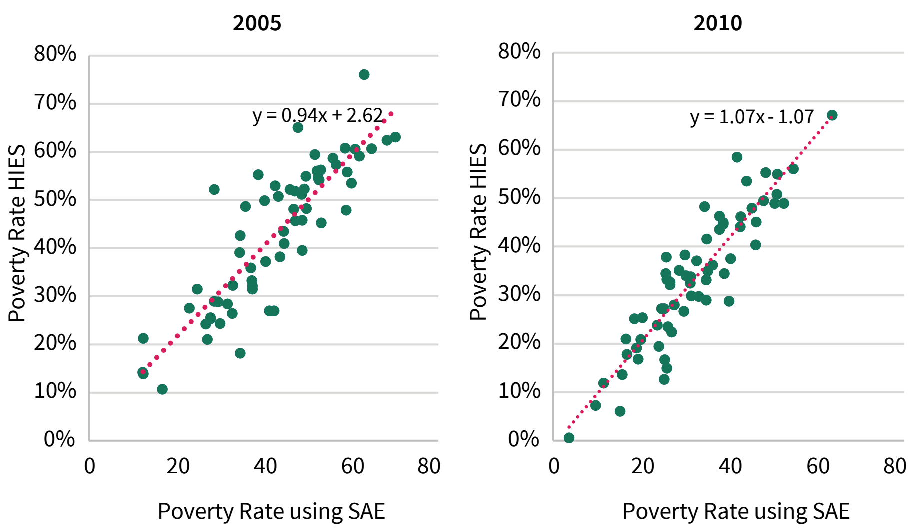
The 2016 HIES was designed to provide representative poverty estimates at the district level.[5] However, in 2000, 2005, and 2010 the samples for the HIES were not designed to provide district-level estimates. They were intended to provide reliable annual poverty estimates for the country's divisions in urban and rural areas separately and for the Statistical Metropolitan Areas. Small area estimation (SAE) was undertaken by the BBS in 2005 and 2010 to generate poverty estimates at the district and sub-district level. For this paper, SAE estimates were also generated for 2000.

Even though the 2000, 2005, and 2010 HIES were not designed to provide district level poverty estimates, it is possible to generate poverty estimates at the district

[5] In 2016, a stratified, two-stage sample design was adopted for the HIES, with 2,304 Primary Sampling Units (PSU) selected from the list of the 2011 Housing and Population Census enumeration areas. PSUs in the HIES 2016/17 were allocated at the district level. Therefore, the sample was stratified at the district level. Since there were a total of 64 districts in Bangladesh, the sample design included a total of 132 sub-strata: 64 urban, 64 rural, and four main City Corporations (CCs). Within each PSU, 20 households were selected for interviews. The final sample size was 46,080 households (Ahmed et al. 2017).

level from these samples as the PSUs cover all districts.[6] We compare district poverty estimates calculated directly from HIES to district poverty estimates from SAE in Figure 1. Estimates are presented for 2005 on the left and 2010 on the right. A linear regression line is displayed on both figures and shows that the correlation between the direct survey estimates and small area estimates is such that the line goes through the origin and has a coefficient that is not significantly different from 1. Most estimates lie along this line, although there are a few outliers. The survey-based estimates of poverty appear quite reliable, though the standard error on the estimates is sometimes quite high. The measurement error in the poverty estimates can be considered white noise, and poverty is the dependent variable in our analysis. Given these facts, coefficient estimates will not be affected. We present results using both the small area estimates and the direct estimates as the dependent variable.

Figure 1. **Comparing survey and small area estimates (SAE) of district poverty rates, 2005 and 2010**



2.2. Sectoral growth

Bangladesh does not produce subnational GDP estimates, so other data sources are used to generate proxies for district growth rates and the sectoral composition of growth. District level growth in a given period is estimated by multiplying the share of employment in the district in a given sector (agriculture, industry, or

[6] The one exception is Bandarban district in 2000.

services) at the beginning of the period by the growth rate recorded by that sector nationally for the period. Identification of the impact of sectoral growth rates on poverty reduction in this estimation strategy comes from two sources: changes in the share of employment in a given sector over time and changes in the sectoral growth rate across time. The sectoral shares of employment are taken from the main sector of employment reported in the census (2000, 2010) and the expanded HIES (2016). Sectoral shares of employment for 2005 are interpolated between 2000 and 2010. For industry and service sector growth rates it is possible to generate estimates using subsector employment and growth rates, given subsector growth rates are reported. These thus represent a Bartik instrument type of proxy for manufacturing and service sector growth. District level poverty reduction is unlikely to influence national sub-sector growth rates allowing this measure to reflect an exogenous source of growth to manufacturing in a district.

2.3 Agricultural output

Annual estimates of agricultural production are collected by BBS's agricultural wing. Data on area cultivated, total production, yield, and irrigation are collected for each crop in rice (Aman, Boro and Aus), wheat, jute and potato. Data on forest cover and fish production is also collected and published with the crop data in the Annual Bulletin of Agricultural Statistics. This data is available annually throughout this period. Data on agricultural wages paid to men and women at the district level is also collected and published in the Bulletin of Agricultural Statistics.

Data on rice prices was collected from the Department of Agricultural Marketing. We use monthly prices from up to 70 markets (at least one per district) for 2002, 2005, 2010, and 2016. The 2002 rice prices were deflated using the food CPI to be used as 2000 prices. The average price for each year across rice varieties was taken. Rice price data was combined with production data to estimate the value of rice production in each district. Rice is a large share of cropped area, and the share of land cultivated to rice stayed quite constant across time. The average of the district shares of total cropped area that was planted to rice was 73 percent in 2000, 72 percent in 2005, 75 percent in 2010, and 72 percent in 2016.

For jute, potato, wheat, and fish production, wholesale prices at the division level for 2000, 2005, 2010, and 2016 were used to estimate the value of the production. These prices came from the same source as the crop estimates. For jute, there were two types of varieties, masta and tossa, and they were averaged. For potatoes, the prices available were for local and Holland variety, and they were also averaged. Wheat had only one wholesale price. Fish production was valued using Rui fish[7] prices. Data on forest cultivation was also calculated and was included in some regressions. There is no data on growth in livestock production.

2.4 Non-agricultural growth

To create proxies for growth in non-agricultural sectors, the 2001/3 and 2013 economic censuses were used, as well as two censuses of firms larger than ten workers in 2006 and 2009 (Shilpi and Emran 2016). We use this data to create the number of firms and employees in 14 broad economic sectors.[8] Given that the 2006 and 2009 data from the Monitoring of Employment Survey are for firms over ten employees, a scaling factor was created from the economic census to expand the 2006 and 2009 numbers. The ratio between firms over ten employees and firms under ten employees in 2013 was used to expand the 2006 and 2009 data. Using the data for 2001/3, 2006, 2009, and 2013, the values for 2000, 2005, 2010, and 2016 were linearly interpolated.

The total number of firms in the industry sector grew 163 percent from 2000 to 2016, while in the service sector the growth rate was 175 percent for the same period. The number of employees reported by the industry sector grew 195 percent over the period, while the workforce reported by the service sector grew 173 percent. It is important to note that, in 2000, 30 percent of the workforce covered by the survey was in the industry sector. By 2016, that figure had increased to 50 percent.

2.5 Migration

The international migration data come from the Bangladesh Bureau of Manpower Employment and Training. The number of people working overseas by district for 2004, 2005, 2006, 2007, and 2008 was taken from Islam (2014, 2015), while the total number of international migrants for 2005 and 2017 was obtained from the Ministry's webpage. This series is interpolated to provide international migration estimates for 2000, 2005, 2010, and 2016.

[7] Rui fish is an expensive variety and represented less than 20 percent of the catch in 2016, so a downward correction of a factor of ten was applied to the value of fish production, so that the ratio of value added from fish and value added from rice approximates that found in national accounts.

[8] These were: 1. Mining and Quarrying; 2. Manufacturing (without garment sector); 3. Manufacturing (only garment sector); 4. Construction; 5. Electricity, Gas, and Water Supply; 6. Wholesale and Retail; 7. Trade Transport, Storage, and Communications; 8. Hotels and Restaurants; 9. Banking, Insurance, and Financial Institutions; 10. Real Estate and Renting; 11. Public Administration and Defense; 12. Education; 13. Health and Social Work Community; and 14. Social and Personal Services.

Within-country migration estimates were generated using the 1991, 2001, and 2011 censuses and the Report on the Sample Vital Registration System (SVRS) of 2016. Ideally, data on net migration at the district level would be available, however the only data available to us across time is the rate of in-migration to the district. The data is reported as the number of in-migrants for every 100 habitants in the census and for every 1,000 inhabitants in the SVRS by district. The 2000, 2005, and 2010 estimates were generated using linear interpolation of the census. For 2016, the SVRS estimates of in-migration at the division level and the national rural and urban breakdown were used to generate division and rural/urban growth rates. Those growth rates were then used to generate district level numbers for 2016 based on the division that the districts were in and their rural/urban share in 2010 and 2016.[9]

The change in population per district (measured as population density) is also included. Given that international migration and in-migration are controlled for, this can be thought of as proxying a combination of domestic out-migration and natural population increase.

In order to explore if the relation between migration and poverty reduction is causal, we instrument international migration using the destination country real GDP growth difference between periods. To determine which countries are relevant to Bangladesh international migration, we use HIES 2016, where the households report if they have an international migrant and in which country the migrant is living. This is used to generate district-level shares of migration destinations.[10] Ideally, we would have used the share of destinations at baseline in 2000, but this information was not available. For those countries in the list we obtain the yearly real GDP growth estimates from the IMF WEO. Then, to create the instrument Z for the period t for district i, we use the sum over the countries c of the product of the share of migrants at the district level going to country c in 2016 M_{2016c} times the country c growth rate differences[11] $(GDP_{tc} - GDP_{t-1c})$ for period t.

$$Z_{ti} = \sum_{c} (GDP_{tc} - GDP_{t-1c}) * M_{2016\,ic}$$

[9] *2010-2016 migration growth rate for distrinct i in division j=[growth rural migration 10 to 16 ∗ share rural population i + growth urban migration 10 to 16 ∗ share urban population i]∗* $\left\{\frac{\frac{Division\ migration\ j\ 2016}{Division\ migration\ j\ 2010}}{\frac{National\ migration\ 2016}{National\ migration\ 2010}}\right\}$

[10] The list the most popular migration destinations in the 2016 HIES included: Australia, Brunei, Canada, Germany, Iran, Iraq, Italy, Japan, Republic of Korea, Kuwait, Libya, Malaysia, Mauritius, Oman, Qatar, Saudi Arabia, Singapore, South Africa, Sweden, Turkey, the United Arab Emirates, the United Kingdom, and the United States.

[11] For example, for the period 2000/2005, $GDP_{2000c} - GDP_{2005c}$

2.6 Weather shocks

The rainfall data used is that used in Bandyopadhyay and Skoufias (2015). This data was obtained from the Climate Research Unit of the University of East Anglia (CRU). They provide an estimate of the monthly rainfall with half-degree resolution from 1902 to 2016. We use monthly data to create our estimates for each district for the four periods. To create the district level data, we generate the weighted average of the different pixels covering a district. In particular, we try to capture the difference in the amount of rain in the monsoon season (July to September). On average, 2016, 2010, and 2000 did not differ in rainfall, while 2005 was 11 percent drier than 2000 and 13 percent drier than 2010. The CRU estimates used are considered reliable, since they use not only data obtained from weather stations within Bangladesh itself, but also data from all the weather stations near the country.

III. Trends in variables used

Figures in Table 1[12] show that GDP growth and poverty reduction have been quite consistent since 2016, with growth at 5-6 percent and the annual percent reduction in poverty at around 4 percent. Within this generally consistent picture, there has been an acceleration of the growth rate and, in recent years, a slowing of the pace of poverty reduction, which has resulted in a slightly lower growth-poverty elasticity. (Growth-poverty elasticity declined from -0.9 to -0.7 percent reduction in poverty for every percent of growth).

These shifts in growth and poverty reduction are in part the outcome of large changes in the structure of Bangladesh's economy, including sectors of work and patterns of residence. Agriculture fell from representing 24 percent of GDP in 2000 to 15 percent of GDP in 2016. Six percentage points of this shift went to industry and three percentage points to services. The structure of employment has shifted even more dramatically, with 24 percent of the workforce moving out of agriculture during this period—roughly half into industry (10 percent) and half into services (13 percent). There was also a seven percentage-point increase in the share of the urban population between the two censuses taken during this period. The number of households reporting a household member working abroad has also risen.

The growth and shifts across sectors have not occurred uniformly during this time. Each of the three periods considered was quite different in terms of the type

[12] Tables are placed at the end of the paper.

of growth and employment shifts observed. The first period (2000-2005) was a period of relatively low growth in agriculture; high but jobless growth in industry; and moderate, job-creating growth in services. The shift of employment from agriculture to services during this period was notable. The second period (2005-2010) was a time of high growth in agriculture, temporarily reducing departures from the agriculture sector (in contrast to the overall trend); high, job-creating growth in industry; and very high but jobless growth in services. This period was notable for its very high agricultural growth and for the start of Bangladesh's boom in manufacturing job creation. The third period (2010-2016) marked a phase of lower agricultural growth; high, job-creating growth in manufacturing; and moderate service sector growth. High manufacturing growth with robust job creation was the period's most notable trait.

The poverty rate among households that derived their main employment from agriculture, industry, and services is detailed in Table 1. It shows, on average, that the reduction in poverty has been faster among households in industry and services, except for 2005 to 2010, when poverty reduction among agricultural households was particularly high.

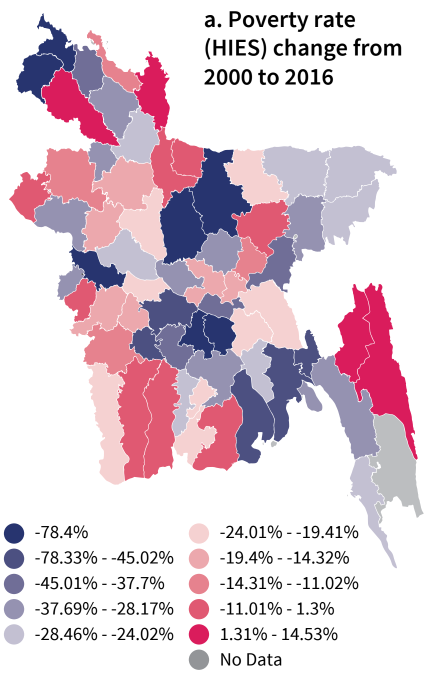
Sectoral growth elasticities can be derived from the data on annual rates of poverty reduction and growth. The reduction in poverty among agricultural households for each percentage point increase in agricultural GDP was high from 2000 to 2010: every percent of growth in agricultural value added per capita resulted in a 1.5 percent reduction in poverty among agricultural households. However, this elasticity was almost halved from 2010 to 2016, falling to 0.8. The elasticities have in general been lower for industry and services, around 0.4 to 0.8 across periods (except for the service sector from 2000 to 2005, which experienced a much higher elasticity). From 2010 to 2016, Bangladeshi households in the industry and service sectors secured 0.6 and 0.8 percent reduction in poverty, respectively, for every percent of value added per capita in these sectors.

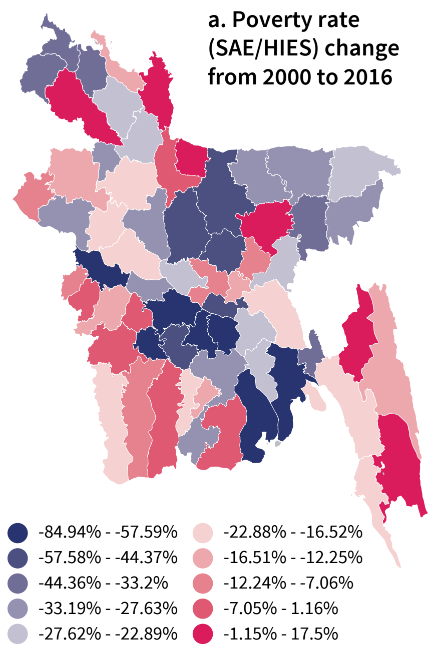
Figure 2 shows that the reduction in poverty rates has not been uniform across space, with faster poverty reduction in the center and northeast, compared to other parts of the country. Figure 3 shows the share of the population engaged in the three sectors across time. Agriculture (left) has had a downward trend across the board, with its strongest decline in the northeast. Industry (center) has grown, with emphasis in the central part of the country. Services (right) has a mixed trend, with strong growth in the western portion of the country. These shifts are not uniformly spread across districts, and it is this spatial and temporal variation in the rate of poverty reduction and structural change that this paper exploits to assess what has driven poverty reduction from 2000 to 2016.

Table 2 presents the average of the district averages for each variable used in the analysis for 2000, 2005, 2010, and 2016. It shows the same trends as were depicted in Table 1. The table shows the significant progress that Bangladesh has made in reducing poverty over time and indicates that this progress in poverty reduction has been commensurate with rapid growth in the value of rice and agricultural output per capita, the number of firms per capita (both industrial and services firms), and the level of international migration.

The average rates of district population growth and in-migration have also been increasing throughout this period. In-migration rates tend to be higher in less-poor districts. The district with the highest rate of in-migration is Dhaka (results for 2016 shown in Figure 4). Population growth net of in-migration is a combination of lack of out-migration, fertility rates, and life expectancy.

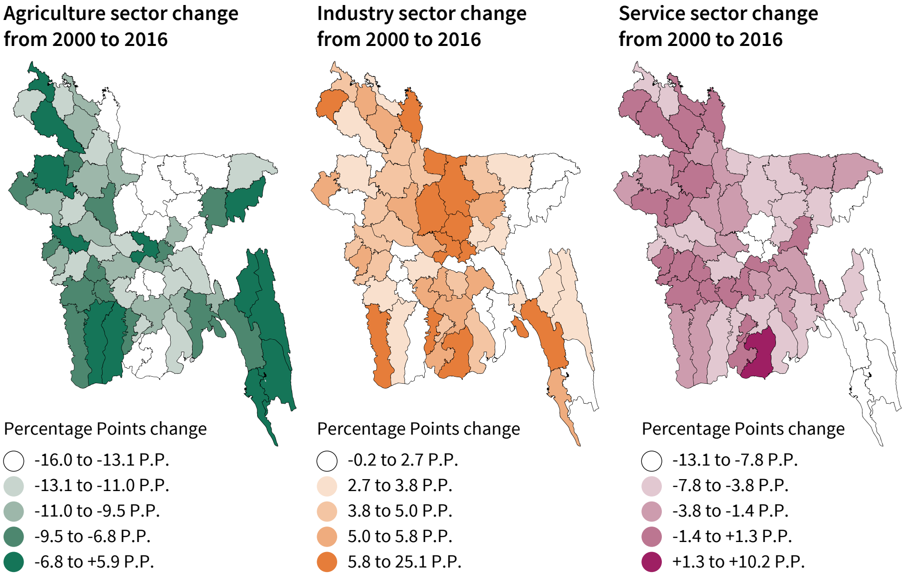
Figure 2. Reduction in poverty over time





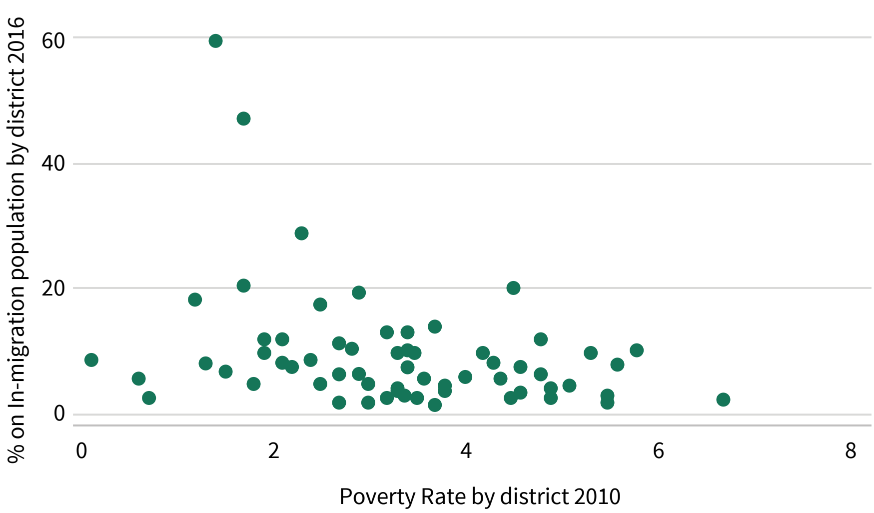
Note: Figures depict the change in the poverty rate between 2000 and 2016 in percentage points.

Figure 3. Sector shifts over time



Note: Figures depict the change in the poverty rate between 2000 and 2016 in percentage points.

Figure 4. Rates of in-migration tend to be higher in districts with lower poverty rates



IV. Empirical Method

The empirical approach we take is similar to that used in Ferreira et al. (2010). We start by abstracting from the sectoral pattern of output growth and examining whether changes in poverty rates have been driven by aggregate output growth in the district. Specifically, we estimate:

$$\Delta \ln p_{zt} = \beta_0 + \beta_Y \Delta \ln Y_{zt} + u_z + e_{zt} \qquad (1)$$

where p_{zt} is the poverty rate in the district z at time t, Y_{zt} is district growth, u_z is a district fixed effect, and e_{zt} is the error term. Y_{zt} is calculated by attributing the subsector growth rates to each district according to the share of the population engaged in that sector at the beginning of the period.

Secondly, we examine the relationship between the nature of sectoral output growth and poverty reduction by decomposing zonal output growth into that coming from agricultural growth and that coming from manufacturing and services. Following Ravallion and Datt (1996) and the subsequent literature on the relationship between the composition of growth and poverty reduction, we estimate:

$$\Delta \ln p_{zt} = \beta_0 + \beta_{Y^a} s^a_{zt-1} \Delta \ln Y^a_{zt} + \beta_{Y^m} s^m_{zt-1} \Delta \ln Y^m_{zt} + \beta_{Y^r} s^r_{zt-1} \Delta \ln Y^r_{zt} + u_z + e_{zt} \qquad (2)$$

where $Y^i_{zt}, i = a, m, r$ is the output of agriculture (a), manufacturing (m), and services (r), respectively, and s^i_{zt-1} is the share of output of sector i at the beginning of the period. Interacting the rate of growth of sector i with the share of sector i in total output allows growth in a given sector to influence poverty according to the size of the sector. The combined expression, $\beta_{Y^i} s^i_{zt-1}$, provides a measure of the elasticity of poverty to growth in that sector. This specification allows us to look at whether particular components of growth are more strongly associated with poverty reduction, and whether the sectoral composition of growth matters (Ferreira et al. 2010).

This specification allows us to control for a number of other factors that might confound the relationship between sectoral composition and poverty rates. The regression is estimated in differences, allowing us to control for any initial district characteristics that affect the relationship between the output of one sector and poverty.[13] District-specific time trends are included in the model, u_Z, through the inclusion of district-specific fixed effects. This allows each district to have a district-specific trend in poverty reduction over the period.

A second set of regressions is then run, in which variables capturing migration are included. Specifically, the following regression is run:

$$\Delta \ln p_{zt} = \beta_0 + \beta_{Y^a} s^a_{zt-1} \Delta \ln Y^a_{zt} + \beta_{Y^m} s^m_{zt-1} \Delta \ln Y^m_{zt} + \beta_{Y^r} s^r_{zt-1} \Delta \ln Y^r_{zt}$$
$$\beta_m m_{zt} + \beta_c c_{zt} + \beta_{intl} intl_{zt} + u_z + e_{zt} \quad (3)$$

where m_{zt} is in-migration to the district, c_{zt} is population density, and $intl_{zt}$ is international migration.

Even with district fixed effects, our estimation strategy is subject to a concern that reverse causation may be driving the results. For us to argue that growth in agriculture caused poverty reduction, we will need to be able to address the argument that gains in poverty reduction might have caused greater agricultural growth. In some papers on the relationship between sectoral growth and poverty, this goes unaddressed, and in other papers it is addressed by instrumenting growth rates with growth rates of neighbors (Ligon and Sadoulet 2008; Loayza and Raddatz 2010), lagged growth (Loayza and Raddatz 2010), or rainfall (Hill and Tsehaye 2018). We use rainfall shocks interacted with changes to the international price of rice as an estimate of exogenous variation in agricultural growth. It is not clear what could be used to instrument for manufacturing growth, so this is not attempted. International migration is instrumented with the weighted average growth rate in countries to which migrants from that district migrate, where the weights indicate the share of migrants from the district to a given country.

V. Results

5.1 Growth and poverty reduction

Growth has been a significant driver of reductions in poverty in Bangladesh. First, we examine the relationship between poverty reduction and total output growth per capita by estimating equation 1. The results are presented in columns 1-2 of Table 3 and indicate that the elasticity of poverty to growth is -2.5. For every 1 percent of growth, poverty fell by 2.5 percent.

[13] Annualized growth rates are calculated for each variable by dividing each growth rate by the number of years over which the growth occurred.

Poverty reduction has been faster in districts and periods where agricultural growth and manufacturing growth have been higher, in particular manufacturing growth. The relationship between the nature of growth and poverty reduction is examined by estimating equation 2 (Table 3, columns 3-4). The coefficient on agriculture and manufacturing growth is similar, but it implies a much higher elasticity of growth for agriculture than for manufacturing, given that the coefficients in Table 2 are for sectoral growth multiplied by the share of the sector in district employment. The implied elasticities are given in Table 4, alongside the average elasticities for 2000-2016 calculated from GDP growth data and sectoral poverty rates.

Services encompass many different types of activities, and in column 4 services are split into service sectors that are dominated by high-skill employees (the "FIRE" sectors of finance, insurance, real-estate, and education) and other services. However, this does not change the insignificance of the service sector. In columns 5 to 8 of Table 3, growth in the value of agricultural production is used to proxy output growth. In columns 5 and 6, the subsector employment shares and growth rates are used to construct a district measure of output growth in industry and services. In columns 7 and 8, growth in the number of firms in industry and services is used to proxy output growth in industry and services. The results are the same (although the coefficients change, given the different magnitudes of the underlying variables). The results in column 8 show that growth in garment industries did not have an additional impact not captured by this measure of manufacturing growth.

Agricultural growth is perhaps more likely to bring about growth in rural areas and manufacturing growth is perhaps more likely to bring about reductions in poverty in urban centers. The districts in this study include both rural and urban areas, however this is tested by re-estimating equation 2, this time weighting the results by the proportion of the district that is urban. In this specification, those districts with very small urban populations are given a low weight, and those that are entirely urban derive the highest weight. In this specification, we would expect that sources of growth that are more important to urban poverty reduction would appear more significant. Coefficients are very similar when this is done, and the results are not shown.

Table 5 presents the same regressions as in Table 3, but using as dependent variables the average consumption growth rate and the average consumption growth rate of the bottom 40 percent of the consumption distribution in a given district. The results show some interesting differences. Agricultural growth is important for consumption growth among the bottom 40 percent, but not average consumption growth in general. Manufacturing growth is important for consumption growth across the distribution, although it becomes insignificant in some specifications. Service sector growth emerges as weakly important for the consumption growth of the bottom 40 percent in some specifications.

5.2 Migration and poverty reduction

In Table 6, we allow for changes in population in the district to impact growth rates, conditional on the nature of economic growth in the district. Specifically, we examine the relationship between poverty reduction and rates of international migration, in-migration, and population growth net of in-migration, controlling for sectoral growth rates. Sectoral growth rates in manufacturing and services are proxied using weighted averages of sectoral growth rates in column 1 and the growth in the number of firms in services and industry in the district in column 2.

The results suggest international migration may have had a powerful role in reducing poverty in Bangladesh. For each additional 0.1 percent of the population migrating, poverty in the district fell by 1.7 percent. This is a very large effect. The number of remittance recipients is unlikely to be 17 for each migrant, so this either indicates very large indirect benefits from international migration or substantial reverse causality with international migration flowing more from places that were reducing poverty for other reasons. This is something that we explore in the following section, instrumenting migration with growth rates of recipient countries.

Higher non-migration population growth is also positively correlated with poverty reduction, although the results are less consistently significant. In one specification, an increase in population growth net of in-migration of 0.1 percent is correlated with poverty reduction that is 0.6 percent faster. The correlation between non-migration population growth and poverty reduction could also reflect different relationships at play. It could reflect the benefits of agglomeration, or it could reflect the fact that places with higher population growth were likely places where improvements in life expectancy had been large. These improvements in life expectancy are in themselves another reflection of improvements in wellbeing. There was no impact of population growth from in-migration on poverty, perhaps indicating that the fact that households tend to move to better-off districts (presumably from poorer ones) offsets some of the gains in agglomeration that would otherwise have resulted from the population growth in-migration brings. However, given that in-migration likely reduces the poverty of those moving, the overall impact of domestic migration on national poverty reduction could be positive. We are unable to test this, as we do not have information on out-migration at the district level.

5.3 Instrumental variable results

None of the relationships presented in Tables 3, 5, and 6 are causal, even though district and year fixed effects are included. Instruments cannot be identified for all the variables examined here, but we examine instruments for agricultural growth (rainfall) and international migration (Bartik instrument using growth rates in destination countries). Table 7 shows how agricultural production has been increasing in the irrigated area of the district, but that nevertheless rainfall shocks do impact agricultural value added, most likely because production during the main summer season tends not to be irrigated.

Results instrumenting for agricultural growth and migration are presented in Table 8. When agricultural value added is instrumented with rainfall, it is still significant in predicting poverty reduction within the district. However, this no longer holds when year fixed effects are included. The instrumented results for international migration are less clear. The first-stage results show the Bartik instrument is significant, but it has the opposite sign from what one would expect, with higher growth rates in receiving countries reducing the likelihood of international migration from the district. International migration is no longer significant when instrumented with this instrument. In case this non-result arises because the IV regression results lack power, results are also presented replacing district fixed effects with division fixed effects in columns 5 to 7. This does not impact the significance of the instrumented international migration variable. In column 7, we instrument for both at the same time, and the results remain unchanged.

VI. Conclusion

This paper has examined poverty reduction in Bangladesh from 2000 to 2016, to understand what aspects of growth and changes in employment drove the gains secured. The findings show that growth in agriculture and growth in manufacturing have been equally important parts of Bangladesh's poverty reduction record. Poverty fell faster in districts and time periods when growth in the value of agricultural output and the number of manufacturing firms was the highest. The results also show the important role that international migration may have played in securing welfare gains in sending districts.

A key question is whether the drivers of agricultural and manufacturing growth can be sustained going forward, and whether this growth can continue to benefit poor households: agricultural growth increases wages and returns to assets for poor households, and manufacturing jobs create unskilled employment. The results suggest that it is also important to examine how to sustain the flow of international migrants and remittances, given the important role this has played in poverty reduction.

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Table 1 Trends in key variables, 2000-2016

	2001-5	2006-10	2011-16	2000	2005	2010	2016
Growth							
	Average per capita growth			*Share of GDP*			
Total GDP growth	5.1	6.1	6.5				
Total GDP per capita growth	3.3	4.8	5.2				
Agriculture	1.5	4.1	2.3	23.8	19.6	17.8	14.8
Industry	5.2	6.8	8.4	23.3	24.6	26.1	28.8
Services	2.3	8.4	4.9	52.9	55.8	56.0	56.5
Inflation	5.1	7.7	7.2				
Sector of employment and place of residence							
	Annual percent change			*Share in employment (%)*			
Agriculture (ILO modeled estimate)	-1.3	-0.1	-0.8	64.8	48.1	47.3	41.1
Industry (ILO modeled estimate)	1.8	1.1	1.1	10.7	14.5	17.6	20.8
Services (ILO modeled estimate)	2.6	-0.3	0.5	24.5	37.4	35.0	38.0
Urban population (census)				23.6		30.4	
Poverty	*Annual percent change*			*Poverty rate (%)*			
National (HIES)	-3.6	-4.2	-3.8	48.9	40.0	31.5	24.3
Agriculture (HIES)	-2.1	-6.2	-1.8	55.8	49.9	34.5	30.8
Industry (HIES)	-3.8	-3.0	-5.2	50.5	40.8	34.7	23.8
Services (HIES)	-3.6	-3.6	-4.0	39.3	32.3	26.4	20.1
Implied growth-poverty elasticity							
Total	-1.1	-0.9	-0.7				
Agriculture	-1.4	-1.5	-0.8				
Industry	-0.7	-0.4	-0.6				
Services	-1.6	-0.4	-0.8				

Note: Staff own estimations. HIES stands for the Bangladesh Household income and Expenditure Survey. ILO stands for International Labor Organization. Poverty by sector of employment was calculated using the number of hours that a household worked in each sector. A household was considered to be in agriculture if the highest number of hours worked was devoted to agriculture.

Table 2: District averages of key variables

	Data source	2000	2005	2010	2016
Poverty headcount rate HIES	HIES	0.51 (0.14)	0.43 (0.15)	0.33 (0.14)	0.28 (0.15)
Poverty headcount rate HIES and SAE	HIES	0.51 (0.14)	0.43 (0.14)	0.32 (0.12)	0.28 (0.15)
Agricultural Growth	BBS		1.9 (0.4)	3.1 (0.7)	1.9 (0.5)
Industrial Growth	Ec Census		0.4 (0.3)	0.6 (0.5)	1 (0.9)
Services Growth	Ec Census		1.9 (0.5)	2.1 (0.6)	2.0 (0.5)
Aggregated Growth	Ec Census, BBS		4.2 (0.3)	5.7 (0.2)	4.89 (0.7)
Nominal rice value per capita (Taka p.c.)	BBS, DAM	262.3 (103.7)	335.3 (130.5)	808.8 (334.8)	776.5 (331.6)
Fish value per capita (Taka p.c.)	BBS, DAM	374.6 (217.2)	397.5 (224.5)	610.5 (436)	383.8 (300.2)
Agricultural value added per capita (Taka p.c.)	BBS, DAM	804.9 (535.2)	1146.1 (902.4)	3026.4 (2199.5)	3444.1 (3022.8)
Real agricultural value added per capita (Taka p.c.)	BBS, DAM	2111.9 (1585)	2364.7 (2049.9)	3995.1 (3174.8)	3174.0 (2975.6)
Industrial firms per capita	Ec Census	0.004 (0.003)	0.004 (0.002)	0.004 (0.002)	0.008 (0.004)
Services firms per capita	Ec Census	0.029 (0.007)	0.024 (0.011)	0.032 (0.014)	0.061 (0.021)
Irrigated area in thousands of acres	BBS	161.6 (115.1)	194.3 (142.4)	264.1 (189.1)	287.6 (206.7)
Rainfall in Monsoon season (mm)	CRU	310.3 (80.25)	275 (46.27)	317.2 (65.69)	317.9 (57.53)
			2001-2005	**2006-2010**	**2011-2016**
Annual international migration as a share of initial population	BMET, Census		0.15 (0.15)	0.37 (0.32)	0.37 (0.37)
Annual population growth net of in-migration	Census		1.14 (0.68)	1.08 (0.71)	1.38 (0.68)
Annual in-migration as a share of initial population	Census		0.25 (0.54)	0.18 (0.49)	0.69 (0.56)

Note: Staff own calculation. Numbers are unweighted district averages. p.c. stands for per capita. HIES stands for the Bangladesh Household Income and Expenditure survey. SAE stands for small area estimation. BBS stands for Bangladesh Bureau of Statistics. Ec Census stands for Economic Census. DAM stands for the Bangladesh Department of Agriculture Marketing. BMET stands for Bangladesh Bureau of Manpower Employment and Training. CRU stands for Climate Research Unit, University of East Anglia. All real variables are express in 2016 prices. Standard errors in parenthesis.

Table 3: Growth, in both agriculture and manufacturing, contributed to poverty reduction

Dependent variable: Change in poverty rate at the district level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Using growth in the value of agricultural production for agricultural growth			
					Using subsector employment shares and growth rates for non-agricultural growth		Using growth in number of firms for non-agricultural growth	
Total growth per capita	-0.0253* (0.0151)	-0.0274** (0.0123)						
Growth in								
Agriculture			-0.127 (0.0791)	-0.129** (0.0637)	-0.717* (0.382)	-0.749** (0.369)	-0.683* (0.347)	-0.669* (0.352)
Manufacturing			-0.114*** (0.0435)	-0.117*** (0.0350)	-0.0488* (0.0291)	-0.0453* (0.0273)	-3.607** (1.449)	-3.123* (1.865)
Services			-0.0487 (0.0977)	-0.0741 (0.0772)	0.00827 (0.0540)		-0.0424 (0.312)	-0.0958 (0.326)
FIRE						0.0002 (0.0006)		
Other services						0.0004 (0.0005)		
Garments								-0.0077 (0.015)
Observations	191	192	191	192	191	191	191	191
R-squared	0.022	0.038	0.068	0.099	0.048	0.053	0.073	0.076
Data on poverty	HIES	SAE	HIES	SAE	HIES	HIES	HIES	HIES
Number of districts	64	64	64	64	64	64	64	64

The dependent variable is the annualized percentage change in the district poverty rate estimated directly from the HIES. Results in column 2 and 4 use small area estimation (SAE). FIRE stands for Finance, Insurance, Real Estate and Education. District fixed effects included but not shown. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: calculated and estimated elasticities of poverty with respect to sectoral growth

	Average over 2000-2016 calculated from Table 1	Elasticities backed out of estimates from Table 3, columns 2 and 4
Total growth	-0.9	-1.0
Agriculture growth	-1.2	-2.7
Industrial growth	-0.6	-0.4
Service sector growth	-0.9	-1.0

Table 5: Growth, in both agriculture and manufacturing, contributed to consumption growth of the bottom 40 percent

Dependent variable: Change in log of consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Using growth in the value of agricultural production for agricultural growth			
					Using subsector employment shares and growth rates for non-agricultural growth		Using growth in number of firms for non-agricultural growth	
Total growth per capita	0.0440*** (0.00529)	0.0482*** (0.00479)						
Growth in								
Agriculture			0.0238 (0.0262)	0.0396* (0.0230)	0.729*** (0.150)	0.776*** (0.140)	0.802*** (0.136)	0.896*** (0.127)
Manufacturing			0.0251* (0.0144)	0.0283** (0.0126)	0.0124 (0.0114)	0.0154 (0.0106)	0.424 (0.569)	0.677 (0.529)
Services			0.00595 (0.0324)	0.0212 (0.0284)	0.0244 (0.0212)	0.0378* (0.0197)	0.201 (0.122)	0.216* (0.114)
Observations	191	192	191	192	191	191	191	191
R-squared	0.355	0.446	0.450	0.556	0.213	0.283	0.231	0.304
Consumption growth of:	All	B40	All	B40	All	B40	All	B40
Number of districts	64	64	64	64	64	64	64	64

The dependent variable is the log of consumption growth for all households in the district or the bottom 40 percent, as indicated. This variable is estimated directly from the HIES. District fixed effects included but not shown. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Migration and poverty reduction

Dependent variable: Change in poverty rate at the district level

	(1) Using subsector growth rates in manufacturing and services	(2) Using growth in number of firms in manufacturing and services
Growth in agricultural value added	-1.085** (0.440)	-0.715 (0.432)
Manufacturing growth	-0.0793*** (0.0297)	-3.719*** (1.416)
Service sector growth	0.00768 (0.0580)	-0.393 (0.339)
Annual international migration	17.26*** (6.387)	17.36*** (6.370)
Annual population growth (net of in-migration)	-6.478** (2.925)	-3.114 (2.851)
Annual in-migration	1.803 (4.149)	3.427 (3.963)
Constant	0.0193 (0.156)	-0.0495 (0.0436)
Observations	187	187
R-squared	0.134	0.144
Number of districts	64	64

The dependent variable is the annualized percentage change in the district poverty rate estimated directly from the HIES. District and time fixed effects included but not shown. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: The relationship between agricultural growth, irrigation, and rainfall over time

Dependent variable: Growth in agricultural value added

	(1)
Irrigated area	7.926*** (1.769)
Average monthly rainfall	6.138* (3.395)
Maximum monthly rainfall	-3.536** (1.397)
Thailand price of rice	0.417*** (0.140)
Constant	-108.2* (809.9)
Observations	256
R-squared	0.1237
Number of districts	64

District fixed effects included but not shown. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Instrumenting agricultural growth and international migration

Dependent variable: Change in poverty rate at the district level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growth in agricultural value added	-1.969* (1.014)	-0.694* (0.368)	-1.775** (0.833)	-0.436 (0.360)	-1.969* (1.014)	-0.694* (0.368)	-0.690** (0.344)
Growth in the number of firms in manufacturing	-4.426*** (1.642)	-4.111** (2.083)	-4.536*** (1.353)	-4.384** (2.048)	-4.426*** (1.642)	-4.111** (2.083)	-3.911*** (1.448)
Growth in the number of firms in services	-0.0518 (0.329)	-0.765 (2.083)	-0.0939 (0.275)	-1.024 (2.029)	-0.0518 (0.329)	-0.765 (2.083)	-0.475 (0.423)
Growth in international migration		44.19 (127.8)		58.56 (124.5)		44.19 (127.8)	26.18 (17.91)
Observations	191	184	192	185	191	184	184
Number of districts	64	63	64	63	64	63	63
Fixed effects	District	District	District	District	Division	Division	Division
Data on poverty	HIES	HIES	SAE	SAE	HIES	HIES	HIES
Instrumenting	Ag growth	Migration	Ag growth	Migration	Ag growth	Migration	Migration Ag growth

The dependent variable is the annualized percentage change in the district poverty rate estimated directly from the HIES or using small area estimation (SAE). District fixed effects included but not shown. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Annex: District poverty rates

Poverty Rate (HIES direct estimates)				
District	2000	2005	2010	2016
BAGERHAT	33.0	46.0	42.8	31.0
BANDARBAN		64.7	40.1	63.2
BARGUNA	49.0	60.9	19.0	25.7
BARISAL	61.0	60.1	54.8	27.4
BHOLA	54.0	48.9	33.2	15.5
BOGRA	42.0	47.3	16.6	27.2
BRAHMANBARIA	51.0	37.1	30.0	10.3
CHANDPUR	50.0	28.7	51.0	29.3
CHITTAGONG	44.0	26.7	11.5	13.7
CHUADANGA	36.0	33.0	27.7	31.9
COMILLA	36.0	30.1	37.9	13.5
COX'S BAZAR	42.0	51.7	32.7	16.6
DHAKA	26.0	16.9	15.7	10.0
DINAJPUR	55.0	49.8	37.9	64.3
FARIDPUR	55.0	44.7	36.3	7.7
FENI	52.0	12.5	25.9	8.1
GAIBANDHA	71.0	52.5	48.0	46.7
GAZIPUR	38.0	37.4	19.4	6.9
GOPALGANJ	71.0	42.4	42.7	29.5
HABIGANJ	42.0	46.9	25.3	13.4
JOYPURHAT	52.0	43.7	26.7	21.4
JAMALPUR	58.0	58.7	51.1	52.5
JESSORE	38.0	56.6	39.0	26.9
JHALOKATI	42.0	47.1	40.5	21.6
JHENAIDAH	41.0	35.8	24.7	26.5
KHAGRACHHARI	49.0	37.3	25.5	52.7
KHULNA	38.0	53.0	38.8	30.8
KISHORGONJ	59.0	24.8	30.3	53.5
KURIGRAM	60.0	68.2	63.7	70.8
KUSHTIA	70.0	27.8	3.6	17.5
LAKSHMIPUR	58.0	34.7	31.2	32.5
LALMONIRHAT	53.0	53.2	34.5	42.0
MADARIPUR	82.0	38.7	34.9	3.7
MAGURA	71.0	28.7	45.4	56.7

Poverty Rate (HIES direct estimates)				
District	2000	2005	2010	2016
MANIKGANJ	60.0	37.4	18.5	30.7
MEHERPUR	60.0	12.4	15.2	31.5
MAULVIBAZAR	36.0	29.5	25.7	11.0
MUNSHIGANJ	43.0	27.2	28.7	3.1
MYMENSINGH	68.0	58.9	50.5	22.0
NAOGAON	45.0	48.7	16.9	32.2
NARAIL	63.0	44.6	20.0	16.8
NARAYANGANJ	19.0	23.1	26.1	2.6
NARSINGDI	22.0	34.7	23.7	10.5
NATORE	40.0	49.7	35.1	24.0
NAWABGANJ	43.0	42.7	25.3	39.7
NETRAKONA	57.0	31.7	35.3	34.0
NILPHAMARI	70.0	70.2	34.8	32.3
NOAKHALI	62.0	34.5	9.6	23.3
PABNA	57.0	49.3	31.5	33.0
PANCHAGARH	75.0	55.9	26.7	26.4
PATUAKHALI	42.0	63.0	25.8	37.2
PIROJPUR	59.0	27.9	44.1	32.2
RAJSHAHI	50.0	41.3	31.4	20.2
RAJBARI	57.0	43.4	41.9	33.8
RANGAMATI	14.0	40.2	20.3	28.5
RANGPUR	73.0	61.9	46.2	43.8
SHARIATPUR	74.0	32.9	52.6	15.7
SATKHIRA	38.0	59.1	46.3	18.6
SIRAJGANJ	52.0	52.7	38.7	30.5
SHERPUR	40.0	47.9	48.4	41.3
SUNAMGANJ	52.0	48.8	26.0	26.0
SYLHET	39.0	12.5	24.1	13.0
TANGAIL	64.0	40.4	29.7	19.0
THAKURGAON	72.0	52.2	27.0	23.5

CHAPTER V.

Regional Convergence of Poverty in Bangladesh

Abstract

The literature on poverty convergence is scant, both for single-country and cross-country studies. This scant literature relies on Ravallion (2012), who failed to find poverty convergence across some 90 developing and less-developed countries during 1980–2007, based on cross-section data. This paper builds on Ravallion's work to assess convergence of headcounts, depths, and severity of poverty across districts of Bangladesh during 2000-2016. Both through direct estimation and indirect aggregation, we find that poverty convergence was present during this period. In addition, our results are robust to alternative frequency of data (cross-sectional vis-à-vis panel) and the consequent estimation techniques; sources of data (direct Household Income and Expenditure Survey estimates vis-à-vis small area estimates); and the alternative transformation of the dependent variable. Both backwardness effect and strong growth effect dominate the adverse effect of initial poverty on growth effectiveness to ensure strong poverty convergence across districts.

I. Introduction

The convergence in per capita income following the neoclassical growth model (Solow 1956; Swan 1956), coupled with the fact that higher mean income is usually associated with lower incidence of poverty, implies convergence in poverty, where initial rates hardly matter. However, using cross-country cross-sectional data, Ravallion (2012) found that countries with higher initial poverty incidences

[1] This paper was written by Mohammad Yunus, Senior Research Fellow, Bangladesh Institute of Development Studies

scarcely experienced faster reduction in poverty, even though they did enjoy faster growth in per capita income. Ravallion concluded that initial high poverty rates nullified the growth in per capita income. However, his cross-sectional analysis leaves out information from the time-series dimension, and so may not satisfactorily answer a perhaps more relevant inquiry: do countries enjoy faster subsequent poverty reduction within themselves as their initial poverty incidences decline over time? Besides, his cross-country analysis, based on national average data, may mask disparities in poverty rates across regions within a country, and hence is of little help to policy makers. That begs a relevant question: do regions within a country experience convergence, even if one fails to see convergence across countries?

There are several grounds for one to expect regional convergence within a country. *First*, there is informational advantage: a national government is more informed about the economic situation, as well as proximate causes of poverty and backwardness, of a region within the country. *Second*, advantage of synergy: a national government can better coordinate activities of different line agencies and distribute funds in a targeted manner for poverty reduction and convergence (Ferrieira, Leite, and Ravallion 2010). *Third*, regions within a country are also more connected and have free movement of labor and goods, in comparison to connectivity between countries at the global level, where factors of production, especially labor, are by and large immobile.

To document the presence of convergence in poverty rates at the regional level, Azevedo et al. (2016) used NUTS2 level cross-section data in Turkey, while Ouyang, Shimeles, and Thorbecke (2018) used district level panel data in Ethiopia and Rwanda. Further, using generalized method of moments (GMM) technique in the panel data, Ouyang, Shimeles, and Thorbecke (2019) found convergence in poverty rates at the cross-country level. Cuaresma, Klasen, and Wacker (2017) argued that Ravallion (2012) had failed to detect convergence in poverty due to logarithmic transformation of data; these authors showed presence of convergence taking linear difference in poverty rates.

Combating regional poverty and disparities is a vital policy issue in Bangladesh. The successive plan documents demonstrate the government's commitment to reducing regional poverty and disparities through promoting growth and development. The strategy suggests a six-fold plan for the lagging regions: (i) creation of lagging-region funds for priority investment in human and physical capital in these regions; (ii) prioritizing public infrastructural investment for bridging gaps between integrated and less-integrated regions, (iii) providing special incentives for private investment in less-integrated regions; (iv) providing agricultural credit and storage facilities to enhance agricultural growth and employment; (v) establishment of technical and vocational training institutions to impart skills and facilitate migration; and (vi) development of salinity-tolerant seeds, combating arsenic contamination in water, and disaster mitigation strategies in the southwest, as well as drought-tolerant seeds in the northwest (GOB 2015). Besides, several safety net programs are put in place through poverty targeting (Yunus 2016) at the regional level.[2] Finally, special economic zones with attractive incentive packages are encouraged, in order to create employment in backward areas and regions (Yunus and Mondal 2019).

Literature on regional poverty convergence is scant (Cuaresma, Klasen, and Wacker 2017; Ouyang, Shimeles, and Thorbecke 2018), even more so for convergence in the depth or severity of poverty. The sparse literature is by and large limited to findings based on data on headcount rates derived from the national household income and expenditure surveys. These findings cannot explain the convergence (or lack of it) regarding the depth or the severity of poverty within or across countries. At the regional level, we find initially poorer Bangladeshi districts to have experienced faster poverty reduction during 2000-2016, as strong backwardness and mean convergence effects dominated the combined positive forces of a less sizeable *positive* direct poverty effect and indirect poverty effect. This observation is true of all three measures of poverty, viz. headcount rate (HCR), poverty gap (PG), and squared poverty gap (SPG), as in Foster, Greer, and Thorbecke (1984), with or without control of initial conditions.

A common feature of existing empirical studies on poverty convergence has been the use of cross-section across countries or regions. However, estimates based on cross-section data suffer from unobserved individual heterogeneity and omitted variable bias. With observations that span both across time and space, more information is available and consequently entails more efficient estimates. The present paper implements a panel data approach to deal with these issues. It takes the work by Ravallion (2012) as its starting point and examines how the results change with the adoption of the panel data approach and within-country regional data. The panel data framework makes it possible to allow for differences of "unobservable regional effects."

[2] Poverty reduction is accounted for mainly by a *redistribution effect* in the whole country. It is evident from the divisional poverty rates and the share of recipients of social safety net programs: there are positive correlations between the upper and lower poverty lines vis-à-vis the share of recipients of social safety net assistance at 0.5 across administrative divisions (BBS 2017).

The fixed effect (FE) estimation technique yields results that are different from the corresponding results obtained from single cross-section methodology. *First*, convergence in poverty rates is evident and robust. *Second*, the poverty convergence elasticity effect consists of: (i) a mean convergence effect, whereby, for a given initial poverty, lower initial mean income (consumption expenditure) contributes to faster growth in mean income (consumption expenditure); (ii) a direct poverty effect, whereby higher initial poverty directly hinders subsequent growth in mean income (consumption expenditure) at a given initial mean income (consumption expenditure); and (iii) an indirect poverty effect, whereby higher initial poverty weakens the effectiveness of growth in reducing poverty, as outlined in Ravallion (2012); in addition, the poverty convergence elasticity effect also includes a fourth channel, which is dubbed a "backwardness effect of poverty."

Several studies have focused on the regional differences in poverty and inequality in Bangladesh. Some of these studies have attributed the difference to geographical indicators, such as land use and productivity, infrastructure, electricity, distance to rivers, roads, and urban areas (Ravallion and Wodon 1999). Some studies have also pointed to human capital, agricultural technology, urban dynamism, and inequality (Sen 2005). Others have cited dependence on agriculture and lower allocations in the annual development programs and social safety nets, as well as low incidence of critical infrastructural facilities, such as transport and communication, electricity, and gas (GOB 2008). The natural border created by rivers appears to hinder migration, causing differences in returns between regions to persist (Shilpi 2008). Other studies have considered proximity to (East) or remoteness from (West) the country's growth poles (Dhaka and Chittagong), along with depressed wage rates in the West[3] (World Bank 2008). The last-cited study coined the term "East-West Divide," based on visual inspection of the district level poverty maps created from 2005 Household Income and Expenditure Survey (HIES) data.

Another strand of literature relates regional disparities to household level characteristics such as average years of education, the percentage of households with electricity connections, and phone ownership accounts (Shilpi 2013). A third strand of literature, in turn, has looked into factors behind the recent narrowing of the previously-observed regional inequality pattern, known as the East-West divide. While the World Bank (2013) argued that changes in labor income and

[3] However, the claims that depressed wage rates in the West might have contributed to the so-called East-West Divide are at odds with Rahman (2009), which shows that wages had increased substantially in Khulna and had declined in Dhaka division, when unit wage rates from HIES 2000 were compared with those from HIES 2005.

the adult population were the two most important contributors to faster poverty reduction in previously lagging regions, Sen et al. (2014) attributed the shift to a growth spurt in agriculture, flourishing small and medium enterprises, growth of microfinance institutions, and better human capital in the West. Khondker and Mahzab (2015) claim that enabling public infrastructure, incentives to private investment, and a favorable credit and subsidy policy for agriculture, while creating opportunities for internal migration, would help in narrowing the gaps between growing and lagging districts.

The rest of this paper is organized as follows. Section 2 elaborates the empirical framework and estimation techniques. Section 3, organized in several sub-sections, describes the data used in the analysis and presents the empirical results. Section 4 concludes the paper.

II. Empirical framework and methods

2.1. Empirical framework

Although Ravallion (2012) failed to find convergence in poverty based on cross-sectional analyses of cross-country data, his conceptual motivation is appealing. Underlying his conceptual framework are a set of equations standard within the neoclassical growth model augmented to allow initial distribution to affect the growth rate. The following model is used for identification of convergence in income.

$$\Delta lny_{it} = \alpha + \beta lny_{it-r} + \gamma_{1i} + \epsilon_{it} \tag{1}$$

where y_{it} and y_{it-r} are, respectively, the level of region *i*'s mean per capita income or consumption at years *t* and *t-r* and $\Delta lny_{it} \equiv (lny_{it} - lny_{it-r})/r$ is the annualized growth between year *t* and year (*t*–*r*). Coefficient β is the mean convergence rate, which implies that, if lny_{it-r} drops by one percent, the growth in mean would increase by β percentage points. And γ_{1i} is the regional fixed effect. Next, assuming a log-linear relationship[4] between poverty and mean per capita income or consumption at any time, as specified in (2), one obtains (3), which will be used to test for poverty convergence.

$$lnH_{it} = \eta_0 + \eta_1 lny_{it} + \gamma_{2i} + \upsilon_{it} \tag{2}$$

[4] Log-linearity remains standard in the literature, albeit considered as a very strong assumption by critics, which may result in lack of convergence. See, for instance, Cuaresma, Klasen, and Wacker (2017).

$$\Delta lnH_{it} = \alpha^* + \beta^* lnH_{it-r} + \gamma_{3i} + \varsigma_{it} \tag{3}$$

where H_{it} and H_{it-r} are, respectively, the level of region *i*'s poverty rate for years *t* and *t-r* and $\Delta lnH_{it} \equiv (lnH_{it} - lnH_{it-r})/r$ is the annualized rate of poverty reduction between year *t* and year (*t*–*r*). Ravallion (2012) augmented (1) into (4) to assess how initial poverty and potentially other initial conditions affect growth:

$$\Delta lny_{it} = \alpha + \beta lny_{it-r} + \beta^* lnH_{it-r} + \gamma_{4i} + \xi_{it} \tag{4}$$

This equation helps identify two contributing effects of poverty convergence: a negative estimate of β would suggest a mean convergence effect conditional upon initial poverty level, whereas a negative estimate of β^* would, in contrast, suggest a direct poverty effect conditional upon the growth effect of initial mean income or consumption.

The following equation is used for identification of a "backwardness effect of poverty" and growth effectiveness of poverty:[5]

$$\Delta lnH_{it} = \delta_0 + \delta_1 lnH_{it-r} + \eta(1 - H_{it-r})\Delta lny_{it} + \gamma_{5i} + \varepsilon_{it} \tag{5}$$

The parameters δ_1 and η in this equation measure the "backwardness effect of poverty" and growth effectiveness in reducing poverty, with growth adjusted to initial poverty level. The above model implies that the relevant growth rate is not fully the "poverty-adjusted rate," as found in Ravallion (2012). Instead, it suggests an additional channel, which may be defined as a backwardness effect of poverty.

Comparing (1) and (3), one can verify the equivalence of the "speed of convergence" for poverty as: $\frac{\partial \Delta lnH_{it}}{\partial lnH_{it-r}} = \beta^* \equiv \beta = \frac{\partial \Delta lny_{it}}{\partial lny_{it-r}}$. Coefficients from (4) and (5) would then help decompose the poverty convergence elasticity as:

$$\frac{\partial \Delta lnH_{it}}{\partial lnH_{it-r}} = \delta_1 + \eta\beta(1 - H_{it-r})\left(\frac{\partial lnH_{it-r}}{\partial lny_{it-r}}\right)^{-1} + \eta\beta^*(1 - H_{it-r}) - \eta\Delta lny_{it} H_{it-r} \tag{6}$$

[5] To decide whether the standard elasticity obtained from regressing growth in poverty reduction on growth in mean income (consumption) or η or $\delta_1 + \eta$ is the relevant elasticity, one needs to run twin tests $\delta_1 = 0$ and $\eta_0 + \eta_1 = 0$ from the regression: $\Delta lnH_{it} = \delta_0 + \delta_1 lnH_{it-r} + \eta_0 \Delta lny_{it} + \eta(H_{it-r} \times \Delta lny_{it}) + \gamma_{5i} + \varepsilon_{it}$. While data does not pass $\delta_1 = 0$ it passes $\eta_0 + \eta_1 = 0$ comfortably. This dictates the specification shown in (5), which points to the presence of both advantages of backwardness and advantages of poverty-adjusted growth following Ravallion (2012).

The first term is the *backwardness effect of poverty*, as mentioned above. It reinforces the effect of the second term, dubbed as the *mean convergence effect,* which is the interaction between the initial level of non-poverty and elasticity of the initial poverty rate with respect to the original mean of income or consumption. The third term is the *direct effect of poverty,* which takes into account the level of the initial non-poverty. The fourth and final term is the *poverty elasticity effect,* which is the interaction between the growth of the mean income or consumption and poverty rate in the initial period.

The equivalence in speed of poverty convergence and the decomposition of poverty convergence elasticity are valid only if one addresses the issues related to region-specific heterogeneity γ_{ki}, $k = 1,2,3,\ldots 5$ as reflected in the corresponding equations. As we report later in detail, panel regression does identify both initial mean consumption and initial poverty as significant factors for regional growth and convergence.

It may be noted that the expression in (6) is not a functional relationship, but rather an accounting identity whose key parameters come from (4) and (5). It is used to identify the relative magnitude of the four effects, and it is expected that the sum largely matches the empirical poverty convergence rate from regression in (1), if the model includes all major factors contributing to poverty convergence.

2.2. Econometric methods

Ravallion (2012) preferred cross-section regression, claiming that the panel specification "is unlikely to have detected the true relationships, given that the changes over time in growth almost certainly have a low signal-to-noise ratio." Despite specifying a set of panel regressions, Ravallion applied cross-section estimation techniques and claimed that (Ravallion 2012: 517) fixed effect regression tends to "heavily underestimate the effects of initial conditions on subsequent growth in mean," and hence was "not useful for detecting true relationships." He also suspected problems of "time-varying measurement errors in both growth rates and initial distribution" in the dataset, which reflect possible "survey comparability problems over time." However, such a claim is untenable, as Islam's evidence on convergence in growth attests that panel regression at least does not distort the relationship (see e.g., Islam 1995). Despite reduced likelihood of measurement errors, unobserved heterogeneity across districts may remain. Therefore, both fixed effect panel estimation and dynamic panel estimation techniques were used to address these unobserved heterogeneities (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998).

III. Empirical results

3.1. Data description

Poverty rates

In contrast to the literature on poverty convergence based on cross-country data, and to explore the dynamics across regions within a country, the unit of observation is a district in Bangladesh. The major sources of the district level Foster–Greer–Thorbecke (FGT) measures of poverty are the quinquennial surveys on household incomes and expenditures for the years 2000, 2005, 2010, and 2016. It may be noted that the 2016 HIES was designed to provide representative poverty estimates at the district level.[6] In contrast, the 2000, 2005, and 2010 HIES were not designed to provide district level estimates: they were intended to provide reliable poverty estimates for the country's divisions, as well as rural and urban areas separately. Even though the 2000, 2005, and 2010 HIES were not designed to provide district level poverty estimates, it is possible to generate poverty estimates at the district level from these samples, as the PSUs cover all districts.[7] Accordingly, small area estimation (SAE) was undertaken by the Bangladesh Bureau of Statistics (BBS) in 2005 and 2010 to generate poverty estimates at the district level. For this paper, SAE estimates at the district level were also generated for 2000. Although it would be preferable to have access to a larger sub-sample of poverty measures, data limitations dictated use of poverty measures from the HIES 2000, 2005, and 2010. This raises a valid concern: are the district level SAE poverty measures representative of the districts? Based on linear regressions separately for 2005 and 2010, Hill and Endara (2019) show that SAE estimates closely track the HIES estimates. Given that poverty reduction rates are the dependent variables in our analysis, the measurement errors in the poverty estimates can be considered as white noise, and hence will not affect the coefficient estimates.

Literacy

Since the 1990s, Bangladesh has made remarkable progress in primary education: the net enrollment rate has reached 98 percent, and gender parity in net

[6] A stratified, two-stage sample design was adopted for the HIES 2016 with 2,304 Primary Sampling Units (PSU) selected from the enumeration areas of the Population and Housing Census, 2011. Insofar as the PSUs in the HIES 2016 were allocated at the district level, the sample was also stratified at the district level. Since there were a total of 64 districts in Bangladesh, the sample design included a total of 132 sub-strata: 64 urban, 64 rural, and four main City Corporations. Within each PSU, 20 households were selected for interviews. The final sample size was 46,080 households (Ahmed et al. 2017).

[7] The one exception is Bandarban district in 2000. The FGT estimates for this district were the population weighted averages of that of Chittagong, Cox's Bazar, and Rangamati districts.

enrollment has been achieved. The primary education cycle completion rate has risen to 81 percent in 2016. However, there is serious persistence of spatial differences in the achievement of education, when it comes to literacy rates extracted from the country's BBS Population and Housing Censuses 1991, 2001, and 2011 across 64 districts. These differences may have positive impacts on poverty reduction (Datt and Ravallion 1998).

Household electrification rate

Public infrastructure is crucial to poverty reduction in a district. The percentage of households with electricity connection has been used to assess the status of public infrastructure. It is usually believed that electricity really helps lift households out of poverty (Datt and Ravallion 1998). However, experimental evidence casts doubt on the claim (see Lee, Miguel, and Wolfram 2018). Data on household electricity connection were extracted from various rounds of the Sample Vital Registration Statistics (SVRS) conducted by the BBS across 64 districts. The latest SVRS data show that about 85 percent of households used electricity in 2017, up from 28 percent in 2000. As electricity enables extended hours of activities, it purports to accelerate poverty reduction across districts.

Infant mortality rate

The most widely available measure of mortality in early life is the infant mortality rate. Infant mortality has a substantive impact on the age distribution of the population. Datt and Ravallion (1998) argue that low infant mortality leads to poverty reduction. However, the relationship is complex and may be bi-directional: while high poverty incidence may lead to infant mortality in the present age cohort, high infant mortality may lead to high poverty for the posterity. Data on infant mortality per thousand were extracted from various rounds of the SVRS.

Sanitary toilet rate

Bangladesh has made remarkable progress in sanitation. Three-fourths of households have sanitary toilet facilities, with (42.8 percent) or without (34.0 percent) water seal. Use of sanitary toilet facilities increased by over 43 percent from 2005 to 2017. Albert and Collado (2004) argue that sanitary toilet facilities may have strong bearing on the poverty reduction rates across regions. Data on the rates of access to sanitary toilet facilities were also extracted from various rounds of the SVRS.

Pucca building rate

Similar to sanitary toilets, Bangladesh has made significant inroads in improving its housing facilities. Close to 21 percent of households have pucca building. A little more than one-third of the households in urban areas, though only about

8 percent of households in rural areas, have pucca buildings. Stephen and van Steen (2011) argue that "net housing income" and "net housing resources" exert a poverty-reducing impact, compared to disposable income alone. Data on the rates of pucca housing facilities were extracted from various rounds of the SVRS, conducted by the BBS across 64 districts.

Table 1: Descriptive statistics on poverty and related initial conditions

Poverty Headcount Rate, Poverty Gap and Squared Poverty Gap				
Year	**2000**	**2005**	**2010**	**2016**
HCR SAE (HIES) (%)	50.2 (48.9)	42.5 (40.0)	32.3 (31.5)	24.3
PG SAE (HIES) (%)	13.2 (12.8)	10.2 (9.0)	6.7 (6.5)	5.0
SPG SAE (HIES) (%)	4.8 (4.6)	3.4 (2.9)	2.0 (2.0)	1.5
Per Capita Consumption (Tk.)	799.63	1139.01	2262.29	3497.33
Covariates on Initial Conditions				
Year		**1991**	**2001**	**2011**
7 Years and Above Literacy Rate (%)		30.87	44.48	50.17
Household Electrification Rate (%)		28.38	38.86	52.51
Infant Mortality Rate (per thousand)		57.71	42.93	37.17
Sanitary Toilet Rate (%)		36.54	51.64	63.24
Pucca Building Rate (%)		5.93	7.03	9.05

Sources: (1) Small Area Estimates and HIES 2000, 2005, 2010, and 2016 for the upper panel; (2) Population and Housing Censuses 1991, 2001, and 2011; and (3) Sample Vital Registration Statistics, various issues, for the lower panel.

Table 1 gives the data on the poverty measures and initial conditions. It may be noted that Bangladeshi households experienced a steady rise in per capita consumption expenditure during this period.[8] This has led the national poverty headcount rate, poverty gap, and squared poverty gap to decline. The poverty headcount rates measured by the costs of basic needs declined annually by 1.78 percentage points between 2000 and 2005, 1.7 percentage points between 2005 and 2010, and 1.2 percentage points between 2010 and 2016. It may be noted that the headcount rate of poverty gives only the percentage value of poverty incidence, it does not measure the distance of the poor households from the poverty line. For that purpose, the poverty gap estimates about the depth of poverty of the population are required to estimate the average distance of poor

[8] Consumption expenditure is viewed as a better welfare measure than income estimated from household income and expenditures surveys.

households from the poverty line and the average of the variations, dubbed the squared poverty gap.

The estimates of the trends in poverty gaps and squared poverty gaps are also presented in Table 1. While the poverty gap declines initially by 0.86 percentage points annually, this annual reduction tapers down to 0.25 in recent years. Similarly, the squared poverty gap—which measures severity of poverty—declines annually by 0.34 percentage points initially, to taper down to 0.08 percentage points in recent years. This indicates that the incidence, depth, and severity of poverty have been reduced during the period. In the regression analyses that follow, specific focus will be on spatial trends in annual per capita consumption growth and poverty measures in 64 districts of the country over 16 years, as a function of initial conditions collected from decennial population and housing censuses conducted in 1991, 2001, and 2011 and the sample vital statistics collected in different rounds by the BBS.

3.2. Empirical results

In the past two decades, have districts experienced faster subsequent reduction in poverty indicators, as their initial poverty incidences, poverty gaps, and squared poverty gaps declined over time? Are these reductions leading to convergence, to wipe out the so-called East-West Divide and similar disparities? Are these convergences unconditional or dependent on a set of initial conditions? What are the initial conditions that could explain the presence or absence of poverty convergence among the districts? This section presents the empirical results.

As shown in Table 2, the 64 districts considered as a group did experience poverty convergence, as a higher poverty reduction rate (larger negative value) is significantly associated with higher initial poverty incidence. This finding is robust to the type of poverty measures and with or without controls. For all three types of poverty measures, the extent of convergence intensifies once the initial conditions with regard to human capital (literacy rate), provision of public infrastructures (electricity connection rate), and other covariates are controlled for. While higher incidence of human capital and public infrastructure appears to intensify convergence, the higher rate of pucca building dampens it. One plausible explanation of the positive association between poverty reduction rate and the pucca building rates is that districts with higher pucca building rates tend to have lower poverty rates, and poverty reduction with initially lower poverty rates appears to be difficult to achieve.

Table 2: Convergence in poverty reduction rate

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE without initial conditions			
Ln (Initial Poverty Rate)	-0.163*** (0.016)	-0.158*** (0.015)	-0.159*** (0.015)
Constant	0.549*** (0.058)	0.273*** (0.033)	0.077*** (0.015)
Number of Observations	192	192	192
Within R-squared	0.355	0.382	0.413
Number of Districts	64	64	64
GMM with initial conditions			
Lagged Poverty Reduction Rate	-0.069 (0.256)	-0.188 (0.183)	-0.194 (0.135)
Ln (Initial Poverty Rate)	-0.258*** (0.083)	-0.210*** (0.053)	-0.198*** (0.038)
Constant	0.853*** (0.305)	0.327*** (0.116)	0.055 (0.046)
Number of Observations	128	128	128
Wald Chi-Squared	43.15*** [0.00]	79.31*** [0.00]	155*** [0.00]
Number of Districts	64	64	64
FE with initial conditions			
Ln (Initial Poverty Rate)	-0.236*** (0.015)	-0.230*** (0.015)	-0.228*** (0.016)
Ln (Initial Literacy Rate)	-0.253*** (0.057)	-0.319*** (0.073)	-0.371*** (0.086)
Ln (Initial Electricity Rate)	-0.050* (0.027)	-0.069* (0.038)	-0.082* (0.045)
Ln (Initial Infant Mortality Rate)	-0.008 (0.029)	-0.010 (0.038)	-0.014 (0.044)
Ln (Initial Sanitary Toilet Rate)	0.057 (0.035)	0.070 (0.045)	0.086 (0.052)
Ln (Initial Pucca Building Rate)	0.025* (0.014)	0.029 (0.020)	0.034 (0.025)
Constant	1.696*** (0.231)	1.573*** (0.277)	1.474*** (0.309)
Number of Observations	192	192	192
Within R-squared	0.551	0.569	0.584
Number of Districts	64	64	64

Source: Author's estimates.
Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

Poverty convergence can occur, albeit a formidable challenge, through redistribution. Even though tax collection effort in Bangladesh is lax compared with neighboring countries, the country's successive governments have introduced and intensified a large number of social safety net programs. At present, there are more than 140 such social safety net programs, some of which target particular groups, while others target a particular region. About 13 percent of the annual government budget, or more than 2 percent of GDP, is spent on these safety net programs, through various forms of targeting. Thus, poverty reduction can be achieved to some extent, even when there is hardly any growth in per capita consumption. However, such poverty reduction cannot be sustained in the medium to long run.

Table 3: Convergence in per capita consumption growth rate

Variables	FE without initial conditions	GMM without initial conditions	FE with initial conditions
Lagged Per Capita Consumption Growth Rate	- -	0.085 (0.194)	- -
Ln (Initial Per Capita Consumption)	-0.253*** (0.014)	-0.301*** (0.066)	-0.279*** (0.014)
Ln (Initial Literacy Rate)	-	- -	0.105*** (0.015)
Ln (Initial Electricity Rate)	-	- -	-0.004 (0.011)
Ln (Initial Infant Mortality Rate)	-	- -	0.003 (0.007)
Ln (Initial Sanitary Toilet Rate)	-	- -	-0.002 (0.009)
Ln (Initial Pucca Building Rate)	-	- -	-0.010** (0.004)
Constant	-0.991*** (0.054)	-1.168*** (0.261)	-1.454*** (0.091)
Observations	192	128	192
Within R-squared/ Wald Chi-Squared	0.675	185.74 ***[0.00]	0.824
Number of Districts	64	64	

Source: Author's estimates.
Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

To verify that the convergence in poverty reduction observed above is an outcome of growth, we estimate equation (1), which explores the mean convergence in per capita consumption. The results presented in Table 4 testify that the convergence in poverty reduction observed above is at least partly explained by the growth in per capita consumption, both with and without initial conditions. Besides, the data also suggest that higher growth rates are associated with higher (proportionate) rates of poverty reduction for all three measures. The fixed effect regression coefficients of growth of headcount, poverty gap, and squared poverty gap rates on that of per capita consumption are -1.3051 (robust s. e. = 0.135), -1.836 (robust s. e. = 0.182), and -2.099 (robust s. e. = 0.234), respectively.

To see what explains the strong poverty convergence found in the regions, equation (4) (which is equation [1] augmented with initial poverty levels) was estimated. It enables us to assess the interrelationship between the growth in mean and poverty reduction. Regression estimates in Table 4 suggests two things. *First*, for a given initial poverty level, districts starting out with lower levels of initial mean consumption subsequently enjoyed a faster growth in mean. *Second,* controlling for initial mean consumption level, initial poverty directly retards subsequent growth in mean. These results are robust to the choice of poverty measures as well as inclusion of the initial conditions. It may be noted that literacy rate actually does not decrease district poverty rate. One of the possible explanations could be that historically poor districts could have lower educational attainment. Besides, there is a clear indication in the results that higher pucca building rate has a negative impact on per capita consumption and hence poverty reduction.

Table 4: Convergence in per capita consumption growth rate with initial poverty

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE without initial conditions			
Ln (Initial Per Capita Consumption)	-0.353*** (0.022)	-0.354*** (0.019)	-0.341*** (0.017)
Ln (Initial Poverty Rate)	-0.056*** (0.011)	-0.040*** (0.007)	-0.030*** (0.005)
Constant	-1.177*** (0.056)	-1.299*** (0.064)	-1.307*** (0.064)
Observations	192	192	192
Within R-squared	0.743	0.746	0.744
Number of Districts	64	64	64
GMM without initial conditions			
Lagged Per Capita Consumption Growth Rate	0.316 (0.234)	0.125 (0.220)	-0.008 (0.217)
Ln (Initial Per Capita Consumption)	-0.423*** (0.097)	-0.349*** (0.111)	-0.285*** (0.107)

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
Ln (Initial Poverty Rate)	-0.037 (0.050)	-0.019 (0.038)	-0.008 (0.026)
Constant	-1.522*** (0.309)	-1.321*** (0.383)	-1.101*** (0.408)
Observations	128	128	128
Wald Chi-squared	255.63***[0.00]	249.83***[0.00]	217.90***[0.00]
Number of Districts	64	64	64
FE with initial conditions			
Ln (Initial Per Capita Consumption)	-0.305*** (0.020)	-0.302*** (0.021)	-0.297*** (0.019)
Ln (Initial Poverty Rate)	-0.016 (0.010)	-0.010 (0.008)	-0.007 (0.007)
Ln (Initial Literacy Rate)	0.095*** (0.016)	0.096*** (0.017)	0.097*** (0.017)
Ln (Initial Electricity Rate)	-0.002 (0.011)	-0.003 (0.011)	-0.003 (0.011)
Ln (Initial Infant Mortality Rate)	0.006 (0.008)	0.006 (0.008)	0.005 (0.008)
Ln (Initial Sanitary Toilet Rate)	-0.002 (0.009)	-0.002 (0.009)	-0.002 (0.009)
Ln (Initial Pucca Building Rate)	-0.010** (0.004)	-0.009** (0.004)	-0.009** (0.004)
Constant	-1.480*** (0.087)	-1.503*** (0.094)	-1.502*** (0.095)
Observations	192	192	192
Within R-squared	0.828	0.827	0.826
Number of districts	64	64	64

Source: Author's estimates.
Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

It is thus evident that there is convergence in per capita consumption, and growth of per capita consumption tends to reduce poverty, while districts with higher poverty rates tend to experience slower growth rates in per capita consumption. To isolate the effects of various confounding factors, it is important to assess how the growth elasticity of poverty reduction depends on initial distribution. Following Ravallion (2012), this can be thought of as the direct effect of the initial distribution on the pace of poverty reduction, as distinct from the indirect effect via the rate of growth in the mean. The results in Table A1 indicate that the (absolute) growth elasticity of poverty reduction tends to be lower in districts with a higher initial poverty rate. The null that =0 in the equation in footnote 5 is strongly rejected. In contrast, the homogeneity test for the null: cannot be rejected, which indicates that the regional growth rates are "poverty-adjusted rates" (Ravallion 2012: 518). Given the presence of poverty convergence due to backwardness effect and failure to reject the null: , one can estimate the parsimonious model as specified in equation (5). Table 5 presents the estimates of the parsimonious model, both with and without initial conditions.

Table 5: Complementarity of advantage of backwardness and advantage of growth

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE without initial conditions			
Ln (Initial Poverty Rate)	-0.095*** (0.026)	-0.097*** (0.017)	-0.110*** (0.016)
(1- Initial Poverty Rate) × Growth in Per Capita Consumption	-1.725*** (0.274)	-1.531*** (0.180)	-1.556*** (0.202)
Constant	0.299*** (0.094)	0.145*** (0.037)	0.032** (0.016)
Observations	192	192	192
Within R-squared	0.546	0.587	0.595
Number of Districts	64	64	64
GMM without initial conditions			
Lagged Poverty Reduction Rate	-0.191 (0.186)	0.032 (0.230)	-0.009 (0.205)
Ln (Initial Poverty Rate)	-0.292*** (0.077)	-0.381** (0.171)	-0.339** (0.149)
(1- Initial Poverty Rate) × Growth in Per Capita Consumption	-1.597** (0.654)	-1.827 (1.161)	-1.551 (1.165)
Constant	0.964*** (0.276)	0.675** (0.337)	0.170 (0.113)
Observations	128	128	128
Wald Chi-squared	31.84***[0.00]	52.61***[0.00]	68.59***[0.00]
Number of Districts	64	64	64
FE with initial conditions			
Ln (Initial Poverty Rate)	-0.156*** (0.031)	-0.148*** (0.022)	-0.158*** (0.022)

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
(1- Initial Poverty Rate) × Growth in Per Capita Consumption	-1.337*** (0.333)	-1.255*** (0.229)	-1.274*** (0.241)
Ln (Initial Literacy Rate)	-0.110 (0.074)	-0.111 (0.089)	-0.145 (0.100)
Ln (Initial Electricity Rate)	-0.081*** (0.022)	-0.108*** (0.029)	-0.125*** (0.034)
Ln (Initial Infant Mortality Rate)	-0.024 (0.027)	-0.032 (0.040)	-0.040 (0.047)
Ln (Initial Sanitary Toilet Rate)	0.047 (0.032)	0.061 (0.039)	0.077 (0.046)
Ln (Initial Pucca Building Rate)	0.017 (0.013)	0.010 (0.018)	0.012 (0.023)
Constant	1.098*** (0.365)	0.916** (0.359)	0.891** (0.385)
Observations	192	192	192
Within R-squared	0.621	0.651	0.659
Number of Districts	64	64	64

Source: Author's estimates.
Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

With estimates from Table 4, Table 5, and Appendix Table A2, together with the sample means of the relevant variables, one can calculate the sizes of the four contributing effects – backwardness effect, convergence effect of per capita consumption, direct poverty effect, and poverty elasticity effect – to gauge the direction and extent of poverty convergence as derived in equation (6).

Table 6: Decomposition of regional poverty convergence elasticity

Components	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE Estimates without initial conditions			
1. Convergence Effect of Per Capita Consumption	-0.0065	-0.0033	-0.0020
2. Direct Poverty Effect	0.0563	0.0357	0.0272
3. Poverty Elasticity Effect	0.0019	0.0017	0.0018
4. Backwardness Effect	-0.0950	-0.0970	-0.1100
Convergence Elasticity Effect:(1)+(2)+(3)+(4)	-0.0432	-0.0629	-0.0831
Empirical Estimate (Table 2)	-0.1630	-0.1580	-0.1590

Components	Poverty Headcount	Poverty Gap	Squared Poverty Gap
GMM Estimates without initial conditions			
1. Convergence Effect of Per Capita Consumption	-0.0071	-0.0018	-0.0005
2. Direct Poverty Effect	0.0345	0.0202	0.0072
3. Poverty Elasticity Effect	0.0018	0.0021	0.0017
4. Backwardness Effect	-0.2920	-0.3810	-0.3390
Convergence Elasticity Effect:(1)+(2)+(3)+(4)	-0.2628	-0.3605	-0.3305
Empirical Estimate (Table 2)	-0.2580	-0.2100	-0.1980
FE Estimates with initial conditions			
1. Convergence Effect of Per Capita Consumption	-0.0017	-0.0008	-0.0005
2. Direct Poverty Effect	0.0125	0.0073	0.0052
3. Poverty Elasticity Effect	0.0015	0.0014	0.0014
4. Backwardness Effect	-0.1560	-0.1480	-0.1580
Convergence Elasticity Effect: (1)+(2)+(3)+(4)	-0.1437	-0.1400	-0.1518
Empirical Estimate (Table 2)	-0.2530	-0.3190	-0.3710

Source: Author's calculations based on estimates in Tables 4, 5, and A2.

The decomposition results are presented in Table 6. It may be noted that the sum of the four effects matches the empirical poverty convergence rates reasonably well, suggesting that they are important contributing factors for poverty convergence found in regions during the period 2000-2016. The convergence elasticity effect is explained by a strong convergence effect of per capita consumption, as well as backwardness effect. While the convergence effect of per capita consumption is partly cancelled by a sizeable direct poverty effect and less sizeable poverty elasticity effect, the overall convergence effect of poverty is sustained, thanks to strong backwardness effect.

IV. Robustness of the results

It may be noted that our results are at odds with Ravallion (2012). The natural question that arises is: what is driving the contrasting outcomes vis-à-vis Ravallion? Are they driven by the method/technique applied? Is it transformation of key variables, especially the poverty reduction rates? Or is it the sources of data definition: i.e., SAE estimates vis-à-vis direct HIES estimates of poverty measures? We applied cross-section estimates on all possible combinations of years to compare with that of Ravallion (2012). We redefined the poverty reduction variable as , as suggested by Cuaresma, Klasen, and Wacker (2017). We used direct HIES estimates of poverty rates and per capita consumption. In all of these cases, the qualitative conclusions do not vary.

V. Conclusions

The paper finds four distinct channels – convergence effect of per capita consumption, backwardness effect, direct poverty effect, and poverty elasticity effect – that affect regional poverty reduction in Bangladesh. While the first two channels accentuate the rate of poverty reduction, the last two retard it. Thus, the evidence of regional poverty convergence in Bangladesh suggests that the convergence in per capita consumption, along with backwardness effects, more than offset the direct poverty effect and the poverty elasticity effect. The dynamics of regional poverty convergence appear to exist with or without initial conditions that help or impede growth and poverty reduction. Despite the niceties of the above decomposition, the analysis in this paper left out the possible impact of inequality. Even though Ravallion (2012) suggested that inequality is irrelevant to the extent that only its change matters for poverty convergence, as the *cross-country average* Gini index remains almost unchanged, this robustness could not be ascertained in this exercise, due to lack of regional estimates of Gini index over time.

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Appendix A: Supplementary results

Table A1. Regression of change in poverty rate on growth in per capita consumption and initial poverty rate

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE without initial conditions			
Ln (Initial Poverty Rate)	-0.095*** (0.027)	-0.097*** (0.017)	-0.110*** (0.016)
Growth in Per Capita Consumption	-1.970*** (0.656)	-1.777*** (0.482)	-1.554*** (0.395)
Initial Poverty Rate × Growth in Per Capita Consumption	2.336* (1.299)	3.917 (4.100)	1.489 (9.342)
Constant	0.295*** (0.098)	0.143*** (0.037)	0.032** (0.016)
Homogeneity Test [F(1, 63)]	0.31 [0.58]	0.34 [0.56]	0.00 [0.99]
Observations	192	192	192
Within R-squared	0.547	0.589	0.595
Number of Districts	64	64	64
GMM without initial conditions			
Lagged Poverty Reduction Rate	-0.226 (0.162)	-0.264* (0.144)	-0.248 (0.188)
Ln (Initial Poverty Rate)	-0.010 (0.052)	-0.047 (0.037)	-0.039 (0.035)
Growth in Per Capita Consumption	-3.653** (1.710)	-1.816 (1.460)	-0.983 (1.113)
Initial Poverty Rate × Growth in Per Capita Consumption	7.454* (4.152)	9.443 (14.034)	-2.089 (25.261)
Constant	-0.046 (0.190)	-0.002 (0.081)	-0.060 (0.057)
Homogeneity Test [F(1, 63)]	2.34 [0.136]	0.37 [0.55]	0.02 [0.90]
Observations	128	128	128
Wald Chi-squared	47.25***[0.00]	45.02***[0.00]	6.62[0.16]
Number of districts	64	64	64
FE with initial conditions			
Ln (Initial Poverty Rate)	-0.157*** (0.031)	-0.149*** (0.022)	-0.158*** (0.022)

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
Growth in Per Capita Consumption	-1.749*** (0.608)	-1.524*** (0.479)	-1.300*** (0.383)
Initial Poverty Rate × Growth in Per Capita Consumption	2.392** (1.175)	3.953 (4.127)	2.086 (9.546)
Ln (Initial Literacy Rate)	-0.114 (0.074)	-0.111 (0.089)	-0.145 (0.100)
Ln (Initial Electricity Rate)	-0.081*** (0.023)	-0.106*** (0.029)	-0.124*** (0.034)
Ln (Initial Infant Mortality Rate)	-0.026 (0.025)	-0.032 (0.039)	-0.039 (0.047)
Ln (Initial Sanitary Toilet Rate)	0.042 (0.031)	0.055 (0.039)	0.076 (0.046)
Ln (Initial Pucca Building Rate)	0.020 (0.013)	0.012 (0.019)	0.012 (0.024)
Constant	1.132*** (0.356)	0.933*** (0.350)	0.893** (0.379)
Homogeneity Test [F(1, 63)]	1.11 [0.30]	0.43 [0.51]	0.01 [0.93]
Observations	192	192	192
Within R-squared	0.625	0.654	0.659
Number of Districts	64	64	64

Source: Authors' Estimates.

Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels. Figures in brackets are p-values.

Table A2. Poverty per capita consumption relationship

Variables	Poverty Headcount	Poverty Gap	Squared Poverty Gap
FE without initial conditions			
Ln (Initial Per Capita Consumption	-1.767*** (0.185)	-2.499*** (0.223)	-2.911*** (0.264)
Constant	-3.287*** (0.726)	-7.666*** (0.874)	-10.449*** (1.035)
Observations	192	192	192
Within R-squared	0.603	0.597	0.541
Number of Districts	64	64	64
GMM without initial conditions			
Lagged Poverty Reduction Rate	0.047 (0.321)	-0.059 (0.239)	-0.088 (0.197)
Ln (Initial Per Capita Consumption	-1.288*** (0.239)	-2.131*** (0.434)	-2.678*** (0.575)
Constant	-1.648 (1.485)	-6.202*** (1.666)	-9.604*** (2.170)
Observations	128	128	128
Wald Chi-squared	29.46***[0.00]	25.13***[0.00]	24.96***[0.00]
Number of Districts	64	64	64
FE with initial conditions			
Ln (Initial Per Capita Consumption	-1.661*** (0.170)	-2.315*** (0.201)	-2.649*** (0.243)
Ln (Initial Literacy Rate)	-0.637*** (0.169)	-0.915*** (0.251)	-1.125*** (0.325)
Ln (Initial Electricity Rate)	0.133 (0.098)	0.126 (0.131)	0.111 (0.167)
Ln (Initial Infant Mortality Rate)	0.158* (0.081)	0.236** (0.102)	0.307** (0.136)
Ln (Initial Sanitary Toilet Rate)	-0.006 (0.067)	0.005 (0.093)	0.005 (0.122)
Ln (Initial Pucca Building Rate)	0.045	0.095	0.130
Constant	-1.628** (0.692)	-5.067*** (0.915)	-7.032*** (1.238)
Observations	192	192	192
Within R-squared	0.745	0.756	0.720
Number of Districts	64	64	64

Source: Authors' Estimates.

Notes: District robust standard errors are in parentheses. Figures with ***, ** and * respectively indicate significance at 1%, 5%, and 10% levels.

CHAPTER VI.

Rural Transformation and Poverty Reduction in Bangladesh: Analysis of Recent Evidence from the Household Income and Expenditure Survey 2016[1]

Abstract

Between 2010 and 2016, 90 percent of the poverty reduction of Bangladesh occurred in rural areas. The gains in poverty reduction were largely driven by non-agricultural sectors (i.e., both industry and services). This paper describes the recent evolution of employment and wages in rural Bangladesh. The analysis highlights the increasing trend into non-farm employment in the rural sector and some of the factors linked to the choice of non-farm jobs. The paper relies on the Household Income and Expenditure Surveys for 2010 and 2016/17, complemented with the Labor Force Survey. Overall, there has been a more pronounced non-farm orientation of jobs in rural areas since 2010. This process has been observed for both males and females, and for those with higher education levels. Better connectivity and microfinance are also positively linked with off-farm employment. The increase in non-farm employment was much faster in Eastern than Western divisions of the country, which can partly explain the re-emergence of the East-West divide in terms of welfare after 2010.

[1] This paper was written by Binayak Sen, Senior Research Fellow, International Food Policy Research Institute, IFPRI.

I. Introduction

Bangladesh has experienced an impressive reduction in poverty in the past two decades. Between 2000 and 2016, the upper poverty rate fell from about half to 25 percent of the population. Extreme poverty also fell from 34 to 13 percent of the population. Between 2010 and 2016, poverty continued to decline, though at a slower pace. Importantly, about 90 percent of the poverty reduction observed since 2010 occurred in rural areas (Hill and Genoni 2018).

This paper uses the Household Income and Expenditure Survey (HIES) to describe some important features of the rural transformation in Bangladesh and its potential implications for poverty reduction. It describes the structure and recent trends in rural employment and wages, the spatial variation in job growth, and factors that can be related to households' choosing off-farm labor.

The main data source for this paper is the HIES for the years 2010 and 2016. The HIES cross-sectional survey is the main official source of information about households' consumption, poverty, and income in Bangladesh. The HIES 2016/17 data was collected from April 2016 until March 2017. The previous rounds of HIES data were collected in 2000, 2005, and 2010.[2] The analysis is complemented with information from the Labor Force Survey, as well as macro-economic indicators.

The paper relies on sector of activity and wage data from HIES and does not focus on studying changes in individual and household income. This is determined by the fact that income data in HIES 2016/17 was found to suffer from some quality issues that would require a careful treatment of missings and zeros, which is beyond the scope of this paper.[3]

The next section describes some important trends that show the rapid transformation of Bangladesh's economy. Section 3 describes factors that could be linked to participation in off-farm activities and assesses their relative importance with a

[2] For more information about the HIES, see Ahmed, Arias-Granada, Genoni et al. (2017) and Ahmed, Roy, Yanez-Pagans et al. (2017).

[3] An analysis of the quality of the income data in HIES in 2016/17 compared to 2010 was conducted for this poverty assessment (Hill and Endara 2019b). Overall, it was found that, although there is no obvious systematic error that undermines the 2016/17 income data entirely, the income data is less complete and noisier than the income data collected in 2010, with coding errors also limiting the number of observations for which accurate income data was recorded in 2016/17. A larger proportion of 2016/17 households lack complete income data than was the case in 2010. Richer households in rural areas in self-employment activities are more likely to be missing income data. Wage information seems to be less affected, although it is also noisier in 2016.

regression model. Section 4 presents recent trends in real wages. Finally, Section 5 summarizes the main findings and discusses some of their implications for poverty reduction.

II. Changes in sectoral shares of output and employment

Before we proceed to discuss the nature of rural transformation, a few structural aspects of the macro context may be highlighted. These aspects can be grouped into two broad categories. The first category relates to indicators that stand for positive structural change in the long term, i.e. compared to the benchmark status of the early 1990s, when the country embarked on the path of market liberal economic reforms. Three aspects of long-term growth and structural change may be emphasized.

First, the rate of economic growth has accelerated in Bangladesh over the last three decades (Table 1). The key growth indicator of per capita GDP had stagnated at a meagre 1.5 percent in the 1980s, but has been on the rise since then, posting higher growth in each subsequent quinquennial, making Bangladesh a striking example of the least volatile growth in the post-1990 period. Thus, the average growth in per capita GDP accelerated from 2.6 percent in 1991-95, to 3.3 percent in 1996-00, 3.9 percent in 2001-05, 4.5 percent in 2006-10, and 5.1 percent in 2011-16, rising further to 5.9 percent in 2016/17. In terms of growth rate in per capita GDP, Bangladesh now belongs to the club of the top 20 growth performers.

Second, impressive growth acceleration has been accompanied by noticeable shifts in the composition of output. Agriculture's share in GDP declined from 29.5 percent in 1989/90 to 20.3 percent in 2009/10, falling further to 14.7 percent in 2016/17. The most dramatic expression of structural change is seen in the rising GDP share of industry, which increased from 20.8 percent in 1989/90 to 29.9 percent in 2009/10, climbing further to 32.4 percent in 2016/17. The service sector's share in GDP initially stabilized at 50 percent during the period between 1989/90 and 2009/10, but rose faster in the 2010s, reaching 52.8 percent in 2016/17.

Third, all these changes have been achieved at a low level of fiscal deficit (not exceeding the 4 percent cut-off point over the last two decades) and a relatively well managed inflation (kept well within 8 percent over the last decade), while maintaining a private sector-oriented, liberalized trade regime.

The second category of macro aspects relate to recent changes, especially over the last five years. This sub-group of issues is pertinent to our subsequent analysis

Table 1: Long-term macro-economic performance in Bangladesh, 1991-2014

Five-Yearly Average		Years				
		1991-95	1996-00	2001-05	2006-10	2011-16
GDP Growth Rate		4.50	5.21	5.44	6.03	6.45
Per Capita GDP Growth Rate		2.62	3.33	3.96	4.55	5.15
Share in GDP	Agriculture	29.23	25.68	25.03	19.65	16.12
	Industry	21.04	24.87	26.20	27.67	30.17
	Service	49.73	49.45	48.77	52.69	53.71
Investment (as percent of GDP)	Overall	18.75	21.50	23.62	26.44	28.78
	Public	6.65	6.78	6.44	4.78	6.50
	Private	12.10	14.74	17.18	21.66	22.28
Trade Ratio (as percent of GDP)	Overall	22.20	28.32	32.88	41.42	42.38
	Export	8.30	11.08	13.36	17.72	17.95
	Import	13.90	17.24	19.52	23.70	24.43
Remittance (in Billion US $)		0.97	1.57	2.93	7.87	14.35
Budget Deficit excluding foreign grants (as percent of GDP)		-5.20	-4.50	-4.52	-4.48	-3.85
Inflation		6.10	5.83	3.12	7.66	6.26

Source: Bangladesh Bureau of Statistics (*Statistical Year Book 2017* and year books for previous years). Remittance, budget deficit, and inflation figures are averages for FY13-FY18 and calculated from World Bank, Bangladesh Development Update (October 2018).

because they directly affect wellbeing outcomes as captured by the 2016 HIES. While the progressive features of growth acceleration and structural change in GDP have been retained in this specific sub-period as well, there are some disconcerting signs. First, the private investment rate has barely increased during 2011-16 compared to 2006-10. The public investment rate has increased considerably, as a result of which the total investment rate has risen by more than two percentage points (from 26.4 to 28.7 percent).

Second, the growth of exports during this period has visibly decelerated. The export-GDP ratio has remained almost flat (17.7 percent in 2006-10 and 17.9 percent in 2011-16). The sluggishness in private investment combined with deceleration in exports led to a very slow growth of imports during the period. Third, although the absolute value of workers' remittances sent from abroad has increased from US$ 7.87 billion in 2006-10 to US$ 14.35 billion in 2011-16, it has declined as a proportion of GDP. Thus, the amount of current transfers as a share of GDP has declined from 9.9 percent in 2012/13 to 6.9 percent in 2015/16, dipping to 5.6 percent in 2017/18 (Table 2).

Table 2: Macro indicators on the recent performance of the Bangladesh economy

Description	FY13	FY14	FY15	FY16	FY17	FY18
GDP Growth Rate and Per Capita Income						
GDP Growth (%, 2005-06 base year)	6.0	6.1	6.6	7.1	7.3	7.9
GDP Growth Per Capita (%)	4.8	4.8	5.4	5.9	6.1	6.7
Per Capita GDP (US $, official estimate)	976.0	1110.0	1236.0	1385.0	1544.0	1675.0
Per Capita GNI (US $, official estimate)	1054.0	1184.0	1316.0	1465.0	1610.0	1751.0
Inflation						
Rate of Inflation (CPI, %) (year on year)	6.8	7.3	6.4	5.9	5.4	5.8
Savings & Investment (% of GDP)						
Gross Domestic Saving	22.0	22.1	22.2	25.0	25.3	22.8
Gross National Saving	30.5	29.2	29.0	30.8	29.6	27.4
Private Investment	21.7	22.0	22.1	23.0	23.1	23.3
Of which: FDI	1.2	0.8	0.9	0.6	0.7	0.6
Public Investment	6.6	6.6	6.8	6.7	7.4	8.0
Central Govt. Budget (% of GDP)						
Total Revenue	10.7	10.4	9.6	10.0	10.2	10.6
Total Expenditure	14.5	13.8	13.5	13.8	13.6	15.1
Overall Budget Deficit	3.8	3.6	3.9	3.8	3.5	4.5
Balance of Payment (% of GDP)						
Trade (merchandise export + merchandise import)	40.1	38.4	35.0	33.1	31.0	32.9
Exports	17.7	17.2	15.7	15.1	13.6	13.1
Imports	22.4	21.2	19.3	18.0	17.4	19.7
Current Transfers	9.9	8.6	8.1	6.9	5.3	5.6
Current Account Balance (including transfers)	1.6	0.8	1.5	1.9	-0.5	-3.5
Public Debt and official reserves						
Total Debt as % of GDP	32.1	31.7	31.8	31.5	30.6	31.2
External Debt as % of GDP	14.9	14.1	12.2	11.9	11.3	12.0
Gross Reserves (in months of imports)	5.5	5.8	7.0	7.9	8.0	6.2
Money and Credit						
M2 Growth (%, year-on-year)	16.7	16.1	12.4	16.3	10.9	9.2
Ratio of Private Sector Credit to GDP (%)	37.7	37.8	37.9	38.7	39.3	40.3
Population (millions)*	157.2	159.1	161.0	162.9	164.9	166.9
Population growth Rate	1.2	1.2	1.2	1.2	1.2	1.2

Source: World Bank, Bangladesh Development Update: Powering the Economy Efficiently (October 2018).

All these long-term trends and recent changes in the composition of national output may have implications for the structure of rural personal income and employment.

2.1 Structure and trends in rural employment

Consistent with the changes in the structure of GDP and rural personal income, the pattern of rural employment has also changed during the two decades since 1995/96. Several points are noteworthy. First, during the period between 1995/96 and 2010, agriculture's share in total rural employment dropped by only 5.6 percentage points, compared to the larger decrease in the share of agricultural GDP, which fell by 9.2 percentage points (compare Table 3 to Table 2). This is expected in the initial phase of rural structural transformation. However, this familiar reality has changed on the ground in the 2010s. First, agriculture's share in total rural employment decreased by 16.6 percentage points over the six-year period 2010-16, compared with a 5.6 percentage point drop for the entire period from 1995/6 to 2010. Second, the rapid decline in the proportion of agricultural employment has been matched by an equally rapid increase in the share of industrial employment (with a 9.5 percentage point increase in manufacturing and a 5.6 percentage point rise in the construction sector).

Table 3: Sectoral distribution of rural employment, 1995/96-2016

	1995/96 (%)	2010 (%)	2016 (%)
Agriculture	59.3	53.7	37.14
Industry	11.2	18.2	33.32
Manufacturing	7.5	14.5	23.98
Construction	3.7	3.7	9.34
Services	29.5	27.1	29.53
Total	100	100	100

Note: In making sectoral classification of workers, the following route was adopted. Workers working in multiple sectors are dropped from the analysis. Only workers who work exclusively in one sector have been considered, for example, those who only work in agriculture have been compared with those who only work in manufacturing.
Source: Calculated from primary data of HIES, various rounds.

We also check for the consistency of the HIES-based findings with the Labor Force Survey (LFS) data (Table 4) and find the following congruent trends: (a) the share of agricultural employment for male workers is declining fast; (b) the employment share of the industrial sector for both male and female workers is rapidly increasing; and (c) the rural service sector's employment share for both male and female workers is decreasing fast (or stagnating as per HIES). The previous thesis that the declining share of agricultural employment is matched by an acceleration in service-sector-driven rural non-farm employment (Hossain and Bayes 2009; Khan 2015) is not vindicated by either HIES 2016 or LFS 2013. We surmise that, by the end of the 2000s, service sector employment in rural areas was already much overblown, acting like a sponge to absorb the surplus farm labor. The earlier trend of crowding into activities at the “lower end of the productivity scale” in trade and service sectors needed structural correction, hence the decline in the employment share of rural services.

Table 4: Sectoral distribution of rural employment by gender, 2000-2013

	Male workers (2000)	Male workers (2013)	Female workers (2000)	Female workers (2013)
Agriculture	63.28	52.81	58.27	65.21
Industry	8.75	29.48	17.23	24.12
Manufacturing	5.77	11.79	15.99	19.07
Construction	2.98	17.69	1.24	5.05
Services	27.97	17.70	24.19	10.66
Transport	19.19	7.55	6.0	0.46
Other Services	8.78	10.15	18.19	10.20
Total	100	100	100	100

Source: Calculated from primary data of LFS, various rounds

The upshot of the above is to assert that a distinct tilt towards non-farm jobs, and away from farm employment, has been more pronounced in the decade of the 2010s. We have also seen that, within the plethora of non-farm activities, it is the manufacturing sector (followed by construction) that emerged as the most promising source of rural employment. It is, however, difficult to unpack the nature of industrial activities within the manufacturing sector based on either LFS or HIES.

Table 5 presents evidence from the LFS on three categories of households: (a) “pure farm” (where all workers are engaged in agricultural activities), (b) “pure non-farm” (where all workers are engaged in non-agricultural activities), and (c) “mixed” (where some workers have non-farm occupations and others have farm occupations). For each of these categories, we classify the workers further according to their labor status, which includes four categories: (a) self-employed, (b) casual wage laborer, (c) salaried or regular wage laborer, and (d) unpaid family helper. The evidence shows that the proportion of salaried workers listed in the pure non-farm category increased dramatically, from 21 percent to 37 percent, between 2000 and 2013. The share of casual wage workers also increased, though the rise was much less pronounced. In contrast, the share of non-farm self-employment decreased by 20 percentage points during the same period. Clearly, the rural non-farm sector has taken a decisive turn towards wage employment, especially in favor of salaried jobs, in the 2010s. The latter is suggestive of a perceptible transition from short-term to durable employment arrangements and augurs well, with the emergence of the industrial sector as the main source of demand for rural non-farm jobs.

Table 5: Distribution of rural workers by household types and labor status

Household Types	2000				2013			
	Self	Unpaid	Casual	Salaried	Self	Unpaid	Casual	Salaried
Pure Farm	42.10	13.95	42.10	1.85	49.76	26.33	22.52	1.39
Mixed	44.80	20.98	18.84	15.38	39.31	27.84	16.13	16.72
Pure Non-Farm	59.30	7.21	12.75	20.74	39.56	5.32	18.35	36.76
All	48.04	13.51	27.61	10.84	43.18	21.66	19.01	16.15

Source: Sen et al (2018).

In addition, there are gender differences in the form of wage remuneration, which is one criterion to distinguish casual wage employment from salaried work. Applying this criterion, we see that the proportion of salaried jobs in total non-farm wage-employment jobs, as estimated from HIES, is higher for females. The latter was assessed at 43 percent for male wage workers and 66 percent for female wage workers in 2016. Compared to 2010, the share of salaried workers among female wage workers has increased (Annex tables).

Overall, the main message of this sub-section is that the rural labor market has continued its non-farm orientation in the last decade. In addition, this process does not seem to be taking place through the expansion of self-employment opportunities, but is being increasingly defined by more wage-employment opportunities, such as salaried jobs.

2.2 Spatial variation in the growth of non-farm jobs

The other important issue to consider is whether rural non-farm jobs are spatially concentrated in a few places or instead represent widely dispersed activities. The first aspect to note is that there is considerable variation in the proportion of rural workers with non-farm occupations across the eight divisions of the country (see Tables 6a and 6b). Dhaka, Chittagong, and Barisal report the highest prevalence of non-farm jobs (some 70 percent or above), in contrast to Rangpur, Rajshahi, and Khulna (50 percent or less); the third group of Mymensingh and Sylhet belongs to the middle order (ranging from 54 to 58 percent).

Table 6a: Variation in the incidence of non-farm jobs by division, 2016

Division Code	Division Name	Percentage of individuals in non-farm jobs (weighted)	Percentage of individuals in farm jobs (weighted)
10	Barisal	75%	25%
20	Chittagong	69%	31%
30	Dhaka	71%	29%
40	Khulna	50%	50%
45	Mymensingh	54%	46%
50	Rajshahi	49%	51%
55	Rangpur	47%	53%
60	Sylhet	58%	42%

Source: Calculated from the primary data of HIES 2016.

Table 6b: Variation in the incidence of non-farm jobs by division, 2010

Division Code	Division Name	Percent of workers in non-farm jobs (weighted)	Percent of workers in farm jobs (weighted)
10	Barisal	66%	34%
20	Chittagong	53%	47%
30	Dhaka	58%	42%
40	Khulna	42%	58%
50	Rajshahi	43%	57%
60	Sylhet	61%	39%

Source: Calculated from the primary data of HIES 2010

Secondly, this pattern of unevenness has become more pronounced during the 2010s. Dhaka and Chittagong divisions—the leading regions of the Eastern part of the country—experienced the largest quantum increase in non-farm orientation, while Rajshahi (and Rangpur) divisions—the lagging regions of the Western part of the country—experienced the least growth in rural non-farm jobs. Khulna division witnessed some moderate growth in rural non-farm jobs during the period but is still a long way from reaching the league of leading regions.

Thirdly, Barisal and Sylhet were the two leading divisions in terms of rural non-farm jobs in 2010. Sylhet division has experienced decline in the incidence of non-farm jobs since then, while Barisal has continued to witness impressive growth in non-farm jobs. The divergent fortunes of Sylhet and Barisal are showing up not only in the trends in non-farm jobs but also in schooling rates, with Barisal gaining an edge over Sylhet, despite being the poorer region income-wise.[4]

Finally, the unevenness of the incidence and growth of rural non-farm jobs broadly corresponds to—and may be driving—the worsening East-West divide in the 2010s. Dhaka and Chittagong not only led the league, but also experienced the fastest growth in the creation of rural non-farm jobs, compared to the lagging regions of Rajshahi and Rangpur, which experienced the least expansion.

III. What drives the occupational choice?

The preceding analysis of rural employment points to the major structural shift that has occurred in the 2010s towards non-farm sectors—highlighting the importance of "wages and salaries" income—with attendant emphasis on non-farm wage employment, especially in the manufacturing sector. The latter emerged as a destination of labor movement for both male and female workers (Table 4). This is the crux of the rural transformation in Bangladesh. At the same time, we have seen that there is a large spatial variation in the spread of non-farm jobs. What are the factors that are likely to be associated with the occupational choice of rural workers (broadly defined, i.e., including both self-employment and wage employment) in opting for non-farm jobs as opposed to farm jobs?

We focus on six sets of factors that may correlate with occupational choice among rural workers: (a) accumulation of human capital, (b) access to finance, (c) adoption of agricultural technology, such as farm mechanization, (d) access to domestic and international migration, (e) proximity to large cities, and (f) susceptibility to natural shocks. The relevance of these factors is highlighted by the development literature on the role of the non-farm sector in the process of rural structural transformation. Each of these elements is briefly sketched out below.

3.1. Human capital and financial capability: drivers relating to capability

Human capital

The relevance of educational human capital has long been recognized in explaining the transition of rural populations—especially over the generations—from the

[4] The puzzle of Barisal versus Sylhet may be explained by a range of economic and social circumstances, such as lower fertility rate, higher female schooling, higher female labor force participation, greater out-migration propensity, enhanced reliance on domestic migration (highest among all divisions), and the least exposure to foreign migration (which can often discourage labor force participation in the receiving communities). However, this falls outside the scope of the present paper.

farm to the non-farm sector (Galor and Zeira 1993). This is because non-farm work such as regular wage employment (salaried work) in non-agricultural sectors requires some threshold level of educational human capital. Access to formal service sector jobs, as well as most manufacturing jobs, such as employment in the ready-made garment (RMG) industry, is usually conditional on having some forms of human capital. Most of the female workers employed in the RMG sector have at least primary education (Heath and Mobarak 2015). However, it remains unclear which aspect of human capital is crucial to accessing non-agricultural jobs—beyond literacy and numeracy. Whether it is the power of reasoning that comes with exposure to education, or the capacity to receive on-the-job training, or simply a screening device for recruiting relatively skilled workers in non-agricultural jobs possibly requires further research. These ambiguities notwithstanding, there is adequate evidence to state that human capital increases the chances of being in the non-farm sector and, through that channel, aids rural structural transformation. Accordingly, we use the information on the "completion of various levels of education" as the indicator of human capital and expect that chances of getting into non-farm jobs are likely to increase with each level of education.

Access to finance

Non-farm occupations are often out of the reach of many rural workers, because such activities require considerable investment in a business enterprise. In the context of widespread credit market failure, the choice of self-employment over wage employment depends critically on initial asset endowments and type of endowments, and ultimately on the initial distribution of assets (Banerjee and Newman 1993). However, in the context of rural Bangladesh, the credit access problem may not be as severe as in the typical developing country, due to the vast presence of microfinance institutions (MFIs). Non-farm orientation by way of accumulation of non-farm assets can be facilitated by the access to financial capital provided by MFIs, which have continued to expand at a moderate pace in the 2010s. In this study, we use the information on "borrowing of loans from MFIs" as an indicator of access to finance for the rural context.

3.2 Mechanization, urban proximity, and migration: drivers relating to opportunity

Access to agricultural mechanization

Access to improved agricultural technology has been an important driver of production growth in agriculture. In the 1980s and 1990s, the prevalent technology was HYV seed-fertilizer-irrigation technology. The rapid progress of the HYV technology—popularly known as the "green revolution"—has been initiated first in the eastern region (Dhaka and Chittagong divisions) in the 1970s and 1980s, then moved to the western parts of the country (Rajshahi and Rangpur divisions) in the 1990s and 2000s, before it moved to the south (Khulna and Barisal divisions) in the 2000s and 2010s. By 2016, this new seed-fertilizer-irrigation technology reached almost every nook and corner of the country. However, rural regions differ in other technological aspects, commonly known as the mechanized service market for renting services for tillage and threshing operations. Some regions have moved faster in the use of power tillers, tractors, and power threshers. The use of these mechanized services enabled considerable cost savings, hence their growing popularity among land-poor farmers. Consequently, we hypothesize that access to farm mechanization technology is likely to counteract the tendency to opt for non-farm work and encourage new agricultural practices.

Another possibility must also be considered. To the extent that the use of mechanized technology requires less farm labor, it may shift farm labor towards non-farm work. This process may have a gender dimension, as well. For instance, it is possible that male farm labor is replaced and sent to non-farm work, while female labor may take former male workers' place in the farm sector. In other words, we may find a non-farm orientation of male workers alongside the farm orientation of female workers. However, the counter-argument is that there are likely to be very minimal labor substitution effects from the use of these technologies—more in the case of the power thresher than in the case of tillage operations (Hossain et al 2017). Hence, the matter needs to be resolved empirically. Accordingly, we use the information on "whether the household has made use of mechanized services for tillage and threshing operations" as the indicator of agricultural mechanization.

Urban proximity

Urban proximity may matter for occupational choice for several reasons. First, it directly increases the likelihood of finding non-farm jobs in the urban sector through the migration channel. Commuting to urban areas for seasonal work becomes feasible with closer proximity. Second, it increases the productivity of existing rural non-farm production through improved marketing and technology linkages with upstream urban markets (World Bank 2009). Third, as the economic transformation proceeds, towns become important centers of demand, creating new market opportunities for both production inputs and consumption goods originating in rural sectors (Islam 2006). Urban areas start subcontracting many lower-level manufacturing processes to rural non-farm enterprises. The combined outcome of these three effects will tend to increase the share of non-farm occupations in rural areas, especially near towns that have marketing and employment links to the rural neighborhoods. However, the effects of urban proximity on non-farm occupations may vary by the "size" of cities (see Christiansen and Kanbur 2017 for a review of small versus large cities). Another question remains about the trigger point behind the "size" issue: is it the proximity to "ports," "seats of political power," "market concentration," or simply "infrastructural development" that is driving the potent effects of larger agglomerations? Here, our scope of analysis is limited: we capture the effect of urban proximity by using the measure of actual physical distance from the capital city (Dhaka) as the principal hub of economic activities.

Access to migration

Migration to cities and abroad on the part of some household members—whether induced by natural shocks or stimulated by economic opportunities—may encourage a search for jobs in the non-farm sector on the part of household members who stay behind in the places of origin. In other words, there is a "signaling" involved in the migration process. However, whether the remaining members of the household follow in the footsteps of the migrant members would depend on a variety of circumstances, including: success of previous migration, cost of new migration, other economic opportunities in the village influencing the channel of remittance use, and restrictive social norms on physical mobility of female workers. For instance, if the bulk of the remittance is used by the receiving households to accumulate non-farm assets, then it may encourage non-farm occupational choice. However, the reverse possibility also exists: if the additional household income acquired through transfers is used for buying land or agricultural machinery, then it can benefit the farm activities more than the non-farm activities. In the latter case, the strength of non-farm "signaling" from migration would be muted.

In the proposed empirical exercise, we use the information on whether there is "at least one domestic migrant worker working outside for more than six months" (the migrant's workplace may be cities or other rural parts of the country) as the proxy for domestic migration and whether "the household has at least one foreign migrant worker who is currently staying abroad" as the proxy for international migration.

3.3 Drivers relating to vulnerability: response to natural shocks

Movement out of the farm sector is often seen as a response to expected risks and realized shocks, especially to natural disasters. Droughts, floods, or salinity intrusions make farm households vulnerable, depreciate farm assets, and discourage farm production. In contrast, susceptibility to risks can encourage the accumulation of "portable assets" such as human capital which, in turn, put a worker on the pathway out of agriculture. Rural non-farm activities such as trade and manufacturing are often considered more resilient to natural shocks.

In some contexts, moving out of the farm sector is often a gendered phenomenon: while male workers leave for work in non-farm sectors outside of villages, female workers remain behind in the rural areas. Thus, one often sees a sharp rise in the female work force participation rate, especially as the “unpaid family helper,” both in farm and rural non-farm sectors. The uncertain part in this story is that one does not know, on balance, which way the occupational choice of a rural worker shifts—towards farm or non-farm jobs—after experiencing natural risks, nor how durable the transition may be. In other words, it remains unclear whether natural risks generally spur only short-term coping responses, while workers mostly remain within the farm sector, or whether such risks tend to promote long-term exit decisions out of the farm sector. The other consideration is whether the type of risks matters. The farm to non-farm transition path is different for different agro-ecological settings (drought-prone versus flood-prone areas, for example).

In this exercise, however, we use a proxy for natural risks—by applying a measure of the “variability of rainfall”—which has been extensively used in previous studies. For the 2016 round, we use a lagged variable for risks (captured by the “standard deviation of the rainfall during 2000-2010”); for the 2010 round, we use the lagged variable “standard deviation of the rainfall during 1990-2000.” We expect that the exposure to natural risks would motivate a rural worker to opt for non-farm jobs. Admittedly, the measure that we have could reflect the impact of expected risk as much as realized shocks. Indeed, the lag between the measured period and the labor outcome is quite large and may suggest this variable is really picking up the impact of risk rather than shock realizations.

3.4 Discussion of results

Apart from the above indicators of human capital, access to finance, agricultural mechanization, urban proximity, shocks, and access to domestic as well as international migration opportunities, we also include in the full model standard controls such as age, land ownership, log of per capita expenditure, and divisional fixed effects. We estimate the probit model with the individual worker level data where the dependent variable is “whether the worker is engaged in non-farm occupation” (non-farm=1, farm=0), conditional on the covariates listed above. We estimate both male workers and female workers (aged 15 to 64) separately. We present the marginal effects from the probit model for 2016 and 2010 separately (see Table 7 and Table 8). A note of caution in interpreting the results: we are looking here for “robust association,” rather than “claiming causality,” given the cross-sectional nature of the data set-up.

Table 7: Marginal effects from the probit model of occupational choice of male and female workers in farm households (non-farm job=1, farm job=0): individual worker level regression for 2016

VARIABLES	(1) Male Worker Age 15 to 64	(2) Female Worker Age 15 to 64
Age	-0.0139*** (0.00260)	-0.0255** (0.0102)
Age squared	6.97e-05** (3.12e-05)	0.000276** (0.000131)
Ref: No education		
Class 1 to 5	0.0472*** (0.0128)	0.0227 (0.0426)
Class 6 to 8	0.123*** (0.0166)	0.120*** (0.0456)
Class 9 to SSC	0.134*** (0.0173)	0.149*** (0.0495)
HSC and above	0.299*** (0.0232)	0.346*** (0.0768)
Ref: Married		
Widowed/Divorced/Separated	-0.0575 (0.0578)	0.00864 (0.0496)
Never married	0.0771*** (0.0189)	0.141** (0.0612)
HH deposited in microcredit institution	0.0759*** (0.0147)	0.146*** (0.0354)
Use of mechanized services (adopter=1, non-adopter =0)	-0.139*** (0.0197)	0.00388 (0.0450)
Cultivable land owned by HH	-0.00710* (0.00386)	-0.00591 (0.00388)
Use of mechanized services*Cultivable land owned	-0.00150 (0.00674)	0.0119* (0.00636)
HH has at least one migrant abroad	-0.0153 (0.0214)	-0.184** (0.0753)
HH has at least one domestic migrant	0.0946*** (0.0290)	-0.0287 (0.120)
HH size	0.0329*** (0.00358)	0.0365*** (0.00979)
Log of per capita expenditure	0.0718*** (0.0120)	0.115*** (0.0352)
Distance of district from Dhaka	-0.000453*** (0.000165)	-0.00122*** (0.000413)
Total rainfall 1990 to 2000	-4.88e-05 (5.23e-05)	-0.000127 (0.000139)
Standard deviation of rainfall 1990 to 2000	0.000551* (0.000285)	0.00151* (0.000786)
Observations	12,289	1,772
Divisional FE	Yes	Yes

Notes and Source: *** p<0.01, ** p<0.05, * p<0.1. Parenthesis contain the robust clustered standard error at Thana level. Estimated from the primary data of HIES 2016.

Table 8: Marginal effects from the probit model of occupational choice of male and female workers in farm households (non-farm job=1, farm job=0): individual worker level regression for 2010

VARIABLES	(1) Male Worker Age 15 to 64	(2) Female Worker Age 15 to 64
Age	-0.000358 (0.00362)	-0.0256** (0.0113)
Age squared	-8.35e-05* (4.47e-05)	0.000302** (0.000143)
Ref: No education		
Class 1 to 5	0.0968*** (0.0168)	0.124** (0.0623)
Class 6 to 8	0.112*** (0.0209)	0.209*** (0.0677)
Class 9 to SSC	0.188*** (0.0198)	0.346*** (0.0772)
HSC and above	0.470*** (0.0272)	0.507*** (0.0766)
Ref: Married		
Widowed/Divorced/Separated	-0.0962 (0.0975)	-0.0196 (0.0558)
Never Married	0.0353 (0.0252)	0.0442 (0.0885)
HH deposited in microcredit institution	0.124*** (0.0221)	0.0128 (0.0474)
Use of mechanized services (adopter=1, non-adopter =0)	-0.198*** (0.0204)	-0.154*** (0.0408)
Cultivable land owned by HH	-0.000202** (8.85e-05)	-0.000475** (0.000191)
Use of mechanized services*Cultivable land owned	-6.07e-06 (0.000104)	0.000367* (0.000198)
HH has at least one migrant abroad	-0.000638 (0.0202)	-0.213*** (0.0819)
HH has at least one domestic migrant	0.0836** (0.0420)	-0.0525 (0.0699)
HH size	0.0175*** (0.00371)	0.0189* (0.0109)
Log of per capita expenditure	0.0361 (0.0220)	-0.0335 (0.0521)
Distance of district from Dhaka	-0.00104*** (0.000197)	-0.000474 (0.000362)
Total rainfall 1990 to 2000	8.80e-05 (6.17e-05)	-6.73e-05 (0.000133)
Standard deviation of rainfall 1990 to 2000	0.000648*** (0.000216)	0.000209 (0.000500)
Observations	4,708	468
Divisional FE	Yes	Yes

Notes and Source: *** p<0.01, ** p<0.05, * p<0.1. Parenthesis contain the robust clustered standard error at Thana level. Estimated from the primary data of HIES 2010.

Several features are noteworthy. First, each successive level of education (after completion of the primary level) is associated with higher likelihood of being in non-farm occupation. This holds true for both male and female workers. Those who have crossed the bar of the Higher Secondary Certificate (HSC) have a three times higher probability of choosing non-farm jobs than those who completed junior secondary level (grades six to eight).

Second, access to microfinance is linked with increased chances of selecting a non-farm occupation (by a margin of 10 percent), and this is equally valid for male and female workers.

Third, access to the use of agricultural mechanization is associated with lower chances of household workers being in non-farm occupations. This is possibly because it enhances farm profitability and perhaps encourages specialization in the farm sector. However, it may allow female workers in the large land ownership group to go for non-farm jobs (as indicated by the interaction term between land and mechanization).

Fourth, domestic and foreign migration have different associations with the occupational choice of male workers. The non-farm "signaling" works in the case of domestic migration, but migration abroad has no correlation with occupational choice. Thus, having at least one domestic migrant in cities is associated with greater chances (by a margin of about 10 percent) of choosing a non-farm occupation. In contrast, migration abroad reduces the likelihood of non-farm orientation for female workers. This can be the result of two effects: (a) in the absence of a male worker who has migrated abroad, the erstwhile female non-farm worker may now have to enter the farm sector as family helper or manager of farm activities, especially when foreign remittances are used for buying land or farm machinery services (the labor substitution effect); (b) migration abroad on the part of male workers leads to substantive remittance flows which, in turn, allow female workers to withdraw from the non-farm labor market (the wealth effect).[5] In principle, these effects should have been in the same direction for both domestic and international migration. The differential association of domestic

[5] One suspects that variation in female labor force participation rates in Barisal versus Sylhet comparisons—high in Barisal division and low in Sylhet division—illustrates the two effects. Barisal is known to be a division from which much of the country's internal (male) out-migration takes place. In the absence of male workers available for farm work, female-managed agriculture has emerged in Barisal. This is an example of the labor substitution effect. In contrast, Sylhet is traditionally known to be the foreign remittance receiving region, where remittance inflows discourage female participation in non-farm (or farm) work—an example of the wealth effect.

and international migration with the non-farm orientation of female workers may be due to much larger remittance flows associated with migration abroad.

Fifth, urban proximity matters for the occupational choice. Villages located far from Dhaka city are strongly associated with favoring farm occupations, and this effect is valid for both male and female workers.

Sixth, experience of natural shocks is correlated with the choice that favors non-farm jobs. Both male and female workers adopt non-farm orientation in the face of natural shocks as a coping method.

Finally, a statistical point to note is that the above results are robust to the choice of survey rounds. Both HIES 2016 and 2010 yield broadly similar results. Between the two surveys, the effects of financial access, farm technology, urban proximity, and shocks have become stronger for female workers in 2016.[6]

The main message is that non-farm orientation of employment may be an outcome of labor market response to both opportunities (mechanization, urban proximity, and migration) and shocks (natural shocks) mediated by capability (human capital and access to finance). This seems a valid reference point for understanding both male and female labor supply responses, and the nature of rural structural transformations in present-day Bangladesh.

3.5 Differential characteristics of female employment

The pronounced shift of employment to the non-farm sector has influenced both male and female workers. The general features of the farm to non-farm transitions have been discussed earlier. We now turn to specific attributes of female labor supply compared with their male counterparts.

Human capital influences the likelihood of obtaining non-farm jobs equally for both male and female workers. Just educating girls up to primary education no longer seems to matter for getting non-farm jobs in rural areas. The coefficient

[6] This exercise can be enriched by considering the following avenues: (a) implement the occupational choice model in a panel framework, (b) by distinguishing large from small-size towns, (c) by demarcating different kinds of natural and idiosyncratic shocks, (d) by differentiating migration to cities as opposed to other rural parts, (e) by identifying different destinations of migration abroad, (f) by considering different "household value systems" influencing gender norms dictating occupational choice, and (g) by differentiating categories of non-farm occupations. This is, however, beyond the scope of the present aggregative exercise.

for primary education was statistically significant in 2010 but turned out to be insignificant in 2016 (see Tables 7 and 8). The results show the importance of secondary and post-secondary education for availing non-farm jobs for rural women (the matched effects of post-primary education are larger for women than men in both 2010 and 2016).

Access to microcredit is positively associated with non-farm orientation of female workers in 2016, while it was insignificant in 2010. Spread of farm technology also influences occupational choice. Use of mechanized services is linked with increasing farm orientation, so is the factor of land ownership. However, the interaction effect between land and rural mechanization suggests a contrasting scenario: it indicates farm orientation for male workers and non-farm orientation for female workers (the result is valid for both 2010 and 2016). This could indicate that female workers in larger farms substitute farm labor for non-farm labor in the presence of rural mechanization.

Migration of workers to the cities is positively associated with non-farm orientation of the *other* male workers of the sending households but does not have any matched influence on the female workers. Migration of workers abroad does not have any influence, however, on the occupational choice of the remaining workers—male or female—of the sending households.

Non-farm orientation is correlated with higher expenditure (lower poverty), and this is valid for both male and female workers. Similarly, remoteness is associated with farm orientation for both male and female workers. Natural shocks seem to encourage non-farm orientation for both male and female workers. These results, by and large, are valid for both 2010 and 2016.[7]

IV. Trends in real agricultural wages

The sign of tightening of the rural labor market was already visible by the early 2010s (Zhang et al. 2013). Development of the rural non-farm sector, combined with rural-urban migration, were the primary factors behind this upbeat trend in farm wages. Entry of landless households into the tenancy market may have given further stimulus to the tightening of the rural labor market and positively influenced the growth of farm wages. Analysis of the newly available data from the HIES 2016 shows that this trend continued unabated in the 2010s.

[7] The only exception is the natural risk variable. It was insignificant for female workers in 2010. In 2016, such shocks are associated with the non-farm choice among female workers.

Four features of wage trends are noteworthy (Table 9). First, mean real rural wages have increased by about 46 percent between 2010 and 2016. In rural areas, agricultural wages have registered a 41 percent increase, while non-agricultural wages grew faster (54 percent) over the period. The growth in wages is observed across all divisions. However, there was variation in the extent of the change. The divisions of Barisal, Dhaka, and Khulna witnessed the fastest growth in farm wages (around 50 percent).

As expected, non-farm wages are higher than farm wages in rural areas, indicating the potential gains for transition from the farm to rural non-farm sectors. In addition, urban wages are higher than the rural wages for all the divisions. At the national level, the urban-rural wage gap has increased in the 2010s—from 24 percent to 33 percent. This is consistent with the pattern of declining poverty amidst rising inequality trends.

Table 9: Trends in nominal and real agricultural wages between 2010 and 2016 for agricultural laborers by division (taka per day)

	Nominal Wage 2010						Nominal Wage 2016					
Division	Rural Agricultural Wage	Urban Agricultural Wage	Rural Non-Agricultural Wage	Urban Non-Agricultural Wage	Rural Wage	Urban Wage	Rural Agricultural Wage	Urban Agricultural Wage	Rural Non-Agricultural Wage	Urban Non-Agricultural Wage	Rural Wage	Urban Wage
Barisal	161	169	179	198	173	198	318	340	353	392	339	390
Chittagong	176	163	211	229	191	223	312	292	422	473	357	462
Dhaka	149	171	191	196	171	194	313	359	382	464	344	458
Khulna	114	140	130	157	120	155	232	241	294	328	256	324
Rajshahi	121	123	127	162	123	155	227	237	273	300	243	294
Sylhet	136	137	123	222	128	204	262	303	329	425	293	412
Bangladesh	136	142	160	189	147	183	264	290	338	399	295	392
	Wage 2010 in 2016 Value						Wage 2016 in 2016 Value					
Barisal	212	222	235	261	227	260	318	340	353	392	339	390
Chittagong	246	228	295	320	267	312	312	292	422	473	357	462
Dhaka	211	242	270	278	242	275	313	359	382	464	344	458
Khulna	156	191	178	214	164	212	232	241	294	328	256	324
Rajshahi	163	165	171	219	165	208	227	237	273	300	243	294
Sylhet	191	191	172	310	179	284	262	303	329	425	293	412
Bangladesh	187	195	219	259	202	251	264	290	338	399	295	392

Note and Source: Divisional real wages have been derived by using the spatial deflators based on the "lower poverty line." Estimated from the unit-record data of 2010 and 2016.

V. Conclusion

The nature of rural transformation has important implications for poverty reduction and inequality trends. One caveat, though, would be in order. Since we do not have panel data for the period at our disposal, there is a risk of telling a dynamic story about “what happened” solely on the basis of cross-sectional data.

The main message is that the decade of the 2010s continues the positive trends already witnessed in the previous decade. This relates to acceleration of national growth at the macro level and sustenance of moderate consumption growth, as well as poverty reduction in rural areas (on this, see BBS 2018).

The role of non-farm jobs has become visibly more important over time. Between 2010 and 2016, the share of agricultural employment has declined rapidly, with most increases happening in the manufacturing and construction sectors. Both HIES and LFS data support this conclusion of much more pronounced non-farm orientation of the rural labor force in the 2010s, compared to previous decades. In addition, our analysis of the occupational choice shows the importance of human capital, urban proximity, and shocks as correlates of non-farm occupations.

The above process of non-farm orientation did not bypass the female labor force, with fast spread of education and connectivity supporting this trend. However, the recent declines in female labor force participation are a cause of concern.

Moreover, the transition of the labor force from the farm to the non-farm sector has had implications for the tightening of the agricultural wage labor market. Real farm wages continued to rise in the decade of 2010s, reinforcing the trends of farm mechanization and the sustained drop in rural extreme poverty. Yet, average non-agricultural wages increased more consistently with findings that non-agricultural sectors drove the largest share of the poverty reduction in rural areas (Hill and Genoni 2018).

Finally, considerable spatial variation in farm/non-farm employment and wages is noticeable. The western regions (Rajshahi and Rangpur) exhibited lower growth in non-farm jobs and wages, compared to the eastern regions. This supports the broad thesis of re-appearance of the East-West divide in the 2010s. However, the implications of these changes for the trends in rural personal income inequality need to be examined further.

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Annex Tables

Table 1a: Distribution of male workers by household types and labor status in rural areas

Household Types	2000				2013			
	Self	Unpaid	Casual	Salaried	Self	Unpaid	Casual	Salaried
Pure Farm	46.46	8.09	43.45	2.00	63.41	6.97	28.08	1.54
Mixed	52.88	8.57	21.63	17.22	55.87	6.98	19.68	17.48
Pure Non-Farm	63.52	4.14	12.84	19.50	47.35	2.60	17.92	32.13
All	53.15	6.92	29.27	10.66	56.39	5.79	22.35	15.47

Source: LFS

Table 1b: Distribution of female workers by household types and labor status in rural areas

Household Types	2000				2013			
	Self	Unpaid	Casual	Salaried	Self	Unpaid	Casual	Salaried
Pure Farm	19.04	44.92	34.94	1.11	13.29	78.08	7.64	0.98
Mixed	27.08	49.24	12.50	11.17	8.66	66.45	9.56	15.33
Pure Non-Farm	38.22	22.51	12.30	26.96	14.05	14.27	19.76	51.91
All	27.02	40.59	20.81	11.58	11.30	59.98	10.95	17.77

Source: LFS

Table 2a: Bangladesh rural employment of males aged 15 to 64 by types of earning for farm and nonfarm workers, 2010 and 2016

		2010	2016	2010	2016
		Pure Farm	Pure Farm	Pure Non- Farm	Pure Non- Farm
Casual Wage	Percent	96.22	96.00	55.02	56.14
	Millions	5.58	6.28	4.23	6.04
Salaried	Percent	3.64	2.48	44.66	43.12
	Millions	0.21	0.16	3.43	4.64
Mixed	Percent	0.14	1.52	0.33	0.74
	Millions	0.008	0.10	0.03	0.08
Total	Percent	100.00	100.00	100.00	100.00
	Millions	5.80	6.54	7.70	10.77

Source: Calculated from Bangladesh Household Income and Expenditure Surveys 2010 and 2016.

Table 2b: Bangladesh rural employment of females aged 15 to 64 by types of earning for farm and nonfarm workers, 2010 and 2016

		2010	2016	2010	2016
		Pure Farm	Pure Farm	Pure Non- Farm	Pure Non- Farm
Casual Wage	Percent	95.75	92.73	41.94	33.32
	Millions	0.62	0.70	0.62	0.67
Salaried	Percent	3.48	3.48	57.60	64.97
	Millions	0.02	0.03	0.85	1.31
Mixed	Percent	0.78	3.78	0.46	1.71
	Millions	0.005	0.03	0.007	0.03
Total	Percent	100.00	100.00	100.00	100.00
	Millions	0.65	0.75	1.47	2.01

Source: Calculated from Bangladesh Household Income and Expenditure Surveys 2010 and 2016.

CHAPTER VII.

Poverty in Urban Bangladesh[1]

With rapid urbanization and concomitant rise in urban poverty, a better understanding of urban poverty and urban income dynamics has become an urgent priority. One in five poor households now live in urban Bangladesh and many more urban households are aspiring to be middle class yet vulnerable to falling back into poverty. Progress in reducing poverty has slowed in urban areas, particularly in larger cities. As a result, there are now more people living in extreme poverty in urban Bangladesh (3.7 million) than in 2010 (3 million). At current rates of urbanization and poverty reduction, more than half of poor households will live in urban areas by 2030. This paper examines what can be learned about trends and drivers in urban poverty from recent nationally representative surveys. It also analyzes additional data sources on the capital city, Dhaka, to shed light on spatial inequality within the city. The paper highlights the need for increased data collection and evidence on urban poverty to inform public policy to address this emerging challenge.

I. Introduction

With rapid urbanization and a concomitant rise in urban poverty, a better understanding of urban poverty and urban income dynamics has become an urgent priority. The last census in 2011 counted 28 percent of the population as

[1] Background paper prepared for the Bangladesh Poverty Assessment by Hossain Zillur Rahman and Ruth Hill with inputs from Joaquin Endara, Kelly Yelitza, Yurani Arias Granada and Maria Eugenia Genoni.

urban, with the intercensal change indicating the urban share of the population is increasing by 0.4 percentage points per year. UN population data shows that Bangladesh is urbanizing faster than both the southern Asia and all Asia regional averages (UN 2018). One in five poor households now live in urban Bangladesh (Table 1) and many more urban households are aspiring to be middle class yet vulnerable to falling back into poverty. The urban share of the population, and of the poor population in particular, has increased.[2] As a result there are now more people living in extreme poverty in urban Bangladesh (3.7 million) than in 2010 (3 million). At current rates of urbanization and poverty reduction, more than half of poor households will be urban by 2030.[3]

Table 1: Poverty in Bangladesh is becoming more urban

	Urban share of population from census data (year) / projections	Urban share of population (percent)	Urban share of poor (percent)	Urban share of extreme poor (percent)
2000	23.8 (2001)	20.1	14.4	11.7
2005		24.7	17.5	14.4
2010	28.0 (2011)	26.3	17.8	11.5
2016		29.1	22.3	18.0
2030	45.6		51.5	

Source: Staff calculations using HIES 2000, 2005, 2010 and 2016 and UN-DESA 2018

Yet despite an increasing urbanization of poverty, nearly all analysis of poverty and income dynamics in Bangladesh has been focused on rural poverty and mobility. This has important policy implications. For example, the graduation approach that was developed in Bangladesh and which has received international recognition, is an approach that was developed in rural Bangladesh based on in-depth analysis of rural poverty. The approach is focused on physical asset

[2] The definition of urban changed in the 2011 census (which is the sampling frame for the 2016/17 Household Income and Expenditure Survey - HIES). The newer definition used a stricter definition of urban area that excluded some areas of statistical metropolitan areas. An expert panel on the census met and advised that the new definition of urban used in the census be modified to include these areas again (BBS 2014). This adjustment was made in the HIES also by reclassifying these EAs as urban accordingly. However, there was an error in classifying 13 urban areas as rural which is why the published share of the urban population in the BBS HIES 2016/17 reports is lower than the share reported here which corrects this mistake (and updates the poverty estimates accordingly).

[3] Urban population projections for 2030 are taken from UN-DESA World Urbanization Prospects 2018, and the rate of progress in reducing urban and rural poverty from 2010 to 2016 is projected to continue for 14 years to predict an urban poverty rate of 14 percent and a rural poverty rate of 11 percent.

transfer (often involving livestock) and livelihood support that is well suited for rural Bangladesh but has little applicability in urban centers.

Limited survey data on urban households has hampered our understanding of urban income dynamics and urban poverty. One is the absence of urban panel surveys that follow the same households across time. There are many long-run and well-used rural panel surveys in Bangladesh, but no urban panel survey that follows urban households across time. As a result, it is not clear whether slower progress is a result of poor households migrating from rural to urban areas, and on their way to becoming better off; weak income growth among urban households that have been poor for many years; or poor households doing quite well but being replaced among the ranks of the poor by once non-poor urban residents that have lost their jobs or experienced other setbacks. Likely policy responses to each of these narratives may differ so it is critical to understand which of these prevail and to what degree. In addition, cross-section data that is available for urban areas does not allow for disaggregation within a city to see how dynamics differ in different parts of the city such as the center and periphery or slum and non-slum areas.

In addition, there are critical knowledge gaps on qualitative understanding of urban poverty dynamics. Issues such as nature of multi-dimensional poverty in large urban centers such as Dhaka, community in fluid urban contexts, urban spaces that may facilitate or hinder entry into labor markets and influence the nature and quality of urban services need research to enable formulation of more effective policies to address urban poverty and inclusive growth.

This paper uses available data to present key facts on who the urban poor are and what is driving or constraining progress for these households. It uses the data that is available, but it also discusses the data that will need to be collected in future years to provide the information for evidence-based urban policy. Given the available data the paper uses specific definitions of urban and poverty, but first it is worth noting the spectrum of urban areas in Bangladesh and factors to take into account when measuring poverty in urban areas.

Defining urban in Bangladesh. At 1,015 people per square kilometer, Bangladesh is one of the most densely populated countries in the world, surpassed only by city-states and small-island countries. Many rural areas in Bangladesh have population densities as high as urban areas in other countries. In fact, when using agglomeration indices rather than official definitions of urban areas, the proportion of people living in urban areas in Bangladesh is much higher than reflected in Table 1.[4] According to these measures the share of the urban population is as much as 20-36 percentage points higher than official estimates.[5]

The urban spectrum. Within the official definition of urban there is still a large spectrum of urban areas (Rahman 2016). At one end, Dhaka comprises one third of the urban population, making it one of the largest cities in the world. It is also one of the most densely populated cities in the world. It is a primate city in that its population is three times larger than Chittagong, Bangladesh's second-largest city. Secondary cities—Khulna, Rajshahi, Sylhet, Barisal, Comilla and Rangpur—are much smaller. Non-metropolitan municipalities and upazilla headquarters comprise the rest of the urban population. Bird et al (2018) show how Dhaka is disproportionately important relative to these much smaller urban areas. Not only is Dhaka large in absolute terms, but secondary cities in Bangladesh are disproportionately small. Within Dhaka there is also considerable variation in urban spaces, something discussed further below.

Measuring poverty in urban areas. The standard measure of consumption poverty (expenditure per capita) is not always a good measure of poverty in urban areas. A larger share of household expenditure (namely rent) is shared among household members making economies of scale more important. Urban poverty has additional dimensions which have not traditionally been well captured in quantitative analyses such as crime and mental health (Rahman 2016). Finally, getting prices right—for both goods and particularly housing—for urban poverty lines can be challenging. This analysis uses the Households Income and Expenditure Survey (HIES) collected by the Bangladesh Bureau of Statistics in 2000, 2005, 2010 and 2016/17 (referred to as 2016 throughout) and the national official poverty measurement methodology which is defined as per capita expenditure and deflated using the methodology set out in BBS and World Bank (2017), complementing this measure with indicators of other dimensions of wellbeing as much as possible.

On nearly all measures, wellbeing is better in urban areas. Monetary poverty rates in urban areas are much lower than in rural areas, across the urban spectrum

[4] Agglomeration indices use census data to determine whether an area is sufficiently population dense to be considered an urban area.

[5] Uchida et al (2010) suggest an urban population share that is 20 percentage points higher whilst Robert et al (2017) show that agglomeration indices predict an urban population share 30-36 percentage points higher and other methods would suggest an even larger divergence.

(Table 2).[6] By other dimensions of wellbeing households also appear better off: children are less likely to be undernourished; adults have more education; and access to electricity, improved water and sanitation is better. However, vulnerability to poverty is higher in some cities than in rural areas, and children are not more likely to be in school.

However, there are three causes for concern.

First, urban poverty is relatively high. Almost 1 in 5, 19 percent, of the urban population lives in poverty, which is high both in absolute terms and in relative terms—in South Asia, only Afghanistan has a higher urban poverty rate (Ellis and Roberts 2015). As is discussed further below the poverty rates in Dhaka and Chittagong are particularly high given their strong contribution to economic power. Vulnerability to poverty, defined as the population that live between the national upper poverty line and twice the national upper poverty line, is also high in urban Bangladesh with 1 in 2 households, not poor but vulnerable to falling into poverty. And the size of the middle class (defined as living on more than twice the national upper poverty line) is small: across cities, less than a third of the urban population are middle class on average.

Deprivation in other dimensions is also quite high. About a third of household heads have no education, and children are slightly less likely to be in school than in rural areas (76 percent of children are in school compared to 82 percent in rural areas). Rates of access to sanitation and water are much higher, but still quite low. Malnutrition in urban areas is lower than in rural areas, but 10 percent of children suffer from severe stunting and 31 percent are moderately stunted. Other aspects of deprivation—such as crime, or the need to move repeatedly because of rent increases—that we do not typically measure in household surveys are also present (Rahman 2016). The majority of households in Dhaka rent the property they live in (72 percent). In Dhaka 43 percent of households changed residence in the last three years and for 39 percent of movers this was due to an increase in rent (Rahman 2016). In Chittagong fewer households rented (62%) or moved in

[6] The 2016 HIES was the first HIES to use the City Corporation as a strata rather than the Statistical Metropolitan Area which was used in previous HIES. This allows poverty rates to be defined for four City Corporations of Dhaka (North and South City Corporation combined), Chittagong, Rajshahi and Khulna. When statistics are presented just for 2016 in this chapter, statistics are presented for the City Corporations. When statistics are presented across time, the Statistical Metropolitan Area (SMA) is used and the definition of SMA is carried into the HIES 2016 to make the numbers comparable across time.

the previous three years (25%) but increases in rent was still the main reason for moving (34%).

Table 2: Urban households are better off, but still poor and vulnerable to poverty

	Rural	Urban	Urban			
			Dhaka CC	Chittagong CC	Other CCs	Other urban areas
Monetary poverty						
Population in poverty	26.7	19.3	9.0	12.1	21.1	22.0
Population in extreme poverty	15.0	8.0	0.5	3.1	8.2	10.0
Non-poor population that are vulnerable to poverty[7]	54.6	50.9	41.9	55.2	55.0	52.2
Middle class[8]	18.7	29.9	49.1	32.7	24.0	25.9
Poverty gap	5.4	4.1	1.3	1.8	3.7	4.9
Non-monetary poverty						
Household head has no education	45.6	32.5	27.6	32.9	25.6	33.8
Household has sanitary toilet	18.9	41.3	63.7	49.3	44.5	35.6
Household has piped water	2.1	35.6	95.5	42.7	11.1	22.4
Household has electricity	68.1	94.2	99.8	98.9	97.2	92.5
Child poverty						
Proportion in school (6-18 years)	82	76.4	77	64.6	83.7	77.2
Moderate to severe stunting	38	31				
Severe stunting	12	10				

Source: Staff calculations using HIES 2016/17 (stunting from Govindaraj et al 2018 using DHS 2014). CC stands for City Corporation. "Other CCs" includes Rajshahi and Khulna City Corporations.

Second, there is considerable spatial disparity within large cities, with some neighborhoods (slums) having levels of welfare equal to or worse than rural areas. Slums have traditionally been outside of the usual sampling frame used for the HIES,

[7] Defined as living above the poverty line but less than twice the official upper poverty line
[8] Defined as living on more than twice the official upper poverty line

but they were included for the first time in the HIES 2016/17. In addition, for the first time an additional sample of 600 households from slums in Dhaka City Corporation (CCs) were interviewed at the same time as the HIES, and provides a poverty estimate for slums that is comparable to the official poverty estimate for Dhaka CCs. Poverty rates in slum neighborhoods are two and a half times higher than in Dhaka CC on average and are at the same level as national poverty rates (Figure 1).

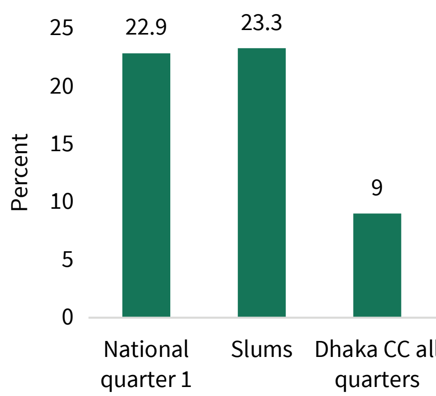
Third, progress is slowing in urban areas. It is the slowdown in poverty reduction in urban Bangladesh that has driven the overall slowdown in national poverty reduction. Poverty has been falling in urban areas from 2000 to 2016, but the rate of poverty reduction has been much slower in urban areas since 2010 and there was a small increase in extreme poverty (0.3 percent points) (Figure 2). The number of extreme poor in urban areas increased from 3 million in 2010 to 3.7 million in 2016. Answering the question of how to increase the pace of progress in reducing poverty in urban areas is essential to increasing the pace of national progress in poverty reduction.

It is worth discussing Bangladesh's urbanization trends and two important changes that took place in the sampling frame for the household survey between the last two rounds of the HIES. First, the 2011 census provided for a new sampling frame for the 2016 HIES. Secondly, slums were included in the urban sampling frame in the 2016 HIES for the first time. Can either of these changes explain the slowdown in urban poverty reduction? The change in sampling frame is unlikely to cause a change as the same definition of urban that was used previously was used to define urban in the HIES. This definition includes counting urban areas that are defined as being part of statistical metropolitan areas as urban.

The inclusion of slums in the sampling frame for the first time could at most only explain part of the slowdown. For the first time a separate survey of slums was conducted in Dhaka CC that allows an estimate of poverty rates in Dhaka CC to be estimated. Poverty rates in slums in Dhaka are about three times higher than poverty rates in non-slum areas. The inclusion of slums thus could increase the urban poverty rate. It is unlikely that there is such a divergence between slums and non-slum areas outside of Dhaka CC, but even assuming there were, the non-slum urban poverty rate would still be quite high at 17.3 percent. Slums were estimated at 2.2 million in 2014 (BBS 2015) compared to a likely urban population of about 45 million that year (assuming the intercensal urban population growth rate continued from 2011 to 2014). This includes some very small slums of less than 5 households that were likely to have been included in the sampling frame of the HIES in previous years. However, if we assume that no slums were included in previous years and that poverty rates in slums are three times the urban average throughout Bangladesh, urban poverty still fell at half the speed as rural poverty and half the speed of urban poverty reduction from 2005 to 2010.

The following sections explore the spatial nature of poverty in Dhaka, and trends in urban poverty reduction and employment. First, section 2 provides a profile of urban poor households. Section 3 examines trends in urban poverty and employment and use decomposition analysis to point to some of the factors underlying the urban slowdown in poverty reduction. Section 4 focuses on poverty in Dhaka given its dominance in the urban spectrum and the evidence that poverty rates are higher than they should be for a city of such economic power. It uses new surveys to examine the spatial nature of poverty in Dhaka highlighting the pockets of extreme poverty that exist in Bangladesh's wealthiest city. In concluding, the paper discusses some of the interventions that may be needed to help them escape poverty.

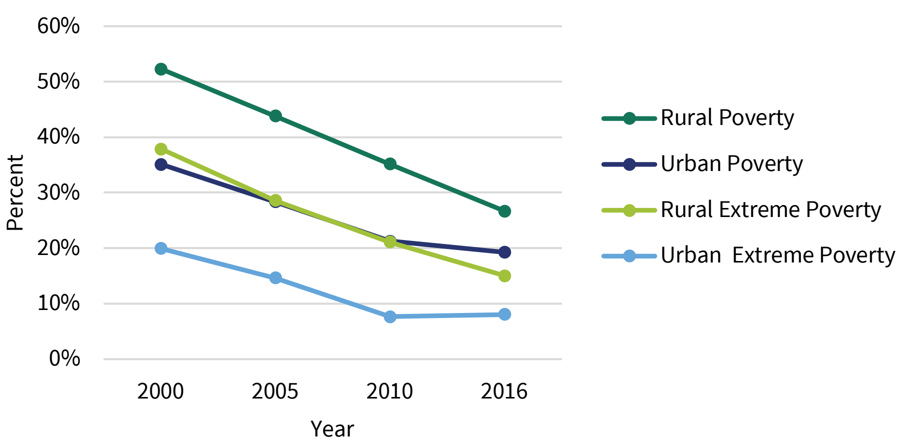
Figure 1. Poverty rates in slums in Dhaka, 2016



Source: Survey of slums and informal settlements (2016), HIES 2016.

Figure 2. The slowdown in national poverty reduction is driven by limited urban progress

Poverty and extreme poverty headcount rates, urban and rural



II. Poverty profile

Just as in rural areas, urban households are more likely to be poor at certain points in their life-cycle. Larger households and higher dependency ratios are associated with higher poverty, although household size and dependency ratios have been decreasing over time (Table 3). Poor urban households are also more likely to have a higher share of adults who are non-earners, increasing the number of people a working adult has to support further. Transfer programs that help households through times when they have young children or elderly members will help address urban poverty.

The age and gender of a household head does not have a large impact on the likelihood the household will be poor. Household heads in urban areas are slightly younger on average than household heads in rural areas (42 years on average compared to 44 years). This may reflect the fact that household independence occurs at a younger age in urban areas, or retirement of some elderly urban residents to rural areas. The age difference between poor and non-poor household heads is significant in urban areas, but it is small. Households in urban areas are no more likely to be headed by a female than other households. Female headship is also becoming more common over time.

About two fifths of household heads of poor households are engaged in the service sector with the other half being split almost evenly between industry (24 percent) and urban agriculture (17 percent). Non-poor households are much more likely to be in services and industry and very few non-poor households are in urban agriculture.

The most important asset of urban households is their education, and this is where the largest differences between poor and non-poor urban households are observed. Land ownership is uncommon among poor urban households, making labor their prime asset. However, education levels are extremely low among the urban poor. Literacy rates among poor urban households have improved across time but are still only 42 percent. More than half of all household heads living in poverty (55 percent) have no education. Only 3 percent of poor household heads had completed secondary education. This was much higher—20 percent—among the non-poor, although still low.

The low rates of school attendance in urban areas does not bode well for the next generation. Table 2 highlighted that the share of 6-18 year old children in school is lower in urban areas than in rural areas. More needs to be done to ensure the next generation of urban workers is skilled. Investing in education and skills for poor households is an important part of tackling urban poverty. This will require ensuring children in urban households are in school, but also working with adults with little or no education to increase their skills.

Urban areas comprise a spectrum, and the characteristics of the urban poor vary with the type of city considered. Rahman (2016) identifies four distinct urban areas: Dhaka, Chittagong, the secondary cities comprised of the other city corporations and “mofussil” urban areas—the smaller towns that fall outside the city corporations. Table 2 indicates that rates of deprivation tend to fall in smaller towns. The characteristics of households also differ with family sizes increasing, educationally attainment falling and service sector employment more common in smaller urban areas.

The nature of vulnerability to poverty is also different for urban households. Households are often small, dependent on one wage and are at risk of losing everything is this job is lost. Housing is insecure for many who lack property rights and the risk of flooding is high, particularly for poorer households who are more likely to live in areas subject to flooding. Sudden increases in food prices are not reflected in immediate increases in wages posing another source of vulnerability to poverty. Crime and violence have also become a source of risk in bigger cities such as Dhaka, affecting in particular the poor and slum areas. A sociological study in Dhaka slums for 2015 shows that child criminalization is high and associated to poverty conditions and bad peers.[9]

Moreover, safety nets are incomplete in urban Bangladesh leaving many without anything to fall back on. One in ten poor households receives remittances, often domestically, but non-poor households are more likely to be remittance receivers. Currently 18 percent of poor households in urban areas receive social transfers (compared to 35 percent in rural areas). Government and NGO support is more important in smaller urban centers. Only 1.1 percent of households in Dhaka CCs receive government or NGO support. This is higher in slums, but still low: 4.6%. Out of those, 50 percent of the support came from NGOs.

[9] Kamruzzaman, Md, and Md Abdul Hakim. “Child Criminalization at slum areas in Dhaka City.” American Journal of Psychology and Cognitive Science 1.4 (2015): 107-111.

Table 3: Poverty profile over time: all urban Bangladesh

	2000				2005				2010				2016			
	Mean non-poor	Mean Poor	(1)	(2)	Mean non-poor	Mean Poor	(1)	(2)	Mean non-poor	Mean Poor	(1)	(2)	Mean non-poor	Mean Poor	(1)	(2)
Demographics																
Household size	4.91	5.58	***	***	4.59	5.12	***	***	4.30	4.86	***	***	3.79	4.59	***	***
Household dependency ratio (3)	0.61	1.03	***	***	0.55	0.97	***	***	0.58	0.88	***	***	0.52	0.87	***	***
Age of household head	45	43	***	**	44	42	**	***	45	43	***	**	42	42		**
Household head is female (%)	9.43%	10.28%			9.27%	8.02%			11.65%	9.32%	*		12.26%	13.62%		
Work and income																
Share of adults who are earners	NA				33.37%	29.40%	***		34.11%	31.86%	**		38.22%	30.48%	***	
Household receives:																
International remittances	9.85%	3.64%	***	***	10.41%	3.09%	***	***	9.20%	1.61%	***	***	4.01%	1.72%	***	***
Domestic remittances	18.69%	14.57%	*	**	17.11%	19.22%		***	7.46%	6.94%		*	11.07%	9.93%		*
Social transfers	NA				3.70%	12.25%	***	*	7.26%	18.51%	***	*	6.55%	17.84%	***	*
Household head in agriculture	8.76%	13.62%	**	R	8.31%	19.45%	***	R	7.00%	16.61%	***	R	7.31%	17.38%	***	R
Household head in industry	20.78%	23.99%			21.72%	27.17%	*		26.29%	33.76%	***		28.03%	24.20%	**	
Household head in services	50.32%	45.58%	*		56.63%	45.49%	***		48.64%	37.92%	***	*	44.46%	39.41%	**	*
Asset ownership and services																
Household owns land	14.13%	7.12%	***	***	31.39%	14.92%	***	**	26.40%	11.98%	***	***	24.19%	11.17%	***	***
Household owns a mobile phone					35.35%	2.49%	***	***	89.10%	56.12%	***	***	96.94%	89.44%	***	***
Household has electricity	90.93%	58.29%	***	***	90.46%	60.52%	***	***	94.66%	71.05%	***	***	96.53%	82.60%	***	***
Household has piped water	41.49%	12.28%	***	***	34.62%	11.18%	***		39.33%	19.86%	***		38.83%	17.83%	***	
Household has Sanitary toilet (%)	39.92%	13.85%	***	***	41.56%	20.94%	***	***	34.31%	14.87%	***	***	44.10%	27.19%	***	***
Household has microcredit									21.23%	34.13%	***		20.73%	30.08%	***	
Human capital																
Member with illness / disability	0.30	0.30			0.26	0.24			0.32	0.27	**		0.27	0.21	**	
Household head is literate	75.06%	29.46%	***		75.67%	36.94%	***	***	71.77%	34.28%	***		69.80%	41.93%	***	
Head has no education	25.29%	71.07%	***	R	24.33%	63.06%	***	R	28.23%	65.72%	***	R	30.79%	58.90%	***	R
Head has some primary	4.40%	5.04%			4.91%	6.28%		**	4.80%	7.50%	**		6.87%	10.40%	***	
Head has completed primary	11.14%	8.43%	**		9.26%	11.09%			10.16%	8.50%			10.81%	10.41%		
Household head has at least some secondary education	59.18%	15.46%	***	**	61.34%	19.58%	***	O	56.56%	17.31%	***	*	51.43%	19.99%	***	*

Source: Own calculations using HIES 2000, 2005, 2010 and 2016

Notes: (1) Stars indicate whether mean for non-poor and poor is significantly different using a Wald test. Significance at the *10%, **5%, and *** 1% level. (2) Significance values are calculated for each year separately including division fixed effects. Significance at the *10%, **5%, and *** 1% level of probit regression correcting for the clustered nature of the errors. (3) Dependency ratio was calculated as the population aged zero to 14 and over the age of 65, to the total population aged 15 to 65. R stands for reference group. O stands for omitted category. Household head sector assigned using hours. The sector shares do not sum to 100 since there are Households head where not assigned to any sector due to lack of information.

High levels of vulnerability affect households' investment strategies as they choose to underinvest in activities where the returns are particularly uncertain. High levels of environmental pollution, inadequate water and sanitation, overcrowding, fear of eviction and bad quality of housing can also negatively affect the health of slum residents. A 2009 study for slums in Dhaka found that the mental well-being of dwellers is correlated with socio-economic factors such as job satisfaction, income generation ability, and population density, as well as contextual factors such as environmental pollution, lower flood risk, better sanitation and quality, sufficiency and durability of the house.[10] Poor health is a source of vulnerability that can lead to negative income shocks due to higher health expenditures or inability to work. In addition, high levels of stress have been shown to affect decision making, making individuals more focused on the present and less focused on longer-run decisions such as investments in education of children ("present bias").

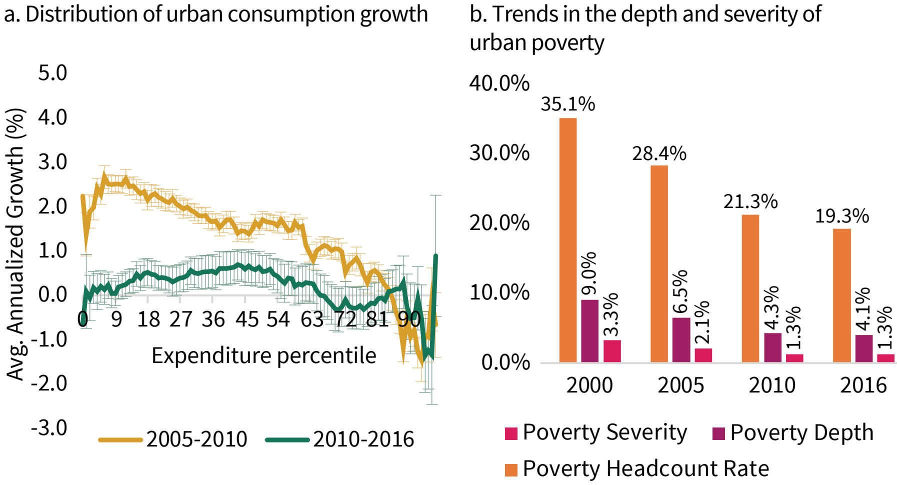
III. Trends in urban poverty

Consumption growth fell dramatically in urban areas across the consumption distribution, causing the slowdown in national poverty reduction. Figure 3a depicts how household consumption grew across the consumption distribution between 2005 and 2010 and between 2010 and 2016. Except for the top 15 percent, consumption growth was much higher from 2005-10 than from 2010-16. The difference in consumption growth was particularly large for the poorest half of the distribution, as this was the part of the distribution that did the best during 2005 to 2010. In addition, from 2010 to 2016 the rate of consumption growth was particularly low for households living under the extreme poverty line (the poorest 8 percent of the urban population) and as a result there was no progress on reducing extreme poverty in urban areas (Figure 2) and the depth and severity of poverty barely decreased (Figure 3b).

Lower poverty reduction in urban areas was not associated with increasing inequality. Standard summary statistics of the inequality of the consumption distribution suggest that inequality fell in urban areas (the Gini fell from 0.33 in 2010 to 0.32 in 2016, the Theil with alpha=1 fell from 0.21 in 2010 to 0.19 in 2016), most likely because of higher consumption growth in the middle of the consumption distribution. However, inequality did not fall as fast as it had previously (Figure 4).

[10] Gruebner, Oliver, et al. "Mental health in the slums of Dhaka-a geoepidemiological study." BMC Public Health 12.1 (2012): 177.

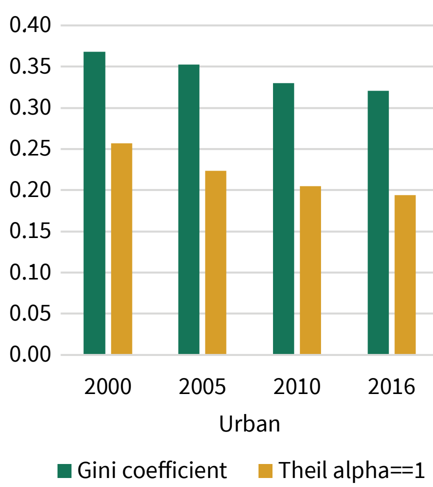
Figure 3. Consumption growth fell dramatically in urban areas, particularly among the poorest



Source: Staff calculations using HIES 2000, 2005, 2010 and 2016.

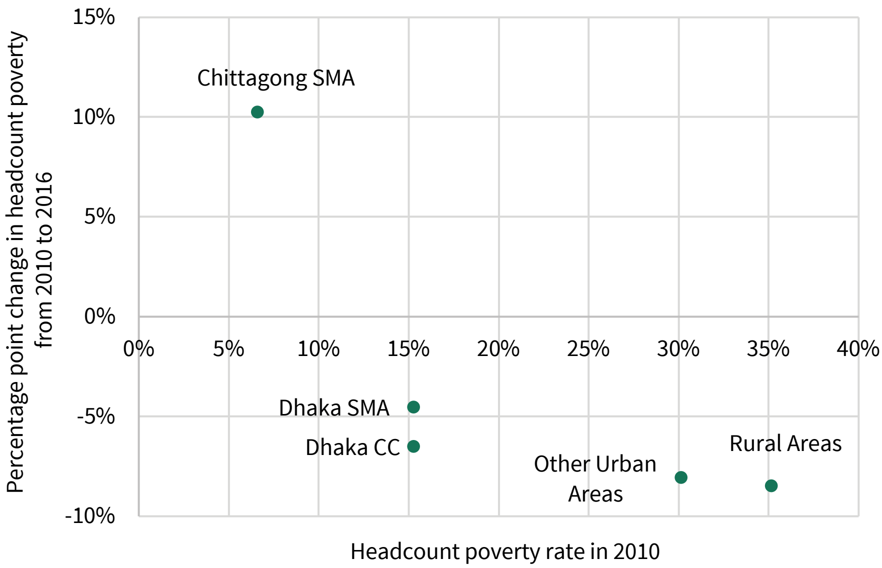
The national urban trends mask a variety of different trends that were experienced across the urban spectrum. The HIES 2016 used different stratum for classifying types of urban areas in 2016 than in 2010 which makes it difficult to follow poverty rates for different cities across time. Reconstructing the old definitions of cities in the HIES 2016 suggests that poverty increased substantially in Chittagong, fell slowly in Dhaka, particularly in Dhaka CC where poverty hardly fell at all and fell at national rates of poverty reduction in other urban centers. However urban areas have high standard errors in HIES, and in particular the surprisingly large jump for Chittagong SMA requires further verification. Increasing the sample size for major cities in the next HIES will be important for generating more accurate city-level poverty estimates.

Figure 4. Trends in urban inequality



Source: Staff calculations using HIES 2000, 2005, 2010 and 2016.

Figure 5. Different trends are observed across the urban spectrum



Source: Staff calculations using HIES 2010 and 2016.
Note: SMA stands for Statistical Metropolitan Area. Dhaka refers to Dhaka SMA (even in 2016, when the SMA was no longer being used, to ensure comparability). Chittagong refers to Chittagong SMA (even in 2016, when the SMA was no longer being used, to ensure comparability). Other urban refers to the rest of urban areas. Dhaka CC refers to Dhaka City Corporation. Given this as not a stratum in 2010 the standard error on this estimate is high. Dhaka CC poverty change in this graph is comparing Dhaka SMA in 2010 with Dhaka CC in 2016. Poverty lines for SMA areas were recalculated entirely after reassigning households accordingly to recover the SMA areas across time, for details refer to Ahmed et al., (2017).

The slower rates of progress in Dhaka mean that although economic density is much higher in Dhaka than in the rest of the country, living standards and poverty rates do not reflect this difference. This is also true for Chittagong. In 2013 Dhaka comprised 10 percent of the population and 36 percent of GDP and Chittagong comprised 3 percent of the population and 11 percent of GDP (Muzzini and Aparicio 2013). On average residents of Dhaka and Chittagong are 3.6-3.7 times more productive than the national average. However, the standard of living does not reflect this higher level of productivity. The poverty rate in Dhaka and Chittagong City Corporations is 9 and 12.1 percent respectively compared with 24.5 percent nationally. Taking a measure that is closer to greater Dhaka, Dhaka SMA[11], suggests a poverty rate of 10.7 percent. Ensuring that the benefits of agglomeration benefit poorer residents in Bangladesh's two largest cities is essential.

[11] Poverty lines for SMA areas were recalculated entirely after reassigning households accordingly to recover the SMA areas across time, for details refer to Ahmed et al., (2017).

Poverty reduction has been very uneven across economic sectors in urban areas, with poverty rates in the urban manufacturing sector falling much faster than in the service sector which saw little change in poverty rates. Households in industry were better off in 2016 than households in industry in 2010, but this was not true for households whose primary employment was in services. Poverty rates were still as high for urban households in the service sector in 2016 as in 2010. Poverty rates were much lower for urban households predominantly engaged in the industrial sector (Table 4 and Figure 7).

This reflects particularly strong progress in construction and garments sectors. Industry and services are broad categories capturing a number of different sub-sectors. Poverty reduction in industry has been concentrated in garments and (to a lesser extent) construction. The service sector is varied, including everything from rickshaw drivers and street vendors to physicians and those employed in the financial sector. Figure 7 shows that different sectors have fared quite differently, poverty reduction in the transport sector was strong, but this comprises a small share of service sector workers. Progress was very slow in commerce and increasing poverty rates were observed in other services.

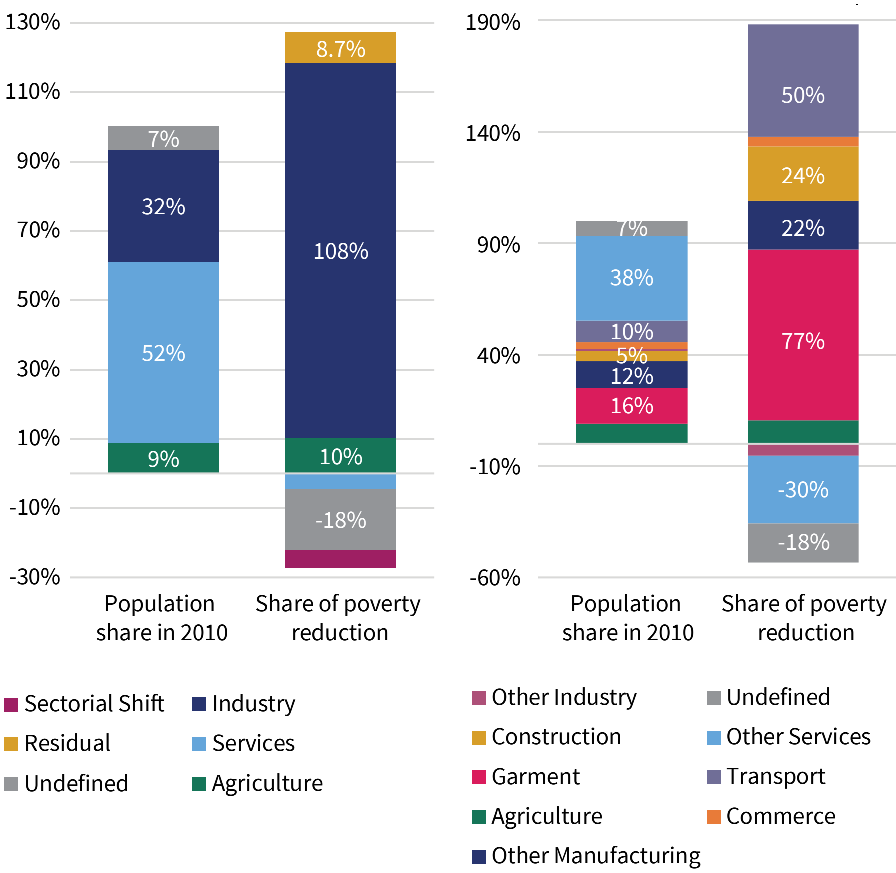
Poverty rates among self-employed in the services sector increased the most, and it was this that set back overall progress. Figure 8 decomposes poverty reduction from 2010 to 2016 based on both the main sector and type of work (wage and daily employment or self-employed). The strongest contributor to overall progress, was poverty reduction among wage and daily workers in industry. This could in part reflect new minimum wage legislation affecting the larger firms of the garment sector. Good progress was also seen for wage and daily workers in services. However, poverty rates increased among the self-employed in the service sector in urban areas.

Table 4: Poverty reduction has been uneven across sectors in urban areas

	2010	2016
Percent of urban population living in poverty with main sector of household work in:		
Industry	26%	19%
Garment Sector	25%	16%
Other Manufacturing	23%	20%
Construction	41%	30%
Services	17%	17%
Agriculture	35%	33%
Not employed or sector data missing	10%	15%

Source: staff calculations using HIES 2010 and 2016. Note: sector is defined by main economic activity using hours, but same findings hold when using income worked and report main sector of household head.

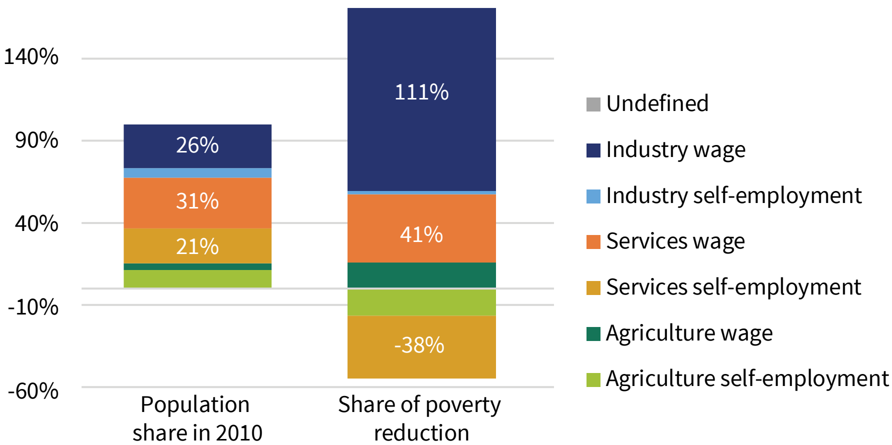
Figure 7. Poverty reduction was fastest among industrial workers in urban areas



Source: Staff calculations using HIES 2010 and 2016. Sector is allocated based on the number of hours worked.

Demographic changes have underpinned some of the reductions in poverty observed. Decomposition analysis highlights significant reductions in household size and the number of children and presents evidence that indicates this may have had an important role in reducing poverty (Hill and Endara 2018). These changes have also been present in urban areas. Household size and dependency ratios have fallen across poor and non-poor households alike (Table 3). Reflecting this, the share of household members under 18 fell from 42 percent in 2000 to 36 percent in 2016. Decomposition analysis suggests that this has been a very important part of explaining reductions in urban poverty rates. It is worth noting that the large contribution of household size and structure to poverty reduction could come in part from the fact that the welfare measure used is total household consumption per

Figure 8. Poverty reduction was fastest among the employed, particularly in industry



Source: Staff calculations using HIES 2010 and 2016. Sector is allocated based on the number of hours worked.

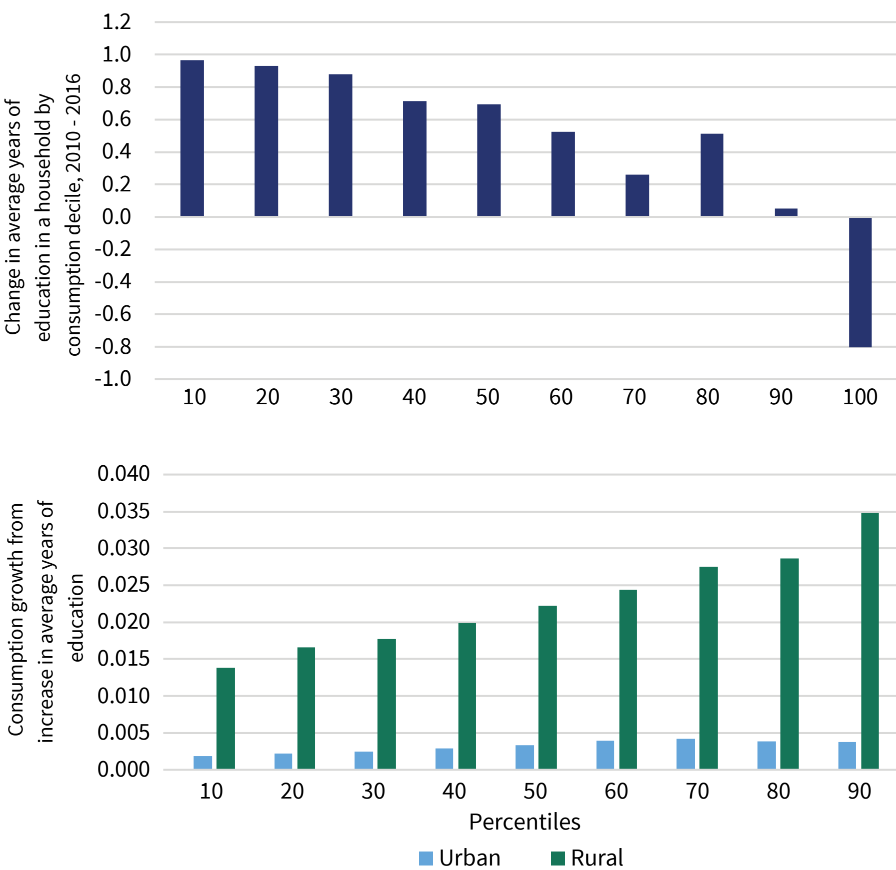
capita. This measure does not account for any scale economies or for the fact that children will consume less than adults. This analysis was repeated using consumption measures that do allow for scale economies and calculate consumption per adult equivalent and even in those cases reductions in household size contributed significantly to poverty reduction, although to a lesser extent.

Unlike in rural areas, increases in individual educational attainment do not appear to have been a strong driver of progress in urban Bangladesh. On average, education levels have increased in urban areas at the bottom of the consumption distribution, but at a slower pace than in rural areas. This could be because of migration, with newer migrants having less education and reducing the overall average growth in education. The absence of migration status in the HIES does not allow this to be assessed. A comparison of the estimated contribution of increases in education to consumption growth at each decile of the consumption distribution for rural and urban areas are presented in Figure 9 and shows that the likely contribution of education to poverty reduction in urban areas has been much lower than in rural areas.[12] **Concerningly, the private returns to education have fallen in urban Bangladesh, particularly in the middle of the consumption distribution.**

[12] These estimates come from Hill and Endara (2018) and estimate the impact of changes in average years of education in the household on consumption growth by assuming that the relationship between education and consumption has remained unchanged during this time and that it is well-estimated by the coefficient on education in a multivariate regression.

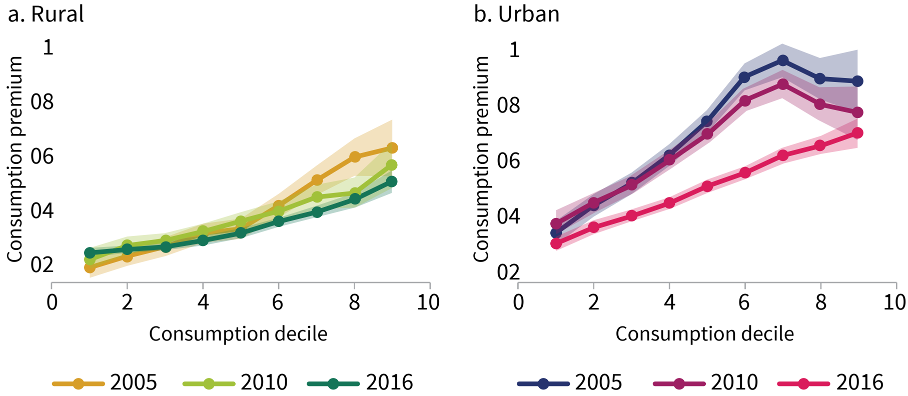
The overall contribution of education to poverty reduction has been lower than that shown in Figure 9 because the private returns to education have not been constant in urban areas but have fallen. Figure 10 shows the conditional correlation between years of education in a household and per capita consumption of the household. It shows that although the returns to education are higher in urban areas than in rural areas, they have fallen significantly since 2010. The fall has been largest in the middle of the consumption distribution where the proportion of households with some secondary education is largest. This is consistent with estimates of the return to education estimated from earnings data in the HIES (Bhatta, Genoni et al 2019) which shows that the returns to primary and secondary education have fallen from 2010 to 2016, and the returns to education estimated in using LFS data (ADB and ILO 2016) which shows higher returns in urban areas than in rural areas.

Figure 9. Progress on education has been modest in urban areas



Source: Staff calculations using HIES 2010 and 2016.

Figure 10. The private return to education appears to have been falling in urban areas: the correlation between the average years of education and per capita consumption (household level) by consumption decile



Source: Staff calculations using HIES 2005, 2010 and 2016.

Although there are important public benefits to education in urban areas, the reduction in private returns is concerning and highlights the challenge of creating an environment in urban areas where investments in human capital are rewarded with more remunerative income earning opportunities. Some of the return to education in urban areas is not captured privately, but instead have public benefits through human capital spillovers that occur as a result of the concentration of human capital in one location (Moretti 2003). Data that can be disaggregated by more urban neighborhoods and cities would allow this to be estimated.[13] However, this public benefit notwithstanding, the reduction in private returns is concerning and indicate that very real constraints to entrepreneurship and labor productivity may have been present in urban areas in Bangladesh in recent years. ADB and ILO also note that returns to education in Bangladesh were already low by international standards in 2013 (ADB and ILO 2016).

IV. Spatial inequality, slums and access to work: Dhaka

Dhaka has been characterized as being disproportionately important in the urban spectrum in Bangladesh (Bird et al 2018). Some of this reflects its strategic

[13] If it were possible to disaggregate the household data by multiple urban cities and neighborhoods it would be possible to estimate the size of this public return to average education levels (see for example Tiwari et al 2018 for Indonesia). However, given the HIES is representative of very few cities and no neighborhoods within cities this is not possible to estimate, but it is important to bear in mind that the aggregate return to investing in education is higher than the individual return.

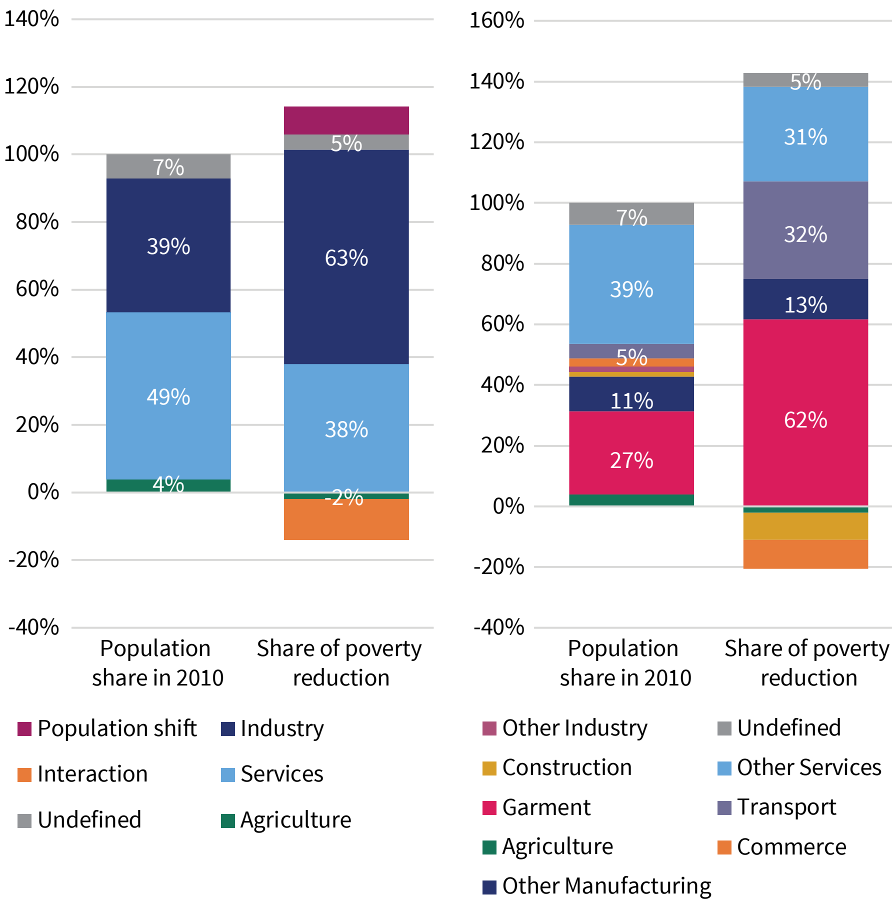
location, its role as Bangladesh's administrative center, and the power of agglomeration economies that have attracted high rates of migration to Dhaka over the last decades. It also reflects the inability of secondary cities to take advantage of their location and agglomeration economies. Using a definition of greater Dhaka, Bird et al (2018) show that 10 percent of population of Bangladesh lives in greater Dhaka, which amounts to 36 percent of Bangladesh's urban population. Given the important role of Dhaka, this section examines poverty in Dhaka more closely, and particularly examines spatial differences in wellbeing across the city. A full treatment of poverty in Dhaka was previously given in World Bank (2007) and another background paper for the Bangladesh Poverty Assessment 2019 focuses specifically on female labor force participation and welfare in Dhaka City Corporation (Kotikula, Hill and Raza 2019).

Dhaka is de facto a city of migrants. Data on migration is not available in the HIES, but data collected by PPRC in 2012 that is representative of Dhaka CCs shows that 80 percent of the city's households are headed by individuals that were not born in Dhaka (Rahman 2016). A staggering 47 percent had migrated in the last 10 years and nearly a quarter (23.8 percent) in the five years prior to the survey. These rates of migration are consistent with those collected in slums in Dhaka that are presented below. The migration rates in slums reported below are higher, but for many migrants this may be the first place of residence in the city. Eight percent of migrants cited work as one of the reasons for migrating to Dhaka.

Industrial growth has contributed to poverty reduction in Dhaka, but service sector growth less so. Bird et al (2018) show that greater Dhaka accounts for 44 percent of the country's formal jobs and that 80 percent of export-oriented garment firms are located in greater Dhaka. Figure 11 shows that growth in industrial wages and incomes has been an important driver of poverty reduction in Dhaka SMA from 2010 to 2016. About a third of the population of Dhaka SMA (39 percent) was engaged in industrial sector in 2010, yet this sector accounted for 63 percent of the poverty reduction that took place from 2010-2016. In contrast the service sector which engages 49 percent of Dhaka's population in 2010, accounted for 38 percent of poverty reduction. However, there has not been much growth in the share of the labor force engaged in industry and this has limited the amount of poverty reduction that has occurred from rapid industrial growth. For those able to get jobs in this sector, progress was good but too few households were benefit.

There is substantial variation in poverty rates within Dhaka which requires using different sources of data to analyze. Existing household survey data does not allow analysis of variation in welfare outcomes within cities, thereby providing

Figure 11. Sectoral sources of poverty reduction in Dhaka SMA



Source: Staff calculations using HIES 2010 and 2016.

no insight on this important reality of urban poverty. To understand the level of spatial inequality within greater Dhaka this paper utilizes four additional sources of information: (i) a slum survey undertaken at the same time as the first quarter of the HIES 2016/17 , (ii) the 2013 Economic Census conducted by BBS which provides information on formal employment opportunities, (iii) a survey of commuting patterns of households funded by JICA as part of the Revised Strategic Transport Plan (DevConsultants Limited 2014), and (iv) poverty and other wellbeing maps generated over the last six years (Annex 1 provides more details on the sources of data used in these maps).

Poverty rates are lower in the center of Dhaka city corporations and along a north-eastern corridor out of the city corporations. The last official poverty map is from 2010/11 and shows that poverty rates are lower in the center, and much higher in the periphery (Figure 12). The southern periphery records a particularly high concentration of poverty. Looking more closely within the North and South Dhaka City Corporations highlights that although there are pockets of poverty in central Dhaka, the same pattern holds of a richer center and poorer periphery (Figure 12a). There is also a corridor of lower poverty going North out of the city and much higher poverty in the North west of the city. A more recent poverty map estimated by Steele et al (2017) suggests the spatial distribution has not changed much in recent years (Figure 12b). This later map uses a different measure of poverty (see Annex 1) so is not directly comparable to the official poverty map, but with some notable exceptions (such as in the North of Dhaka) shows a similar spatial distribution. Maps of income and assets also suggest poorer welfare outcomes in northern Dhaka than the official poverty map (Figures 12c-d).

The correlation across indicators is high suggesting considerable stability in the spatial distribution of economic wealth and deprivation across the city.[14] Further work is needed to compare like indicators across time, but if this pattern holds it highlights that failures of infrastructure and land use planning can be hard to overcome once in place, and points to failures of urban governance of continued disparities in the provision of public goods across the city.

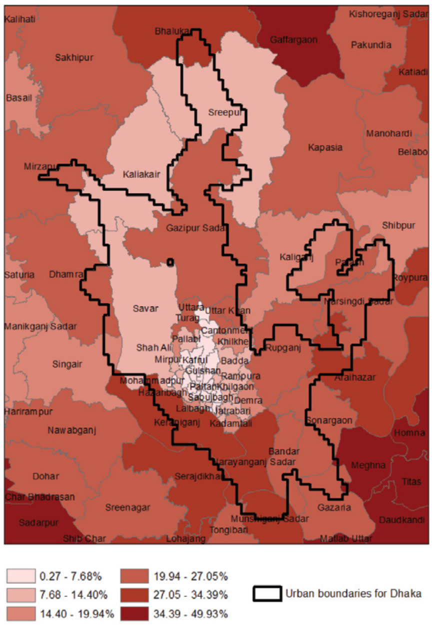
Slums are located throughout the city, but the larger slums are concentrated in the north west. There is considerable variation in what is referred to as a slum. The 2014 census of slum settlements recorded 14,000 slums in urban areas (Bangladesh Bureau of Statistics 2015), many of which were in the Dhaka City Corporations. Three categories of slum were identified in the census of slums and informal settlements. Small slums of 5-10 households are a collection of informal houses on the edge of other neighborhoods rather than forming a neighborhood themselves. Medium-sized slums of 11-200 households and large slums of 200 plus households. Small slums comprise 2% of the estimated population living in slums, medium-sized slums comprise 40 percent of the slum population and 58 percent of the slum population lives in large slums.

The Bangladesh Urban Informal Settlements Baseline Survey (BUISBS) was conducted by the World Bank and BBS in 2016 to provide the first poverty estimates for slums in Dhaka. The main objective of BUISBS was to collect detailed

[14] In the Annex a map of zila level changes in poverty rates for the zilas that greater Dhaka encompasses are shown, this does suggest different trends, but these differences could be spurious, the result of going from a poverty map estimate in 2010 to a survey estimate in 2016. A map of changes in literacy rates suggest the indicated poverty changes may have some underpinning.

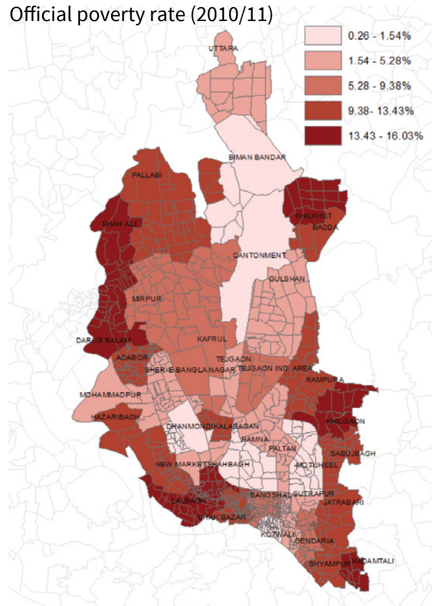
Figure 12. Poverty and wealth maps Dhaka

Poverty map of Greater Dhaka (2010/11)

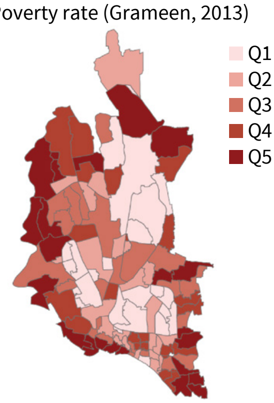


Poverty and income maps of Dhaka City Corporations

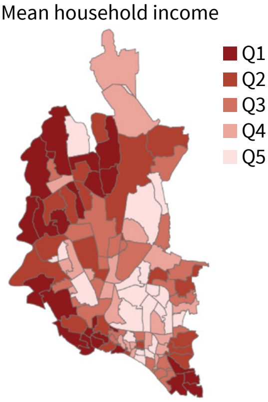
Official poverty rate (2010/11)



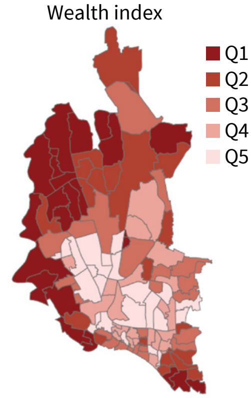
Poverty rate (Grameen, 2013)



Mean household income



Wealth index

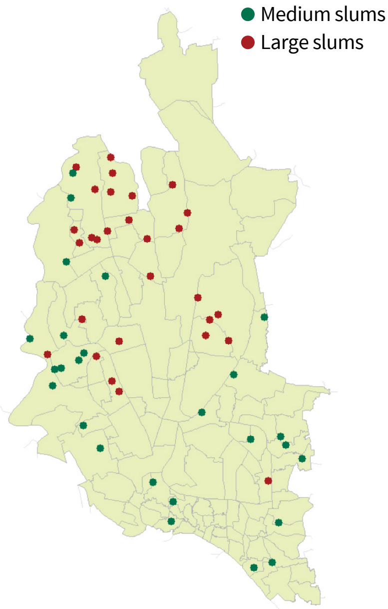


Source: World Bank and Steele et al 2017. Note: for details on the data underpinning these maps see Annex 1.

consumption data from urban slums households following the same methodology used by the Bangladesh Bureau of Statistics (BBS) to collect household consumption data to construct official poverty estimates using the Household Income and Expenditure Survey (HIES). Data on WASH indicators was also collected to inform the World Bank WASH Poverty Diagnostic undertaken in 2017. The BUISBS collected data from a total of 600 urban slum households in the Dhaka City Corporation – 10 slum households from 57 medium and large size slum communities, and 5 slum households from a total of 6 small size slum communities. The sampling frame came from the 2014 BBS Census of Slums and Floating Population.[15] The slums surveyed are indicated in Figure 13.

Slums have much higher levels of monetary poverty, more children out of school, lower levels of access to water and sanitation services. Table 5 compares outcomes for slum households from the BUISBS and non-slum households from Dhaka CC surveyed in HIES 2016. Stunting outcomes are also much higher in slum areas as indicated in Table 6. Malnutrition rates recorded in slums in city corporations are higher than stunting rates in rural areas.

Figure 13. Location of slums in the survey of slums and informal settlements 2016



Source: World Bank staff using BUISBS 2016.

Many poor households in Dhaka locate in slums in order to access affordable housing, trading poor housing conditions, insecurity and overcrowding for affordability. Even then, the cost of living in Dhaka is high for poor households. Households in slums are much more likely to share amenities with other households (Figure 14) and Table 5 indicates that access to water and sanitation services is lower for households in slums. Insecurity of tenure is very high: almost half (49 percent) of slum residents fear eviction.

However, within slums there is a wide variety of housing experiences. In general, rental rates are lower in slums (72 percent) than in Dhaka on average (90 percent). Renters in slums have particularly poor housing conditions. Households that have located in the slum areas of Dhaka City Corporation for longer periods of time have higher tenure security, better housing conditions and lower poverty. This suggests that gradual upgrading of housing is a common strategy for slum

[15] In the BBS 2014 Census of Slums and Floating Population slums are defined as compact settlements of 5 or more households, which generally grow very unsystematically and haphazardly in an unhealthy condition and atmosphere on government and private vacant land. Slums are defined by six characteristics including structure of dwelling, density, ownership of land, water supply and sanitation, lighting and road facilities, and socio-economic conditions.

residents. Housing structure is particularly poor in slums that are located on government land and household heads are more likely to fear eviction in slums on government land. Even tenant units in privately owned land are better than owner-occupied units on government land. Previous studies on slums in Bangladesh emphasize the role of local politicians and leaders who informally govern slums, which powerfully controls the levels of tenure security and access to various resources among slum residents.

Table 5. Poverty, education and WASH in slums and non-slums, Dhaka

	Dhaka CC	Slums
Poverty rate	9.0	23.3
Can write a letter	76	47
Has no schooling	24	42
Some primary schooling	16	41
Some secondary schooling	37	14
Some post-secondary	25	3
Years of education	6.4	3.1
School attendance: overall (6-18 years)	77	57
School attendance: primary (6-10 years)	96	85
School attendance: secondary (11-15 years)	80	60
School attendance: high secondary (16-18 years)	44	20
Percentage of male adults who are earners (18 plus)	86	93
Percentage of female adults who are earners (18 plus)	28	49
Dependency ratio	0.51	0.62
Water is piped into dwelling	96	76
Share a toilet	62	91

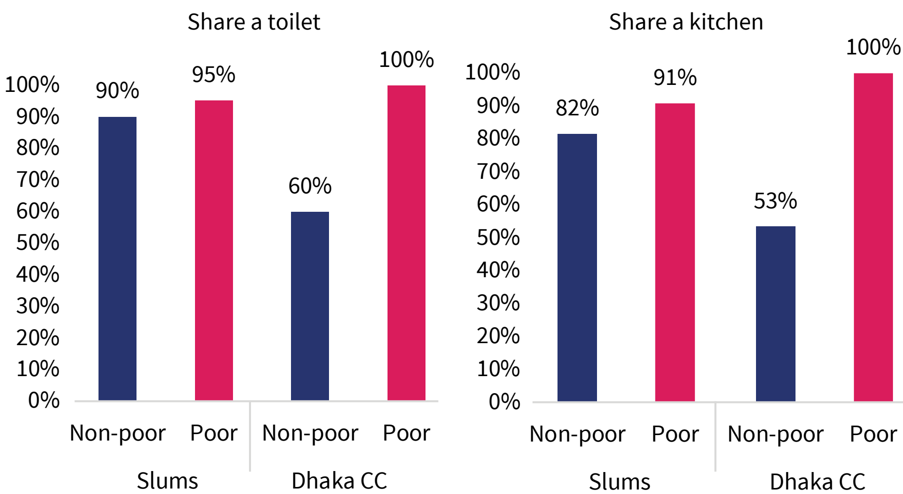
Source: HIES 2016 and BUISBS 2016

Table 6: Average HAZ scores and stunting rates

	City corporations				2014 DHS	
	Full	Slum	Non Slum	Slum-Non slum	Rural	Urban
HAZ scores	–1.69	–1.88	–1.30	–0.58***	–1.60	–1.30
Moderate-to-severe stunting	0.42	0.48	0.31	0.16***	0.38	0.31
Severe stunting	0.20	0.23	0.13	0.10***	0.12	0.10

Source: Ramesh Govindaraj, Dhushyanth Raju, Federica Secci, Sadia Chowdhury and Jean-Jacques Frere. 2018. Health and Nutrition in Urban Bangladesh: Social Determinants and Governance. Note: Estimates are adjusted for sampling weights. Inference is based on robust standard errors, clustered at the neighborhood level. *** denote p<0.01, ** p<0.05, and * p<0.1.

Figure 14. Sharing of amenities is common in slums



Source: HIES 2016 and BUISBS 2016.

Slums combine transient and well-established populations. A third of slum households had been there for year or less, but a quarter (26 percent) have been there for more than 10 years. A key question that emerges when comparing outcomes across slums and non-slums is whether neighborhood effects trap slum residents in poverty or whether slums are stepping stones for households (perhaps new migrants arriving in Dhaka) as they find their way to better living conditions. Whilst panel data is needed to answer this question, survey data on households in slums provides evidence that suggests both might be true.

The most-recent and the most-established residents are the poorest. Households that just got there and households that have been resident in slums for longer than 20 years are the poorest. Poverty rates are 27.8% for those who have been there for a year or less compared to 18.1% for those who have been there for 1 to 20 years. A quarter of those who have been resident in their slum for more than 20 years live in poverty. This relationship does not appear to be driven by life-cycle effects as the difference in poverty rates remains even when controlling for age of household head and household size.

Work was the most-common reason households in slums gave for moving to their current residence. People often move to slums from other slums (39%) and work was their main reason for moving (59%). This was more often the case for female respondents. Those who arrived to the slum most recently are the ones most likely to be working. New arrivals are more likely to be rickshaw drivers, garment sector employees, or employed as day laborers, and they are less likely to be self-employed.

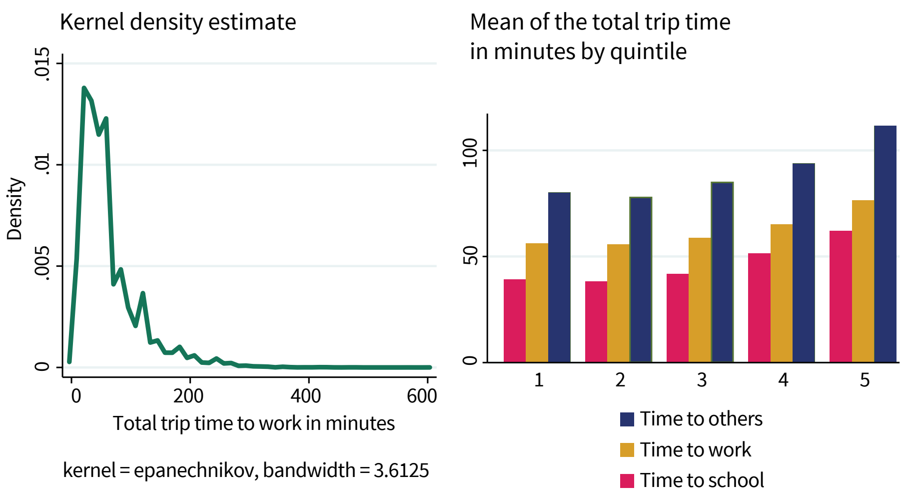
Why is work such a common reason given for residence in a slum? This question is considered by using commuting patterns of 16,000 households in Greater Dhaka. Data on income, employment and transport collected for 16,000 households in Dhaka by JICA in 2014 (RSTP Household Survey) is used to determine how far people travel for work, school and other activities. Data was collected on trips undertaken by households interviewed, and the distribution of the time taken to travel is shown in Figure 15, for all households in total then by income quintile (using self-reporting income per capita. The length of work commutes varies, but the average is 56 minutes for the poorest quintile of households increasing to 77 minutes for the richest quintile. The average is skewed by some very long commutes undertaken and the median commute is 40 minutes for the poorest quintile and 60 minutes for the richest quintile.

The poorest households predominantly commute on foot which means they only have access to jobs within a 4-5km radius from where they live. However, there is considerable variation in the type of transport used by the poorest and richest households. Half of all trip undertaken by the poorest quintile are on foot, whilst this is true of only 16 percent of trips undertaken by the richest quintile (Figure 16). This means that a 40-minute commute for the poorest household gives them access to jobs within a 4-5 km radius from where they live, whilst richer households can access 10-15km. This suggests that poorer households have access to fewer jobs or are required to move residence much more frequently to access work than better off households.

Location of residence thus determines the jobs that are available for a typical poor household. This is seen when comparing employment outcomes in the HIES 2016 with access to jobs in the Economic Census 2013. Figure 17 orders neighborhoods (unions) by the number of garment jobs per capita within 10km. In unions where the number of garment jobs available is low (in the bottom quintile), 26% of households report a member working in the garment industry. In unions where the number of garment available is high (in the top quintile), 61 percent of households report a member working in the garment industry. Without access to garment jobs, the probability of being employed in services is much higher. The probability of being employed in the service sector is twice as high for households in unions with the lowest number of garment jobs per capita compared with households in unions with the highest number of garment jobs per capita.

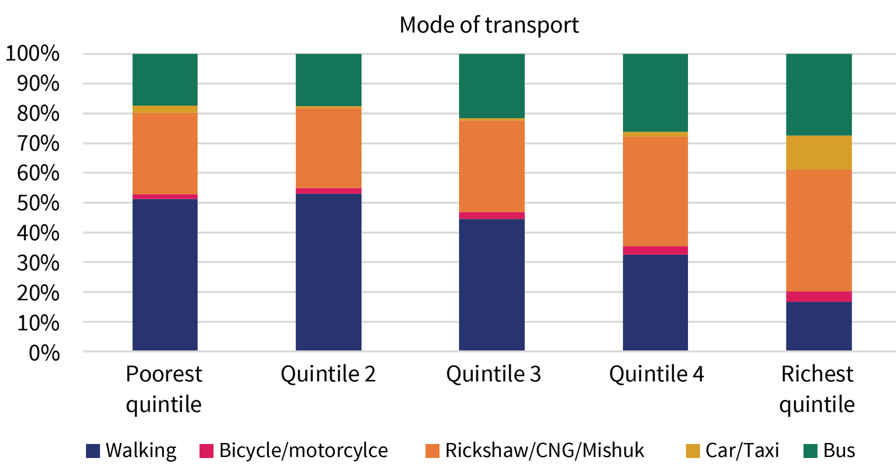
Women's mobility for work is even more constrained. Women are 3-4 times less likely to work than men. Those who do work are more likely to walk, and commute shorter distances compared to men (Figure 18). Their commutes from home are also about an hour earlier than men's. In low-income communities, women are discouraged from taking jobs outside of the neighborhood because of concerns for safety and norms around women's work and mobility (Kotikula, Hill and Raza 2018).

Figure 15. Time spent commuting, by quintile



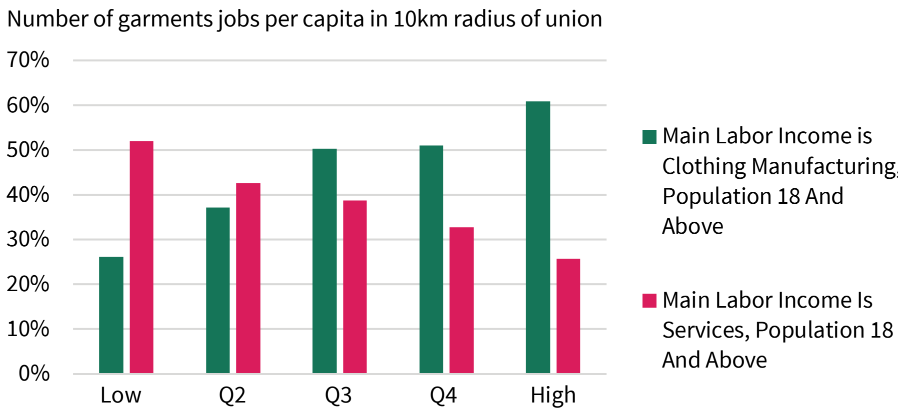
Source: Staff calculations using RSTP Household Survey 2014.

Figure 16. Mode of transport by quintile



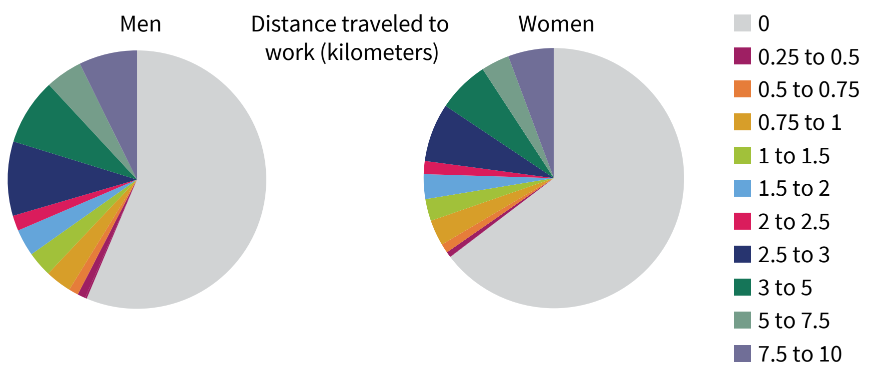
Source: Staff calculations using RSTP Household Survey 2014.

Figure 17. Proximity to garment jobs and employment outcomes



Source: Staff calculations using HIES 2016 and Economic Census 2013.

Figure 18. Women travel less to work



Source: Staff calculations using RSTP Household Survey 2014.

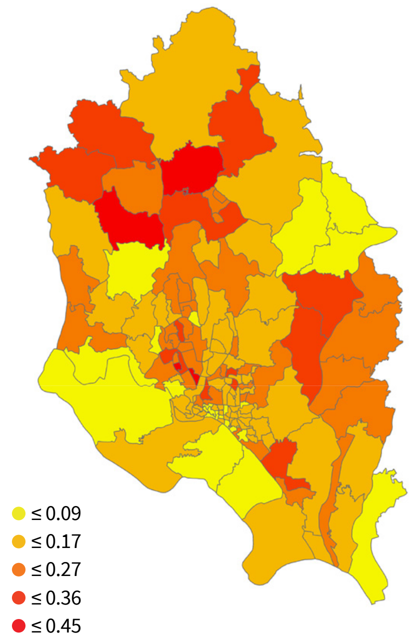
The predominance of female workers in the garment sector means there is a distinct spatial pattern to where women work. Women are much less likely than men to work, but they are more likely to be working in the areas where manufacturing jobs are high (center, north west and south east). Given women commute shorter distances, these are the places where female workers are more likely to live (Figure 19).

Proximity to jobs is an important determinant of the spatial patterns of poverty observed in Dhaka. Section 2 highlighted the importance of sector of employment in explaining poverty trends. So where are the jobs located, particularly in the garment sector that employs low-skill workers and has driven poverty reduction?

Job density is highest in central Dhaka, with higher rates of manufacturing jobs also in the north west and higher rates of high value services along the north-eastern edge of North Dhaka CC. The jobs that are important for raising incomes of low-skilled workers are those in the manufacturing sector in the center and north west (Figures 20 and 21). Job growth has been strongest in the north western periphery of the district (Figure 22).

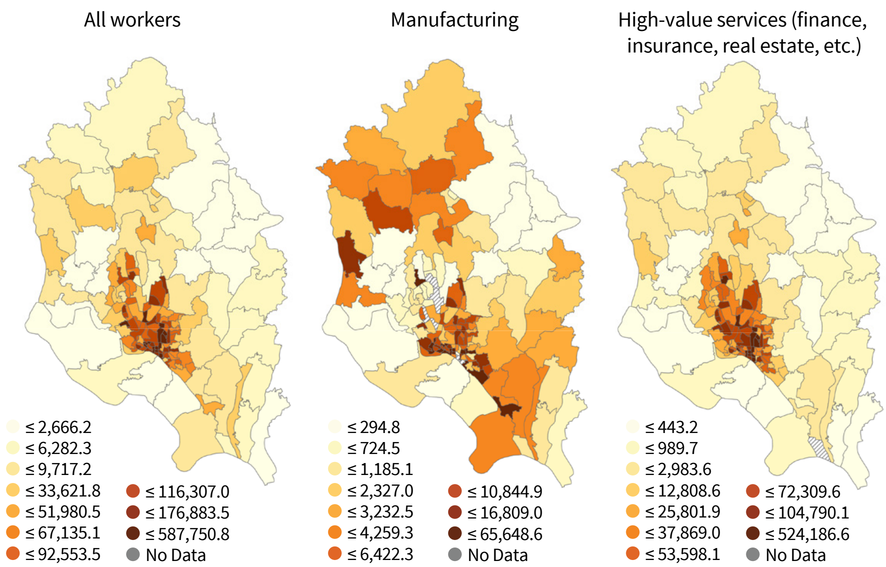
There is some evidence that lack of affordable living options for poor households is more constrained in some parts of the city, particularly the east. Figure 23 indicates the average distance travelled to work by workers in zones across greater Dhaka. The left-hand map shows this for all households

Figure 19. Ratio of Female to Male Employment



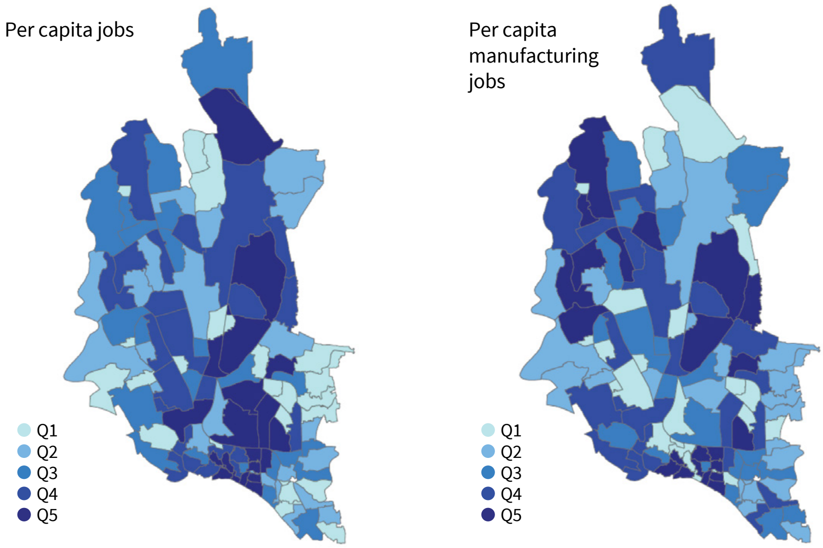
Source: RSTP Household Survey 2014.

Figure 20. Job Density (workers per square kilometer) in greater Dhaka



Source: RSTP Household Survey 2014.

Figure 21. spatial distribution of jobs (wage employment) per capita in Dhaka CCs



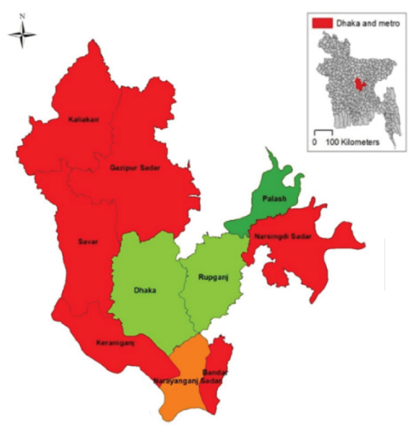
Source: 2013 Economic census, 2010/11 Population and Housing Census.

and the right-hand map shows this for all households in the bottom quintile of reported income. Poor households are more likely to travel further to jobs in the east of Dhaka than the average worker in the east of Dhaka. This may indicate a lack of affordable housing for low-income workers in eastern Dhaka.

Taken together the spatial analysis and the sectoral analysis suggest four priorities: (i) increasing the ability of poor households to commute to the manufacturing jobs in the center and north west of the city that are helping reduce poverty; (ii) encouraging productivity growth in urban informal services across the city, but particularly in areas of the city where access to garment sector jobs are low; (iii)

Figure 22. Growth in large manufacturing firms has been strongest north and west of Dhaka district

Garments and textiles medium and large firms, Percent change 2001 - 2013



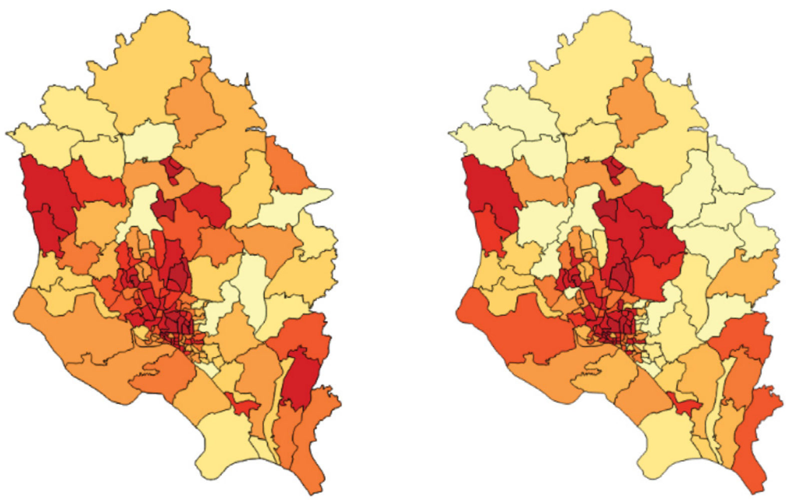
% Change in the number of firms, 2001-13 (Textile/Apparel, Med-Large firms)

Source: Jobs Team Analysis of the Economic Census 2001-2013.

increasing access to affordable housing in the east or affordable and safe public transportation to take low-income workers there; and (iv) improving the quality of services in slums that are located close to employment hubs so that they can provide quality housing at affordable prices to employees.

Figure 23. Average distance travelled to work (km) by place of employment

All workers (left) and poor workers (right)



Source: 2013 Economic census, 2010/11 Population and Housing Census.

V. Conclusion

Making urbanization work for poverty reduction in Bangladesh will require ensuring the agglomeration externalities of larger cities work more in favor of poor households and that the costs of congestion, crime and access to housing and services that the poor face are reduced. Economies of scale and agglomeration effects in large cities often provide poor households with more labor market opportunities and access to services than in rural areas, which strengthens their capacity to generate income. However, life in cities can also entail challenges related to congestion, crime, unemployment, and high living costs and this can constrain and even halt progress for many households.

This chapter has highlighted the need for a much stronger data and evidence base in order to answer the question of how best to do this and to monitor progressive towards inclusive cities.

1. **From the data that is available, some key lessons can be drawn:**

2. **There is a role for urban safety nets for families with young children and elderly:** There is a natural life cycle to poverty in urban areas that can be reduced through well-designed safety nets that target support to households when they most need it: when children are young and for the elderly.
3. **Investments in human capital of the next generation is an urgent priority:** The main asset of poor households is their labor, yet this is often unskilled. There is a need for programs to improve the skills of working-age adults in urban Bangladesh, but there is also a need for addressing the deficiencies in human capital investments in the next generation that are also worryingly prevalent. Too many urban children are out of school and malnutrition rates of young children in urban areas are too high. Addressing this is an urgent priority.
4. **More focus on increasing productivity in the informal service sector needs to complement a drive for job creation in manufacturing**: Access to manufacturing jobs has been an important driver of poverty reduction, but there needs to be more manufacturing jobs created and a greater focus on increasing productivity growth in informal services, particularly in areas of cities where access to manufacturing jobs is low. Policy experimentation on how best to do this is essential for hastening urban poverty reduction.
5. **Better public transportation and better housing close to employment hubs can help reduce stubborn spatial disparities in Dhaka.** Spatial disparities are significant in Dhaka and the cost of getting to work is an important driver of this. Increasing the ability of poor households to commute to the manufacturing jobs in the center and north west of the city that are helping reduce poverty is essential as is increasing access to affordable housing in the east and improving the quality of services in slums that are located close to employment hubs so that they can provide quality housing at affordable prices to employees.

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Annex

Definitions of indicators used in poverty maps

Indicator	Underlying data	Year
Poverty and income indicators		
Poverty rate	Population Census 2011 and HIES 2010/11	2011
Average DHS wealth index	DHS 2011, mobile phone data from 11/13-3/14, and remote sensing data	2011-2014
Probability of being poor (poverty is measured by the progress out of poverty index)	FII nationally representative survey of 6000 Bangladeshi adults undertaken in 2014, mobile phone data from 11/13-3/14, and remote sensing data	2013-2014
Average reported household income (from categories that households selected)	national household surveys conducted by Grameen phone from 11/133/14, mobile phone data from 11/13-3/14, and remote sensing data	2013-2014

CHAPTER VIII.

What Works for Working Women? Understanding Female Labor Force Participation and Incomes in Bangladesh[1]

Executive summary

Labor income growth has been the fundamental driver of poverty reduction in Bangladesh in recent years (Joliffe *et al* 2013; Hill and Genoni 2018). During the last five years urban poverty reduction has stagnated; this has also been a period in which urban female labor force participation (FLFP) rates have fallen. Although the decline in FLFP may be driven in part by changes in the demand for female labor in the ready-made garment (RMG) sector in recent years, it is also possible that it is being driven by supply-side factors—for example, social norms around women's work and travel outside the home, and other factors that affect the cognitive and noncognitive skills of women as they contemplate entering the workforce. As Bangladesh continues to urbanize, understanding the factors that constrain FLFP in urban areas is increasingly important in understanding how to ensure urban income growth and poverty reduction.

This paper explores the factors that constrain women in slums and low-income neighborhoods in Dhaka from engaging in the labor market and supplying their labor to wage earning or self-employment. It uses unique individual-level data

[1] The "What Works for Working Women? Understanding Female Labor Force Participation and Incomes in Urban Bangladesh" report is a joint production of the World Bank's Gender Group and the Poverty Global Practice. It was prepared by a team led by Aphichoke Kotikula, Ruth Hill, and Wameq Azfar Raza. A complete list of acknowledgements appears at the end of the paper.

on labor market participation, time-use, norms, and skills, both cognitive and noncognitive. The data reconfirms well-known patterns associated with FLFP: that is, it is higher in low-income neighborhoods and among women with little education, and younger unmarried women. The paper also highlights the correlation between soft skills and type of work.

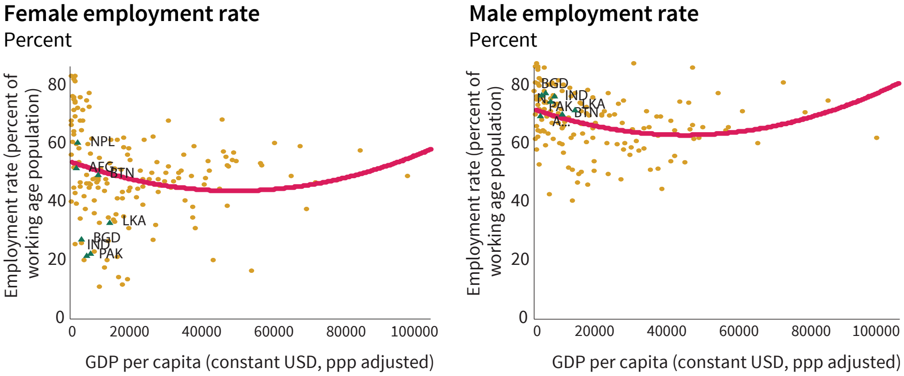
The paper also quantifies the important correlation with the need for childcare, as well as safety in public spaces and in the workplace. Women report the lack of good, affordable childcare to be a constraint, and are often looking after children even while engaging in other activities (something that is impossible to do when working away from home). They are 15 percent less likely to work if they have children less than five years old. The survey revealed that public spaces in Dhaka are often male-dominated spaces, and that this is correlated with women's decisions about employment. Women who do not feel that the environment outside of their home is safe are 10 percent less likely to participate in the labor market. Men spend four times more time outside of their communities than women do. A quarter of women only leave their neighborhood once a month, and one in ten never leaves her community at all. This means that there are many women in Dhaka who live life as if they were in a remote village, despite living in one of the biggest cities in the world.

Finally, the evidence discussed in this report is consistent with the notion that, for many women, working is not deemed desirable, and is something that is not associated with feeling happy about life. Making public spaces more female-friendly; travel safer for women; and female work more socially acceptable may be important in order to increase the ability of women to grow their families' incomes happily, and free of fear.

I. Introduction

Bangladesh has made great strides in female labor force participation (FLFP): it now outperforms neighbors such as India and Pakistan. But the national rate of 36 percent is still considered too low. This rate is still 46 percentage points behind the rate for male counterparts in Bangladesh (82 percent) (BBS 2018). Moreover, the FLFP rate is low compared to countries such as Cambodia (81 percent), Indonesia (51 percent), and Vietnam (73 percent) (World Bank WDI 2019). In fact, the trend for the women's employment rate in Bangladesh is unusually low when comparing it with other countries with a similar income level (Figure 1). The men's employment rate, however, is on par with other countries (World Bank 2018).

Figure 1. U-Shape Curves of Female and Male Employment Rates



Source: South Asia Economic Focus (Spring 2018).

Recently, FLFP rates in Bangladesh have fallen as a result of lower rates in urban settings, and an urbanizing population. In 2017 FLFP was 31 percent in urban areas, compared to 39 percent in rural areas (BBS 2018). However, the FLFP in urban areas has been declining in recent years, from 34.5 percent in 2010, to 33 percent in 2013, and most recently to 31 percent in 2016 and 2017 (BBS 2018). This is a troubling trend, as Bangladesh is urbanizing. And while 37 percent of the country's population currently lives in urban areas, the urban population is projected to reach 112 million, or 58 percent of the total population, by 2050 (UNDESA 2018). In effect, this suggests that almost all future population growth in Bangladesh will be in urban areas.

Lower rates of urban FLFP and gender differences in returns to labor are constraining urban income growth and poverty reduction. Although on average urban areas are less poor than rural areas, the urban poverty rates are still quite high, and there are some urban neighborhoods where the level of poverty is very high. The number of slums has increased substantially, from 2,991 in 1997 to 13,938 in 2014, and the population in slums has increased at an annual rate of 12 percent—from 0.7 million in 1997 to 2.2 million in 2014—nearly double the population growth in urban areas as a whole (BBS 2014).

The main driver of poverty reduction in Bangladesh has been income from labor; as such there is a need to better understand the constraints to FLFP and income growth in urban areas, particularly in low-income areas. The recent literature on urban FLFP, which will be reviewed in Section 2 of this paper, suggests that FLFP in urban areas cannot be fully explained by the same determinants that have been important in the past, such as level of educational attainment and marital status.

There is a need to better understand FLFP in urban areas, and to do so using data that better captures some of the other factors that may be constraining women's participation in the workforce.

Female employment in urban areas is central to the narrative of Bangladesh's economic growth. Large-scale job creation in the manufacturing sector, mostly in urban areas, has been contributing to employment growth (2.4 percent annually from 2003 to 2016), with wage employment growing by 5.7 percent per year. This expansion is also a factor in the growth in female employment, bringing millions of women into the labor force (Farole and Cho 2017). The 2017 Bangladesh Jobs Diagnostics also suggests that declining urban FLFP could be caused by a lower demand for female labor associated with the rapid employment slowdown in the RMG and textile sectors—the largest source of urban female employment—since 2010 (Farole and Cho 2017). However, lower FLFP rates could also be driven by changes in supply-side factors such as changes in skills, demographics, or social norms around female work.

This study attempts to fill in the data and knowledge gaps on women's economic empowerment in urban areas. While an array of national-level datasets has collected a wide spectrum of information, they rarely comprise all of the information needed to study the drivers of FLFP. Quantitative data on urban labor market dynamics in Bangladesh, especially for women, is still quite limited. For instance, the time spent by women on household work and caregiving is an important deterrent to economic activity. This information, however, is collected only through a survey that is separate from the Household Income and Expenditure Survey (HIES) and the Labor Force Survey (LFS), which collect detailed employment-related information. Additional pertinent information that relates to labor force participation, such as information about skills, urban migration, employment patterns and history, perception of social capital, and safety, transportation, and service utilization are collected through a variety of instruments.

The data gap is being filled by the primary data collection of a specialized survey called Dhaka low Income area GeNder, Inclusion, and povertY (or DIGNITY) survey; it is representative of poor urban areas and is specifically designed to address these limitations. DIGNITY collected information from 1,300 urban households living in poor areas of Dhaka in 2018 on a range of issues that affect FLFP as identified through the literature. These range from household composition and demographic characteristics to socioeconomic characteristics such as detailed employment history and income (including locational data and travel details), and from technical and educational attributes to issues of time use, migration history, and attitudes and perceptions.

The existing literature on known constraints to FLFP in Bangladesh will be presented in Section 2, with subsections related to various subtopics. Section 3 discusses the main data used for this paper, the DIGNITY survey, and describes its sampling methodology and key summary statistics. Section 4 presents a descriptive analysis of FLFP, along with discussions of key constraints and enabling factors for women's employment in urban areas. Finally, Section 5 presents our results, drawn from a multivariate analysis of women's work in Dhaka.

II. Literature review

The goal of this paper is to present the factors that contribute to FLFP in low-income areas of urban centers in Bangladesh. Qualitative studies suggest that working women in urban areas tend to exhibit greater measures of empowerment, such as managing household expenditures, having access to savings, and freedom of movement (Kabeer 2017). As extreme poverty is an important factor in explaining some of the rise in female employment in Bangladesh, one may expect a higher level of FLFP in low-income areas than the rest of Dhaka city (Bridges, Lawson, and Begum 2011).

The literature on female employment in low-income areas of Dhaka tends to rely on qualitative studies. Salway, Jesmin, and Rahman (2005) compared married women in Dhaka who were engaged in wage employment with those who had never worked. Drawing on fieldwork in four Dhaka slums, Banks (2013) revealed a complex balance involved in meeting economic and social priorities. Her work suggests that female employment is seen by men as a short-term coping strategy to deal with the high cost of living in urban areas, while women, particularly women working in industries like the garment sector, recognize that their work can contribute to the household income. Still, women need to balance work and domestic responsibilities. Reviewing the existing literature about constraints to—and enabling factors for—women's work in Bangladesh can help guide analysis. The new World Bank publication *Voices to Choices: Bangladesh's Journey in Women's Economic Empowerment* analyzes multiple data sources to understand recent trends and patterns in women's employment. This book identifies the relationships between FLFP and key drivers such as level of educational attainment, marriage, presence of children, and use of time.

Marriage has been a known correlate of FLFP in Bangladesh (Joliffe *et al* 2013; Mahmud and Bidisha 2018). A recent analysis of the Labor Force Survey (LFS) data in *Voices to Choices* reveals that marriage penalizes only urban women's participation in the labor markets, whereas it is associated with *higher* labor force participation (LFP) probabilities for urban men, and for both women and men in rural areas. In 2016, the probability of LFP was 6.4 percentage points lower for urban married women than for urban unmarried women, whereas marriage was associated with a 14-percentage-point premium for urban men. Unlike rural women, who often work in the agricultural sector, urban women's work may more often require leaving the home, which is more likely to result in familial disapproval. Arranging childcare may also be easier in rural settings due to a network of family members who can help care for the children. *Voices to Choices* also show that married women have increasingly been entering the labor markets. While FLFP of married women has shifted upward across all age groups, the highest increase has been among married women in their 30s and 40s. "The LFP rate of married women in the cohort born between 1968 and 1977 (who were thus 26–35 years old in 2003, and 39–48 years old in 2016) increased from 26 percent in 2003 to 42 percent in 2016" (Solotaroff *et al* 2019, p. 32). This shift may suggest an improvement in attitudes of husbands and mothers-in-law toward women's LFP as well as a reduction in childcare duties due to fertility decline. Moreover, having older family members living in the household appears to be positively correlated with FLFP.

The presence of children in the household is significantly related to the LFP probabilities of both men and women, though the relationship varies by the child's age. A cross-country study suggests that having a child can reduce LFP by about two years during a woman's reproductive life (Bloom and Finely 2009). Women with children ages 0–5 in the household are significantly less likely to (re)join the labor force than women without young children. (For men the relationship is not significant). However, both women and men are more likely to be in labor markets if there are children ages 6–10 in the household (compared to women and men without children this age). The negative association between the likelihood that women will be working when children ages 0–5 are present is almost three times greater for urban than for rural women. This finding may suggest that access to childcare services is a crucial factor in women's LFP (Solotaroff *et al* 2019).

The relationship between educational level and LFP in Bangladesh appears to follow a U-shaped curve pattern, according to the analysis of the 2016 LFS in *Voices to Choices*. LFP is high among those without education and those with only a primary education; and it falls with an increasing educational level, with a trough observed at the level of secondary school certificate. On the other hand, the LFP of women with higher education degrees are highest compared to the other groups. Rahman and Islam (2013) also finds that, while the relationship between casual and daily employment and education is negative and significant, the opposite is true for salaried, self, and family employment.

Time-use data analysis shows that traditional gender roles still impose a disproportionate burden of care work on Bangladeshi women. According to the analysis of the Bangladesh Time Use Survey data in *Voices to Choices*, urban women spent about six hours per day on household domestic tasks and unpaid care work, while urban men spent only one hour per day on these activities. Even among working women in urban areas, whose number of hours of work per day is only slightly less than men's (7 vs. 8.6 hours), they still spend about 3 hours a day on domestic tasks and unpaid care work. This data shows that care work may present an even greater obstacle for urban women than for rural women, and that access to child-care services may be most urgently needed in order to bring more urban women into the workforce.

Occupational sex-segregation is another constraint on women's access to jobs. In labor markets across the world, a widespread phenomenon is an imbalance in the types of employment in which men and women engage, and consequently the occurrence of male-dominated and female-dominated sectors or jobs. The concept of "women's work" in Bangladesh is often dictated by gender norms that affect how people form their perceptions about what is appropriate for men and for women. *Voices to Choices* suggests that traditionally low-paid workers such as housecleaners and maids are predominantly female. However, the 2016 LFS data shows an encouraging trend that many manufacturing and higher-skill service occupations showed a high share of female workers.[2] The qualitative data from low-income areas in urban centers provides additional nuance. Women are not only employed in garment factories, but also in PVC tape, small manufacturing and dyeing factories, and bakeries.

Another positive trend is the dwindling of occupational segregation by gender, and the expansion of "mixed gender" industries[3] in the country. As women began to enter male-dominated occupations, the number of mixed-gender industries expanded substantially—from 16 percent in 2003 to 75 percent in 2016. The percentage of women working in female-dominated industries has also fallen,

[2] For example, women account for 39 percent of health professionals and 45 percent of manufacturing workers in food processing, wood working, and garment.

[3] In this context, mixed industries are defined as those whose share of female workers is between 40 and 60 percent.

from 15 percent in 2003 to only 4 percent in 2016. The expanded presence of mixed-gender employment could be a sign that Bangladesh's labor market is now malleable enough to accept women into a wide variety of occupations, and that there is an increased social acceptability of women working with men. In this regard, a study of female engineers in Bangladesh suggests that organizations can create their own organizational culture and practices that are welcoming for female staff, despite the prevailing social norms (Hossain and Kusakabe 2005).

Other constraints to FLFP identified through the literature and qualitative research include the risks of gender-based violence (GBV), restricted mobility, gender norms, and socioemotional skills gaps. However, quantitative data are rarely available. Restricted mobility and the practice of *purdah*[4] are conjectured to prevent women from seeking lucrative jobs outside the home (Kabeer 2013; Ahmed and Sen 2018; Asadullah and Wahhaj 2019). While household surveys such as the LFS and the HIES do not contain such information, the location of work data is telling. In 2016, 62 percent of working women worked from home, whereas almost all men were working outside their homes. Although home-based work may seem like a solution to narrowing gender gaps in LFP, it hurts women financially, as it is associated with low-paid (or often unpaid) and low-skill work. However, the LFS does not have data about mobility restriction. GBV also continues to inhibit women's employment outside the home, as women are likely to face a double risk of harassment—that is, harassment while traveling to and from work as well as in the workplace (Solotaroff *et al* 2019). The DIGNITY survey was designed specifically to collect data about constraints to women's employment; and this paper will attempt to fill in the knowledge gaps by analyzing the data DIGNITY gathered.

III. Data: sampling and summary of statistics

3.1 Sampling methodology

The DIGNITY (Dhaka low Income area GeNder, Inclusion and poverTY) survey was designed to shed light on poverty, economic empowerment, and livelihood in urban areas of Bangladesh. A broad array of information was collected on issues related to women's economic empowerment, ranging from demographic and socioeconomic characteristics to detailed work history, time use, and attitudes about, and perceptions of, work. The key feature of the DIGNITY survey is that it collected economic data directly from the main household members, generally

[4] The concept of *purdah*, or female seclusion practice, will be explained in detail in section 4.6.

the *main couples*, unlike traditional surveys which only interviewed the heads of households (who tend to be men in most cases), and thus failed to gather valuable information from the female population.

The survey instrument has two main modules: the traditional household module (in which the head of household is interviewed on basic information about the household), and the individual module, in which two respondents from each household are interviewed individually. In the second module, two persons—one male and one female—from each household, usually the main couple, are selected for the interview. The survey team deployed one male and one female interviewer for each household, so that the gender of the interviewers matched that of the respondents.

The DIGNITY survey is representative of low-income areas and slums of the Dhaka City Corporations (North and South, from here on referred to as Dhaka CCs), and an additional low-income site from the Greater Dhaka Statistical Metropolitan Area (SMA), following a two-stage stratification design. In the first stage primary sampling units (PSUs) were selected using probability proportional to size (PPS). In the second stage, all of the households in the PSU were listed, and 20 households were selected for interviewing. Strata were used in both stages.

First Stage: Selection of the PSUs

Low-income PSUs were defined as nonslum census enumeration areas (EAs), in which the small-sample area estimate of the poverty rate is higher than 8 percent (using the 2011 Bangladesh Poverty Map). The sampling frame for these low-income areas in the Dhaka CCs and Greater Dhaka is based on the population census of 2011. For the Dhaka CCs, all low-income census EAs formed the sampling frame. In the Greater Dhaka area, the frame was formed by all low-income census EAs in specific *thanas*[5] where World Bank project locations were located.

Three strata were used for sampling the low-income EAs. These strata were defined based on the poverty head-count ratios. The first stratum encompasses EAs with a poverty headcount ratio between 8 and 10 percent; the second stratum between 11 and 14 percent; and the third stratum, those exceeding 15 percent. The number of EAs selected from each stratum in the Dhaka CCs and the greater Dhaka areas is shown in Table 1.

[5] Thana, or *Upazila,* is an administrative unit in Bangladesh, functioning as a subunit of a district.

Slums were defined as informal settlements that were listed in the Bangladesh Bureau of Statistics' slum census from 2013/14. This census was used as sampling frame of the slum areas. Only slums in the Dhaka City Corporations are included. Again, three strata were used to sample the slums. This time the strata were based on the size of the slums. The first stratum comprises slums of 50 to 75 households; the second 76 to 99 households; and the third, more than 100 households. Small slums with fewer than 50 households were not included in the sampling frame. Very small slums were included in the low-income neighborhood selection if they are in a low-income area. The number of slums selected from each stratum is shown in the bottom panel of Table 1.

Table 1. Sample Allocation

Strata	Number of EAs	Selection criteria (poverty headcount ratio or number of households)	Criterion 1 (male and female working-age member)	Criterion 2 (only female working- age member)	Criterion 3 (only male working- age member)
Low-income areas in the Dhaka CCs					
1	20	8%-10%	328	57	15
2	18	11%-14%	181	33	7
3	5	15% +	82	15	4
Low-income area in greater Dhaka					
3	5	15% +	180	31	9
Slums in the Dhaka CCs					
1	3	50 to 75	52	6	2
2	8	76 to 99	137	22	1
3	7	100+	116	21	3

Altogether, the DIGNITY survey collected data from 67 PSUs. Locations of the PSUs are shown in Figure 1.

Second Stage: Selection of the Households

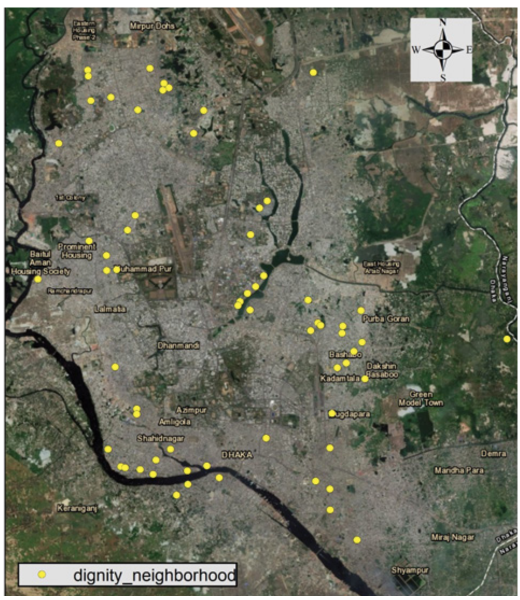
In each sampled PSU a complete listing of households was done to form the frame for the second stage of sampling: the selection of households. When the number of households in a PSU was very large, smaller sections of the neighborhood were identified, and one section was randomly selected to be listed. The listing data collected information on the demographics of the household to determine whether a household fell into one of the three categories that were used to stratify the household sample:

i. households with both working-age male and female members;
ii. households with only a working-age female;
iii. households with only a working-age male.

Households were selected from each stratum with the predetermined ratio of 16:3:1. In some cases there were not enough households in categories (ii) and (iii) to stick to this ratio; in this case all of the households in the category were sampled, and additional households were selected from the first category to bring the total number of households sampled in the PSU to 20.

The total sample consists of 1,300 households (2,378 individuals). Table 1 provides the breakdown of households into each stratum.

Figure 2. Locations of PSUs



Source: Authors' rendition, based on the DIGNITY data.

3.2 Demographic characteristics of sample households

Summary statistics of the demographic characteristics of the sample are presented in Table 2. The respondents are equally distributed across genders as a result of the fact that most households have both men and women of working age, and in these cases one man and one woman were interviewed. The average age of women in our sample is 32.8 years old, while the men on average are

37.1 years old. The majority of respondents (91 percent) report being married, although the proportion is marginally higher among women (92 percent) than among men (90 percent). The average age at marriage is 18.9 years, but this masks a wide variation across genders: the average age of marriage for men is 22.3 years, while for women it is only 15.8 years. The average household size is four people. In terms of education, men and women have both completed an average of 3.5 years of schooling. Ten percent of men had attended technical and vocational education and training (TVET) compared to 7 percent of women.

Table 2 **Demographic Characteristics of the Sample**

	Full Sample		Male		Female		Test (Male – Female)
	Mean	SD	Mean	SD	Mean	SD	
Gender (1=male; 0=female)	0.49	0.50					
Age of respondent (completed years)	34.95	11.63	37.15	11.83	32.84	11.04	***
Respondent is head of household (1/0)	0.50	0.50	0.90	0.30	0.12	0.33	***
Marital status							
Never married (1/0)	0.04	0.20	0.08	0.27	0.01	0.09	***
Married (1/0)	0.91	0.29	0.92	0.28	0.90	0.31	***
Widow/widower (1/0)	0.03	0.18	0.00	0.05	0.06	0.24	*
Divorced (1/0)	0.00	0.06	0.00	0.03	0.01	0.08	***
Separated/deserted (1/0)	0.01	0.12	0.00	0.02	0.03	0.17	**
Age at marriage (continuous years)	18.85	4.68	22.29	4.03	15.78	2.65	***
Household size	3.94	1.55	3.97	1.54	3.91	1.55	
Years of completed education	3.55	3.70	3.58	3.84	3.52	3.55	
Respondent received TVET (1/0)	0.08	0.28	0.10	0.30	0.07	0.26	**
N	2378		1117		1259		

Notes: Table shows individual level weighted means of the sample in the study. * p<0.1; ** p<0.05; *** p<0.01. TVET refers to technical and vocational education and training.

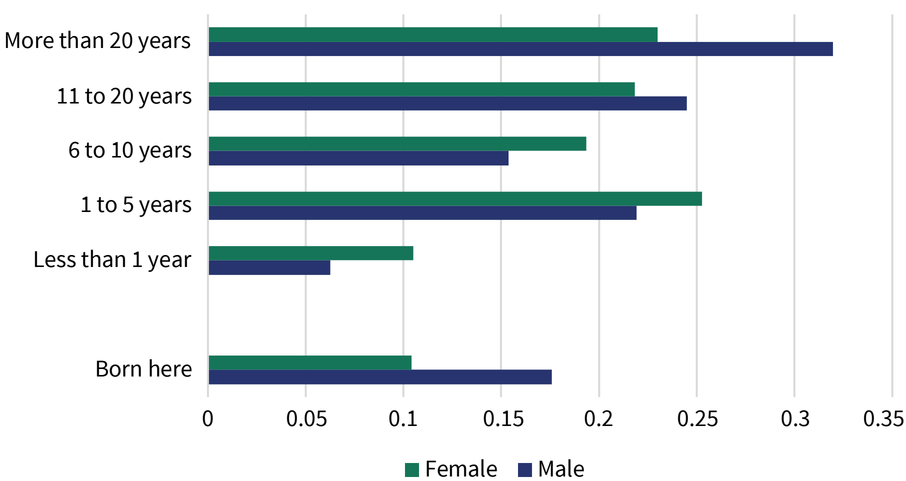
Because migration–particularly rural to urban migration—is synonymous with urbanization in Bangladesh, understanding the migration profile of people in low-income communities is crucial. The DIGNITY data confirm the hypothesis that the majority of the people in the survey are migrants. About 74 percent are from other places, while only 26 percent are from Dhaka *zilla* (or district, including those born in the community) (see Table 3). Migration to urban areas is mostly economically motivated; about seven in ten migrants moved to the city to find work. The migrant ratio among women is slightly higher than among men, reflecting the general trend that women tend to move due to marriage. About 24 percent of female respondents moved to their current community because of marriage, compared to about 1 percent of men. On the other hand, about 75 percent of men reported moving to the community to find work, compared to about 50 percent of the women. In any case, the ratio of adult women who have moved because of work is much higher than the urban average of only 14 percent according to the 2016 LFS.

Table 3 Migration History

	Male		Female		Test (Male - Female)
	Mean	Standard Deviation	Mean	Standard Deviation	
Origin					
From Dhaka Zilla (1/0)	0.28	0.45	0.25	0.43	
From elsewhere (1/0)	0.72	0.45	0.75	0.43	
Primary reason for moving					
Work (1/0)	0.73	0.44	0.47	0.50	***
Marriage (1/0)	0.01	0.09	0.24	0.43	***
With or for family (1/0)	0.09	0.29	0.16	0.37	***
N	1117		1261		

Note: Table shows weighted means at the household level. * p<0.1; ** p<0.05; *** p<0.01.

Figure 3. Duration of Time in Current Community



Source: Authors' rendition, based on the DIGNITY data.

The respondents' duration of stay in the community is distributed across the time spectrum (Figure 3). While about 30 percent have lived the community for five years or less, an equal amount have lived in the community for more than 20 years. Moreover, about 16 percent of the sample were born in the community. The data suggests that these communities have been established with dynamic population movement.

3.3 Comparing DIGNITY to other data

An initial comparison suggests that the population interviewed for the DIGNITY survey is largely comparable to those found in the HIES for household composition and other demographic characteristics (household size, gender ratio, and the adult-to-child ratio) (see Table 4). Understandably, we begin to note divergent trends between the two samples when it comes to housing and socioeconomic characteristics. This is likely driven by the fact that the DIGNITY sample is exclusively focused on poorer areas of Dhaka, and therefore is able to capture a focused range of representative households. For instance, the households from the DIGNITY survey are markedly worse off when it comes to the earner-to-nonearner ratio (the dependency ratio) and completed years of education.

Table 4 Comparison of DIGNITY Sample of National Data

	HIES 2016		DIGNITY Survey	
	Dhaka CC	Dhaka SMA	Dhaka CC	Dhaka SMA
Demographic characteristics				
Household size	3.7	3.7	3.9	4.1
Gender Ratio (Male: Female)	49%	49%	49%	49%
Proportion of adults in the household (>15 years)	72%	72%	74%	72%
Proportion of married adults	93%	92%	91%	90%
Housing characteristics				
Roof material (brick/cement)	47%	21%	24%	38%
Electricity connection	100%	96%	100%	100%
Use of improved source of water	100%	97%	100%	68%
Socioeconomic status and job				
Dependency ratio	39%	36%	53%	47%
Years of education completed	9.3	8.3	3.5	4.2

Note: Table shows weighted means.

3.4 Slums vs. nonslums

Slum spaces are typically characterized by dense and often poorly-constructed living spaces; poor access to basic facilities; and are predominantly occupied by the poor. Approximately 93 percent of households in this survey are located within Dhaka City Corporation (Dhaka CC). Overall, households in slum communities make up about 16 percent of the city's population. Comparison between the slum and nonslum areas reveal few differences in terms of demographic characteristics. Women represent half of the population in both areas, while their average age is approximately 35 years (see Table 5). The average age when individuals marry is fairly young – approximately 19 years. The number of household members is marginally higher in slum areas (4.4) compared to nonslum areas (3.85). Approximately 89 percent of respondents live in male-headed households in both locations. Individuals living in nonslum areas are generally better educated; on average they have 0.86 more years of education. Similarly, a greater proportion of household heads are able to read and write (52 percent vs. 43 percent for slum and nonslum areas, respectively).

Housing in low-income areas of Dhaka is characterized by limited space, but with decent access to services. On average, the houses in slum areas are smaller than those in nonslum areas (121.4 versus 127.5 square feet), and with fewer rooms (1.2 versus 1.3 rooms). Though the number of rooms per person is the same in both locations (0.3 rooms), the space per capita is smaller in slums (32.1 versus 35.1 square feet). Approximately 81 percent of households in nonslum areas have separate kitchens, compared to 59 percent in slum areas. Households in nonslum areas are generally built with better building materials. Roofs made of bricks and cement are seven percentage points higher among nonslum households, while the opposite is true for those made with more temporary materials such as tin. Similarly, the proportion of respondents who can access improved toilets in slums (79 percent) is ten percentage points below that in nonslum areas (89 percent). While access to water from an improved source is universal for slum households, only 94 percent of nonslum households have this: this is likely a positive externality of the comparatively higher levels of population congestion in slums, where a single improved source of water is accessed by everyone in the community. Access to electricity is universal in the sample.

As with housing conditions, access to services varies by household location. Schools, for instance, both public and private, are accessed four percentage points more by slum households. The proportion of slum households with access to public healthcare facilities is four percentage points higher than the 24 percent in nonslum areas. The opposite is true for private healthcare facilities. Perhaps this is driven by the fact that, given the concentration of population in slum areas, many service providers, such as education and healthcare providers, congregate around these areas. Lastly, in terms of transportation, for both short and long-distance modes of travel, nonslum households have more frequent access than slum households (by 10 and 19 percentage points respectively). This could reflect the fact that slums typically form near either potential or existing job sites, thereby precluding the need for vehicular transport. Modes of work-related transport are further discussed in Section 4.5.

Table 5 Comparison of Slum and Nonslum Areas

	Slum		Nonslum		Test (Slum - Nonslum)
	Mean	SD	Mean	SD	
Demographics					
Gender (1=male; 0=female)	0.49	0.50	0.49	0.50	
Age of respondent (completed years)	35.56	12.20	34.83	11.52	
Age of marriage (completed years)	18.70	4.64	18.87	4.69	
Marital status: never married (1/0)	0.03	0.18	0.04	0.21	
Marital status: married (1/0)	0.92	0.28	0.90	0.29	
Household size (continuous number)	4.40	1.82	3.85	1.47	***
Male-headed household (1/0)	0.89	0.31	0.89	0.31	
Education					
Years of completed education (completed years)	2.89	3.52	3.68	3.72	***
Household head can read/write (1/0)	0.43	0.50	0.52	0.50	***
Housing					
Number of rooms in household (continuous numbers)	1.31	0.59	1.16	0.41	***
Number of rooms per capita in household (continuous numbers)	0.33	0.15	0.33	0.14	
Space per household (sq ft)	127.53	54.74	121.44	48.47	**
Per capita space in household (sq ft)	32.14	17.73	35.08	18.32	***
Has a separate kitchen (1/0)	0.59	0.49	0.81	0.39	***
Roof material: tin (1/0)	0.79	0.41	0.70	0.46	***
Roof material: brick/cement (1/0)	0.20	0.40	0.27	0.45	***
Has access to improved toilets (1/0)	0.79	0.41	0.89	0.31	***
Gets water from an improved source (1/0)	1.00	0.05	0.94	0.23	***
Has electricity (1/0)	0.99	0.07	1.00	0.05	

	Slum		Nonslum		Test (Slum - Nonslum)
	Mean	SD	Mean	SD	
Service utilization					
Public primary/secondary school (1/0)	0.23	0.42	0.19	0.40	
Private primary/secondary school (1/0)	0.37	0.48	0.33	0.47	
Public health facility (1/0)	0.28	0.45	0.24	0.43	*
Private health facility (1/0)	0.51	0.50	0.59	0.49	***
Local transport (bus) (1/0)	0.62	0.48	0.72	0.45	***
Long distance transport (1/0)	0.37	0.48	0.56	0.50	***
N	663		1713		

Note: Table shows weighted means of individuals living in slum and nonslum areas. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

IV. Women's work: drivers and constraints

This section presents key patterns related to women's work drawn from the DIGNITY data. We begin with the use of time in activities that individuals perform during the course of the day, then drill down to statistics about work and the nature of work. Data about expected constraints and drivers of female labor are also discussed in this section.

4.1 Time-use data in the DIGNITY survey

Time-use data report the amount of time individuals spend on activities such as paid work, chores, childcare, leisure, and self-care activities. The data allow us to better understand how people allocate their time across a variety of activities. This data also reveals how men and women allocate their time differently, partly due to gender roles, and how this may affect women's economic empowerment.

In most countries where data are available, women bear a disproportionately higher responsibility for unpaid work, and spend proportionately less time in paid work than men. Unfortunately, generally speaking, time-use data is not widely available (Rubiano-Matulevich 2018). In the case of Bangladesh, the only time-use survey that has been conducted is the 2012 Pilot Survey for Time Use. Attempting to fill the data gap and test new methodology on time use, the DIGNITY survey includes a module on time use, building on earlier survey work, such as the 2012 pilot survey, and the Women's Empowerment in Agriculture Index surveys developed by the International Food Policy Research Institute (IFPRI).

The DIGNITY survey used the one-day recall method to collect time-use data: the data reveal sharp gender differences in the use of time (Table 6). Men spend much more time in paid employment, while women spend more time on unpaid domestic work, childcare, and elderly care. Men tend to work long hours, about ten hours on average, while women spend about four hours per day in employment-related activities. Comparing the DIGNITY results with the 2012 Time Use Pilot suggests that women in low-income communities and slums work longer hours, on average, than women in urban areas on the whole (four vs. two hours per day), but allocate fewer hours to domestic and care work. As with the urban average, we observe that time spent on personal maintenance, leisure, and other activities is slightly higher among women than among men. Finally, the burden of childcare and domestic work disproportionately falls on women; women's time spent on these activities is eight times greater than that of men (0.34 hours a day for men vs. 5.16 for women).

Table 6 Typical Day of Men and Women in the DIGNITY Sample

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Main Activities (continuous hours)					
Personal activities	11.45	2.32	12.12	2.61	***
Other activities	2.24	2.85	2.81	2.23	***
Working	9.97	4.14	3.91	4.72	***
Domestic work	0.15	0.6	4.34	2.22	***
Providing care	0.19	0.64	0.82	1.36	***
Total	24.00		24.00		
Secondary activity					
Providing childcare as a secondary activity	0.41	1.42	1.82	2.84	***
N	1117		1259		

Note: Table shows weighted means. * p<0.1; ** p<0.05; *** p<0.01.

Time spent on childcare is prone to omission, as caregivers may combine it with other tasks: for example, they may be preparing meals or watching TV while they are also watching their children (Rubiano-Matulevich 2018). The DIGNITY survey attempts to address this problem by specifically asking respondents whether they also care for children while they are undertaking other activities. The results confirm our hypothesis: time spent on childcare is greater when accounting for the time that people spend caring for children while also performing other activities. The DIGNITY data show that women spend an additional 1.8 hours looking after children while performing other activities, more than twice the amount of time reported for direct childcare. On the other hand, men spend about 0.4 hours on secondary childcare, bringing men's total time spend on childcare per day to about 36 minutes per day. This new data collection effort underscores the risks of not collecting data about secondary childcare activity, which could lead to grossly underestimating the need for childcare.

Comparing the use of time for women who are in and out of the labor force reveals constraints to female labor force participation (FLFP) (see Table 7). Within the economically active population, the number of hours that men work per day is greater than that of women: on average, working women spend about 6.5 hours per day while men spend 3.7 hours longer (10.2 hours per day). On the other hand, working women spend more time on domestic work and providing care. The combined time that working women spend on these activities is comparable to the surplus working hours that men perform. While women who do not work report little time spent in direct childcare and elderly care, the time is complemented with secondary child care because they provide on average 2.6 hours of childcare as a secondary activity (that is, caring for children while they are also doing other activities).

Table 7 Time Utilization by Status of Labor Market Participation

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Panel A: Individuals in the labor market (continuous hours)					
Personal activities	11.37	2.27	11.28	2.48	
Other activities	2.11	2.76	2.06	1.94	
Working	10.20	3.91	6.49	4.69	***
Domestic work	0.13	0.52	3.61	2.08	***
Providing care	0.19	0.64	0.56	1.09	***
Total hours per day	24.00		24.00		
Providing childcare as a secondary activity	0.42	1.44	1.28	2.36	***
N	1086		753		
Panel B: Individuals not in the labor market (continuous hours)					
Personal activities	14.04	2.36	13.28	2.32	*
Other activities	6.19	2.88	3.83	2.20	***
Working	2.80	4.46	0.38	1.00	***
Domestic work	0.74	1.76	5.33	2.02	***
Providing care	0.24	0.60	1.18	1.61	***
Total hours per day	24.00		24.00		
Providing childcare as a secondary activity	0.17	0.69	2.57	3.24	***
N	32		506		

Note: Table shows weighted means. * p<0.1; ** p<0.05; *** p<0.01.

Figure 4. Time-Use among Women, In and Out of the Labor Force

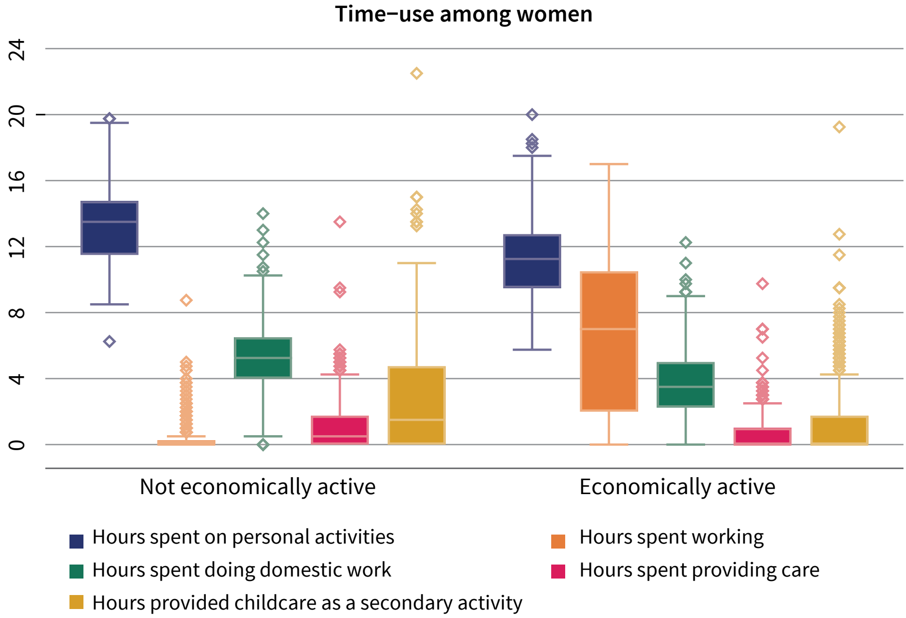
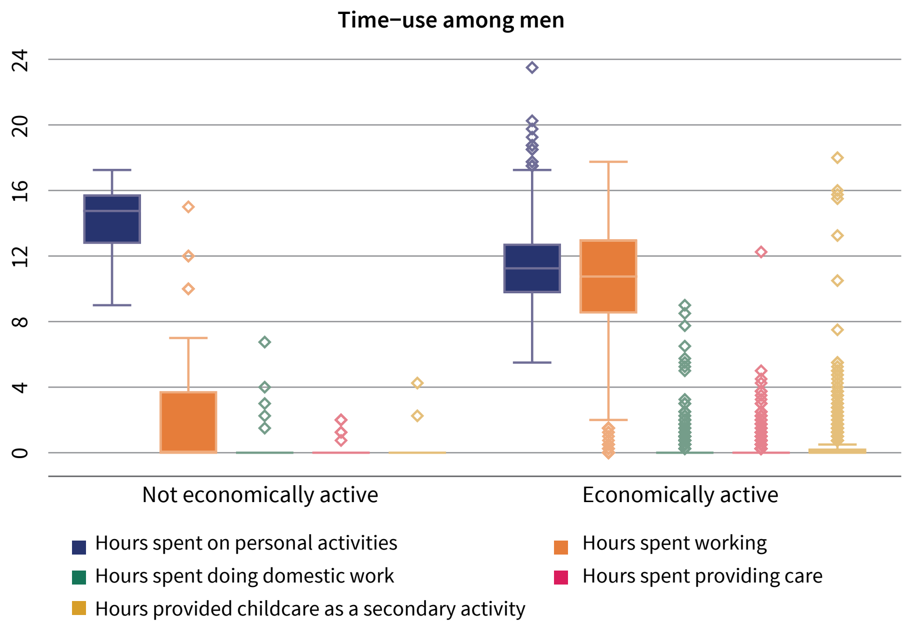


Figure 5. Time-Use among Men, In and Out of the Labor Force



The variation in women's working hours is also high compared to that of men. Figure 4 shows a large variation in women's working hours per day. Among the middle 50 percent of women, the number of working hours ranges from two to 10.5 hours per day. The variation is much greater than that for men; men's working hours in the middle 50 percent ranges from nine to 13 hours per day (Figure 5).

4.2 Work and the nature of work

The labor force participation (LFP) rates are 58 percent and 97 percent among women and men respectively (see Table 8). The FLFP rate is remarkably higher than the norm found in urban Bangladesh: the 2016/17 Labor Force Survey (LFS) reports the labor force participation rate (LFPR) as 33 percent. However, the FLFP is higher in low-income areas in Dhaka than in more well-off neighborhoods. While the LFP of adult men in urban areas of Dhaka is at the same level as in low-income areas (around 94 percent), the participation rate of adult women is 50 percent higher in low-income areas of Dhaka than in urban Dhaka as whole (31 percent) (BBS 2018).

Table 8 Who Works: Demographics and Educational Level of Individuals in the Labor Force

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Individual is economically active (1/0) - full sample	0.97	0.17	0.58	0.49	
Age of respondent (completed years)	36.86	11.65	33.00	10.06	***
Age at marriage (continuous years)	22.26	4.03	15.72	2.73	***
Marital status: Never married (1/0)	0.08	0.27	0.01	0.12	***
Household size (continuous numbers)	3.98	1.53	3.80	1.61	**
Male-headed household (1/0)	0.92	0.27	0.81	0.39	***
Years of completed education (completed years)	3.62	3.85	3.07	3.52	***
Respondent received TVET (1/0)	0.10	0.30	0.10	0.30	
N	1085		753		

Note: Table shows weighted means. * p<0.1; ** p<0.05; *** p<0.01. TVET refers to technical and vocational education and training.

As shown in Table 8, the average working woman is 33 years old, 3.9 years younger than her male peers (36.9 years). Only 1 percent of the women in the labor force have never been married, while the figure is eight times higher among men. Women are marginally less well educated than their male peers. While the average woman has completed 3.1 years of schooling, the corresponding figure for men is 3.6 years. Surprisingly, the proportion of individuals who have received TVET is 10 percent for both genders.

Table 9 Nature of Work

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Individual engaged in wage-employment (1/0)	0.75	0.43	0.75	0.44	
Individual engaged in self-employment (1/0)	0.23	0.42	0.11	0.31	***
Employment industry					
RMG worker (1/0)	0.03	0.16	0.19	0.39	***
Self-employed (1/0)	0.26	0.44	0.11	0.31	***
Service (1/0)	0.27	0.44	0.10	0.30	***
Porter/day labor (1/0)	0.11	0.31	0.08	0.28	*
Maid/servant (1/0)	0.00	0.00	0.31	0.46	***
Payment and terms					
Remuneration received monthly (1/0)	0.44	0.50	0.84	0.36	***
Total monthly income (wage + business) (BDT)	13,076	7,235	5,546	4166	***
Contract type: Permanent (1/0)	0.33	0.47	0.41	0.49	***
Contract type: Temporary (1/0)	0.27	0.45	0.35	0.48	***
Contract type: Casual/daily work (1/0)	0.13	0.34	0.04	0.19	***
N	1085		753		

Note: Table shows weighted means. * p<0.1; ** p<0.05; *** p<0.01.

Among those who work, three-quarters of both men and women work as wage earners, as shown in Table 9. Engagement in self-employment shows some stark differences across gender lines. Only 11 percent of women engage in self-employment, compared to 23 percent of men. The proportion of women working in the ready-made garment (RMG) sector overwhelms the number of men (19 percent vs. 3 percent). The opposite is true in the service sector, where 27 percent of men are engaged, compared to 10 percent of women. The proportion of individuals working as porters or day laborers is more evenly split along gender lines: 11 percent of men, and 8 percent of women. Lastly, being a rickshaw puller is entirely a male profession (about 18 percent of men), while all maids are women (31 percent of women who work). As with the reported national statistics from the LFS, a vast majority (about 80 percent) of women who do not work indicate household work as the reason for not working (Table 10).

Table 10 Primary Reasons for Not Participating in the Labor Force

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Household work (1/0)	0.00	0.00	0.79	0.41	***
Illness (1/0)	0.67	0.47	0.11	0.31	***
Other (1/0)	0.33	0.47	0.10	0.30	***
N	51		556		

Note: Table shows weighted means. * p<0.1; ** p<0.05; *** p<0.01.

While the number of women who report being paid on a monthly basis is nearly double that of men (84 vs. 44 percent), men on average report earning nearly three times as much as women – 13,076 taka compared to 5,546 taka. In terms of contract type, 41 percent of women report having permanent jobs, in contrast to only 33 percent of men, while temporary employment is reported by a higher proportion of women than men (35 percent vs. 27 percent). Finally, casual or daily employment is more than three times as prevalent among men (13 percent) as among women (4 percent).

4.3 Skills

This section explores the standardized cognitive and noncognitive skills of the urban poor. The importance of collecting information about personal attributes in order to account for unobservable innate skills that may play significant roles in the level of educational and/or income attainment has long been discussed. These skills, however, are difficult to quantify, due to the difficulty that respondents in low-capacity development settings often have in comprehending such questions, and/or the difficulty of developing valid measures for them. For instance, the well-used modules that are used to study cognitive capacities, such as the Raven's test,[6] are difficult to compare across different contexts. Data on these skills were recently collected from 1,300 individuals in low-income neighborhoods in urban Bangladesh in partnership with Knack. This company uses a tablet-based game with predictive analytics to quantify the traits of respondents

[6] Raven's test is a nonverbal group test typically used to measure abstract reasoning and fluid intelligence.

in a globally standardized way. These traits include "grit" and "thinking critically," among others. Analysis of this data, if predictive, can provide insight into the skills and hidden talent that can lead toward potential types of careers; and the outcomes can be compared to those of respondents from across the globe. This may also allow the identification of traits that may be holding workers back from excelling and provide concrete policy guidance for interventions. Overall, the data reveal that men show higher Knack scores in areas such as "acting with self-confidence," "growth mindset," and "thinking creatively," while women tend to have a higher score in the "engaging with people" dimension.

The data reveal two general observations about gender and labor force participation. First, working women tend to have different traits than nonworking women. Figure 6 shows that working women show a higher score in "being self-disciplined," but a lower score in "seeking knowledge" than nonworking women. Second, working men show an even higher score in "being self-disciplined" than working women (Figure 7), while working women score higher than working men in "gritting things out."

Figure 6. Cognitive and Noncognitive Skills among Women, In and Not In the Labor Force

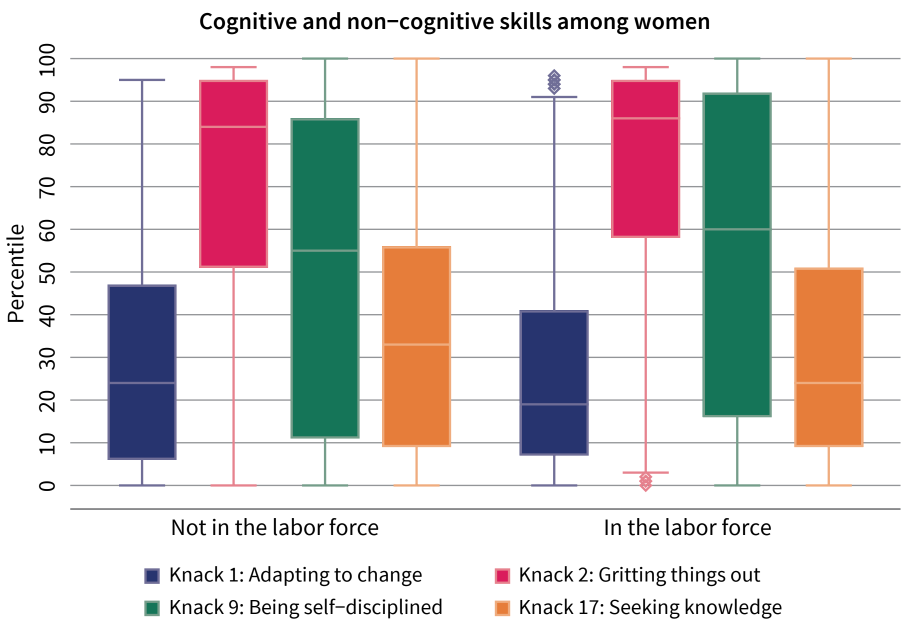
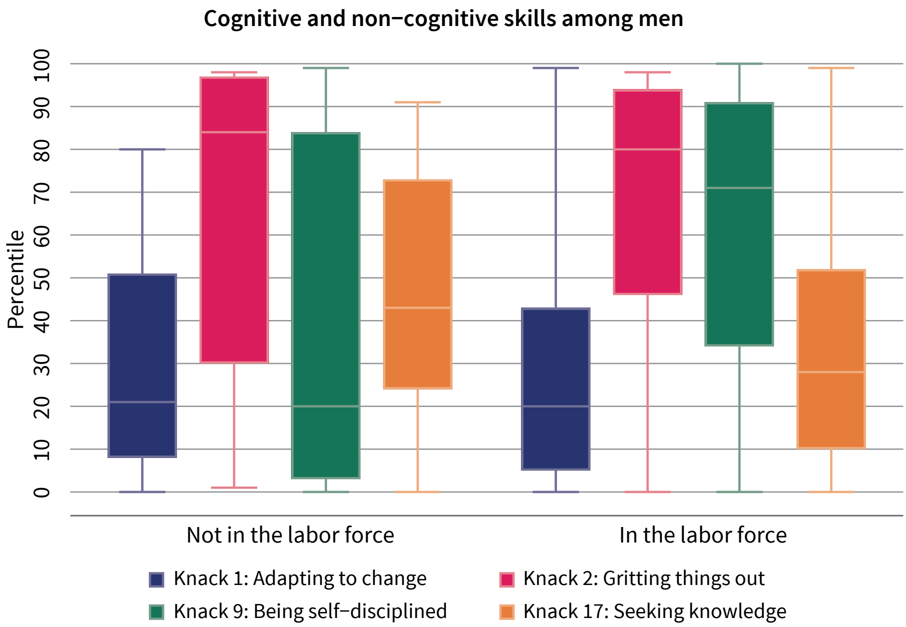


Figure 7. Cognitive and Noncognitive Skills among Men In and Not In the Labor Force



4.4 Childcare

The presence of children, particularly children younger than five years old, has been shown to be a constraint to FLFP in Bangladesh and in other countries (Solotaroff *et al* 2019). The DIGNITY data show that, while most women have children, there are differences in the characteristics of the children and in access to childcare between those women who are in the labor force, and those who are not. Table 11 compares these characteristics. Nonworking women are more likely to have children than working women (87 vs. 84 percent), and their children tend to be younger (7.2 vs. 8.4 years old). Finally, when looking at the figures for young children who need care, the difference becomes more noticeable. While 32 percent of working women have a child that needs care, this ratio is 15 percentage points higher among women who do not work. The DIGNITY data suggest, therefore, that lack of access to childcare appears to be related to women not being in the labor force— or the decision to work at home instead of outside of the home—since the majority of women report that they cannot find childcare when it is needed.[7]

[7] The question is "If you wanted to do something (livelihood-related, training-related, self-care) and could not take your child with you, is there someone who could care for your child in your absence?" and the responses are "yes/no."

Table 11 Need for Childcare

	In the labor force		Not in the labor force		Test (In - out of the labor force)
	Mean	SD	Mean	SD	
Has a child (1/0)	0.84	0.37	0.87	0.34	
Age of youngest child (continuous years)	8.42	5.86	7.22	6.78	***
Has child below 5 years age (1/0)	0.32	0.47	0.47	0.50	***
Childcare is available when required (1/0)	0.15	0.36	0.12	0.33	
N	753		508		

Note: Table shows weighted means of labor force participant and non-participant women. * p<0.1; ** p<0.05; *** p<0.01.

The unmet demand for childcare appears to be large, particularly among working women. The DIGNITY survey also asked respondents with young children about their childcare arrangements while at work. While 63 percent of men rely on their spouses for childcare, only about 13 percent of working women can do so (see Table 12). However, the time that husbands spend in taking care of children (even when the husband is the caregiver) is also relatively limited. In such a situation, working women use other alternatives, such as help from other household members (16 percent) or from relatives outside of the household (14 percent). This apparently leaves a large number of children being cared for by no one. It should be noted that some children may be old enough to take care of themselves,[8] while in other cases, the parents might be working close by. Interestingly, very few people use formal arrangements such as a school or nursery, which may suggest something about the affordability or availability of formal childcare.

Table 12 Unmet Demand for Childcare

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Spouse (1/0)	0.63	0.48	0.13	0.34	***
Other household member (1/0)	0.09	0.29	0.15	0.36	***
Relative not living in the house (1/0)	0.05	0.23	0.14	0.34	***
Other individual (1/0)	0.01	0.08	0.02	0.13	**
School/nursery/other facilities (1/0)	0.00	0.07	0.01	0.10	
No one (1/0)	0.21	0.41	0.55	0.50	***
N	772		516		

Note: Table shows weighted means of sample that participate in the labor force. The question about caretakers is administered to adults with a youngest child younger than 15; the average age of children discussed is 5.6 years. * p<0.1; ** p<0.05; *** p<0.01.

[8] Even when looking at the results for children younger than five years old, many parents (38 percent of women and 6 percent of men) reported that no one was taking care of their children while they are at work.

4.5 Transportation

Access to transportation is of key importance in accessing job opportunities. However, men and women tend to have different kinds of experience with transportation in terms of affordability, reliability, and safety. Recent research has shown high levels of gender-based violence (GBV) in public transport and the adjacent public spaces in many cities around the world (Dominguez Gonzalez, Arango, McCleary-Sills and Bianchi 2015). In Bangladesh, a recent study in the Dhaka area by BRAC reveals that 94 percent of female users of public transportation have experienced verbal, physical, or other forms of sexual harassment. Moreover, 20.5 percent of women have stopped using public transportation due to sexual harassment (Daily Star 2018). Such constraints may cause women to modify their travel patterns and thus their choice of employment. Analysis of daily commuting patterns in Dhaka shows that members of the poorest quintile predominantly commute by foot, with a mean travel time of 40 minutes, and the average distances travelled by women are even shorter. The physical limits of commuting on foot mean nearly all workers in the poorest quintile live within 4-5 kilometers from their place of employment, thereby curtailing their employment opportunities (Hill and Rahman, Forthcoming).

Analysis of the DIGNITY data in Table 13 suggests that unequal access to transportation appears to be a constraint for women's work. Only 35 percent of working women travel outside their community to work, in sharp contrast to men, where working outside the community is the norm for the majority (56 percent). Data about modes of transportation used by workers underscore the gender gaps. Women rely heavily on walking to get to work, about 13 percentage points higher than men. Moreover, very few women use public buses for commuting; only about 3 percent take buses to go to work, while 8 percent of men take the bus. Finally, the data also reveal that women spend roughly the same amount of time as men commuting to work. For example, female garment workers and maids spend roughly 18 minutes in their commute to work. This pattern suggests that women face a constraint finding jobs close to their dwellings.

As indicated in studies on GBV, the risk of GBV inside buses is a strong constraint that prevents women from using buses and taking employment opportunities that are located further away from their homes. The data on travel time shows that travel costs for women are much lower than that of male workers (14 *taka* vs. 25 *taka*); but their commute time is longer than men's (19 minutes each way, compared to 17 minutes for men). The risk of sexual harassment and assault may explain the low rate of female uptake in public transportation.

Table 13 Employment and Transportation

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Works at home (1/0)	0.10	0.30	0.25	0.43	***
Works within the community (1/0)	0.34	0.47	0.40	0.49	**
Works outside the community (1/0)	0.56	0.50	0.35	0.48	***
Transport used for work					***
Walk (1/0)	0.74	0.44	0.87	0.34	***
Bicycle (1/0)	0.04	0.00	0.00	0.00	***
Rickshaw/cycle van (1/0)	0.09	0.18	0.02	0.12	***
Bus (1/0)	0.08	0.27	0.03	0.18	
Cost of one-way travel to a job (BDT)	24.76	21.56	13.85	10.58	***
Time for one-way travel to non-home work (minutes)	16.66	13.40	19.17	12.89	***
N	1085		653		

Note: Table shows weighted means of transport utilization and characteristics among individuals who participate in the labor force. * p<0.1; ** p<0.05; *** p<0.01.

4.6 Perceptions, gender norms, and attitudes

Gender norms affect women's ability to participate in the workforce. These norms can be unpacked into several areas that directly constrain women's ability to work, including mobility restriction and seclusion, among other things. While women's roles in the economic sphere have expanded, conservative gender norms may still be restricting their physical mobility and imposing various social practices on them in relation to the observance of *purdah*. These social practices are seen in conventions or rules about veiling, ranging from the wearing of simple head scarves to full-body burqas (Ahmed and Sen 2018). Moreover, these norms promote the seclusion of women; enforce their exclusion from public places; and specify gender-specific labor (Amin 1997). In addition, as elsewhere, GBV affects Bangladeshi women: in 2015, more than half of married women (54.7 percent) reported experiencing violence at home during the past 12 months. In addition, more than 25 percent of women have experienced physical violence from non-partners during their lifetime, and 6.2 percent reported experiencing it in the past 12 months. The prevalence rate is lowest in city corporation areas (16 percent), which is lower than the urban average (24 percent), as well as that in rural areas (29 percent) (BBS 2016).

The DIGNITY data reveal large gender gaps in mobility; women, on average, have more limited mobility than men and tend to be homebound, with little freedom to travel outside their communities. While 84 percent of men go outside of their community every day, only 40 percent of women do so (see Table 14). What's more, a quarter of women only leave their community once a month, and one in ten never leaves her community. This means that there are many women in Dhaka that live life as if they were in a remote village, even though they live in one of the biggest cities in the world. Going outside the community is often not a decision made unilaterally: 35 percent of women said that they have to ask permission from someone in their household before going outside their community.

Table 14 Frequency of Travel Outside the Home

	Male		Female		Test (Male - Female)
	Mean	SD	Mean	SD	
Frequency of travel outside the home					
Every day	0.84	0.37	0.40	0.49	***
At least once a week	0.09	0.28	0.12	0.32	**
At least once every two weeks	0.01	0.12	0.04	0.20	***
At least once a month	0.02	0.14	0.10	0.30	***
Less than once a month	0.03	0.17	0.25	0.43	***
Never	0.01	0.12	0.09	0.29	***
Time spent (by space - in hours)					
At home	13.85	5.09	20.45	4.63	***
Outside home but within the community	4.50	5.44	2.17	3.80	***
Outside the community	5.66	6.18	1.39	3.53	***
N	1117		1259		

Note: Table shows weighted means of how frequently individuals travel outside the home. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Women's freedom to leave the house, enter public spaces, and participate fully as citizens is an important element in their economic empowerment. Collecting location of activity data is another innovation of the time-use module in the DIGNITY survey. In addition to asking about activities that respondents have performed over the past 24 hours, the survey also asks where the activities take place—at home; outside the home, but inside the community; or outside the community. The results reveal a stark contrast in mobility between genders: men spend four times the amount of time that women do outside the community. The time-use module of the survey reveals that women spend more time at home than men (20 vs. 14 hours per day), while men spend more time than women outside the home, but in the community (4.5 vs. 2.2 hours), and outside the community (5.6 vs. 1.4 hours per day). In short, women spend more than four-fifths of their day homebound.

The risk of GBV also greatly impacts women's decision making. Concerns about safety and security play a large role in determining whether a woman will participate in the labor force. Violence and abuse against women in public spaces and in the workplace are not uncommon. This issue is particularly acute in urban settings, where women, largely poor, are heavily reliant on walking as their primary mode of commuting. The DIGNITY data reveal a big gender gap in perception of safety, especially outside the home. Risk of sexual harassment while being outside the home may therefore be one of the main constraints for women in seeking employment.

Most women feel safe at home during the day (98 percent), which is the same rate as for men.[9] But there is a large gender gap for perceptions of night-time safety outside the home. The percentage of women who reported that they feel safe outside the home at all times (either on their own street or outside their community) is only 69 percent, compared to 96 percent of men. This data shows that the perception of safety has a disproportionate effect on women. Such gender differences may affect their decision to travel outside the home and to participate in economic activities.

Social norms are also reflected in veiling practices. Women reported modifying their veiling practices when they travel further away from their home. About 50 percent of female respondents reported that they wear a burqa when they go outside of their neighborhood, while about 20 percent said they only cover their heads with headscarves while in the neighborhood, but that they wear a burqa when going outside of their neighborhoods.

Table 15 Perceptions, Norms and Attitudes about Safety and Freedom of Movement

Perceptions, norms and attitudes	All women		Not in the labor force		In the labor force		Test (In - out of the labor force)
	Mean	SD	Mean	SD	Mean	SD	
Needs permission to go outside (1/0)	0.35	0.48	0.37	0.48	0.33	0.47	
Feels safe outside home (1/0)	0.69	0.46	0.63	0.48	0.73	0.44	***
Wears veil (burqa) when walking outside own neighborhood (1/0)	0.49	0.5	0.59	0.49	0.42	0.49	***
N	1261		508		753		

Note: Table shows weighted means for women. * p<0.1; ** p<0.05; *** p<0.01.

[9] Data not shown in the table.

Finally, Table 15 reveals a sharp contrast in the indicators related to agency[10] between working and nonworking women. While 37 percent of nonworking women need to seek permission to go outside the community, only 33 percent of working women do. Similarly, working women tend to have a greater perception of their safety; they report feeling safe outside home (either inside the neighborhood or outside the neighborhood) much more than women who are not in the labor force (73 percent vs. 63 percent). Veiling practices are also associated with lower employment rates. These relationships will be explored in a multivariate setting in Section 5.

V. Exploring constraints to work

This section explores how the factors in the previous section correlate to three key labor market outcomes: FLFP; employment choice (whether one works as a wage earner or is self-employed); and labor supply (the amount of time a worker spends working per day). The conditional correlations are explored using a linear model, with neighborhood fixed effects and robust standard errors. The factors considered here are factors that the narrative on female labor market outcomes would suggest are important, but the relationships presented in this section are purely linear correlations: they do not indicate a causal or deterministic relationship. Selection into labor market participation has not been modeled for the regressions presented on employment choice and labor supply.

The right-hand side variables are similar across the models. These variables include age, age at marriage, marital status, household size, years of education completed, years of completed education squared, whether the respondent received technical and vocational education and training (TVET), has a child that requires care, is in a male-headed household, number of years spent in the community, whether they were born in the community, and whether the respondent is depressed (CESD Score > 10). Additional variables related to gender norms are added in order to model specification of regressions for female labor market outcomes—for example, whether the respondent needs permission to go outside the community, feels safe outside the home, and/or wears a burqa whenever outside the home—and also data about the educational level of the spouse.

[10] Agency means an individual's (or group's) ability to make effective choices and to transform those choices into desired outcomes. Agency can be understood as the process through which women and men use their endowments and take advantage of economic opportunities to achieve desired outcomes (World Bank 2011).

Table 16 presents the correlates of female labor force participation (FLFP). The model is restricted to women, since most men (97 percent) participate in the labor market. Younger women are marginally more likely to participate in the labor force; and they are 0.5 percentage points more likely to work for each year younger that they are. The probability of being in the labor force increases by 35 percentage points among never-married women. Women with more education are also less likely to participate in the labor force: each additional year of education reduces labor force participation (LFP) by 4.2 percentage points. While this result may seem surprising, it fits with the U-shaped curve relationship between education level and FLFP in Bangladesh (mentioned in section 2). Specifically, they are located in the left part of the U-shaped curve, as DIGNITY is collected from the low-income areas (the average years of completed education for women is only 3.5 years). However, those with TVET are significantly more likely to work (by 23.1 percentage points), suggesting that TVET is undertaken with specific employment opportunities in mind. In line with the existing literature, women with children five years of age or less that require care are 15 percentage points less likely to participate in the labor force. The duration of residence in a community does not appear to be correlated with the decision to enter the labor market.

Perceptions and attitudes are strongly associated with FLFP. Women who perceive the environment outside the home to be safe and who are comfortable traveling outside their homes by themselves are 9.6 percentage points more likely to participate in the labor market. On the flip side, women with conservative outlook[11] are 8.1 percentage points less likely to engage in the labor market. Lastly, depression is strongly associated with LFP: women who report being depressed are 10.5 percentage points more likely to be working. More research may be needed to understand this correlation. However, during fieldwork a few women reported that the ideal is to not be working, and that they worked only because they had to for financial reasons rather than because they wanted to. This dissatisfaction with life outcomes may account for what is being expressed in this variable.

Table 17 presents the coefficients of a model that explores the correlates of employment type: that is, whether an individual chooses to engage in wage earning or self-employment. (Note that wage earning takes the value of 1 and self-employment takes the value of 0). Column 1 shows the coefficients for women: younger women[12] and women with fewer years of education are more likely to be self-em-

[11] Conservative outlook is proxied by burka wearing practice, which is also used by Ahmed and Sen (2018) and Asadullah and Wahhaj (2019).

[12] It should be noted that the DIGNITY sample mostly comprises the principal couple of the households, thus may not capture young women working in the garment industry.

ployed (0.5 and 3.5 percentage points respectively). Having gone through TVET is positively associated with being self-employed (27.9 percentage points). Women with children of an age requiring care are similarly more likely to be engaged with self-employment than wage employment. Finally, the probability of being engaged in self-employment rather than wage employment is higher among women who require permission to go outside the home, or who wear burqas when they do. By comparison, younger men are more likely to be self-employed.

Using time-use data with a 24-hour recall period from 4 am the previous day to 3:59 am on the day of the survey, we explored the correlates of the number of hours an individual decided to work (Table 18). Among women, while the number of years of education is negatively associated with labor supply (15.8 percentage points), based on the positive sign and significance (1 percent< *p*) of the quadratic term (1.4 percentage points), this correlation may reverse as the amount of education increases (see Column 1). Understandably, a woman with a child requiring care is similarly likely to spend less time at work (by 49.6 percentage points). In line with previous models, age is the sole significant correlate of the length of time a male individual spends at work that is negatively correlated; that is, younger men are likely to spend less time at work (by 1.1 percentage points).

The analysis also explores whether there are any differences between slum and nonslum areas in terms of constraints to women's labor market participation. Table 1 in the Annex presents the results of whether being in slums changes the magnitude of correlations between respondent characteristics and labor market outcomes. Women who have TVET and who live in slum areas are 20.9 percentage points more likely to engage in the labor force than those in nonslum areas. But in slum areas, women who work tend to have received TVET more than women in other areas.

Finally, women who live in slums and who have children who require care are 18.9 percentage points less likely to engage in the labor market than nonslum women, suggesting a greater need for childcare in slum areas. This may also suggest that access to childcare (either through formal or informal sources) is more limited for women in slum areas than for women not living in slums. A household with an additional member is associated with an increase in the likelihood (by 5.2 percentage points) of labor force participation among women living in slums. The correlation between other factors, such as duration of living in the community, perceptions about social norms, and LFP does not vary between slum and nonslum areas. Finally, in terms of perception of safety and FLFP, being in a slum is no different from being in a nonslum area.

In the same table, Column 3 examines whether the correlation between respondent characteristics and the choice of whether to engage in wage earning or self-employment differs by type of location. We find that women in slum areas are 0.9 percentage points more likely to work as wage employees as their age increases by one year than women from nonslum settings. With regard to the amount of time spent at work (Column 5), each additional year of education is correlated with 30.5 percentage points more time spent at work by women living in slum areas than nonslum ones. The negative and significant coefficient of the quadratic education term, however, suggests that the effects may reverse for slum-dwelling women faster than for their nonslum counterparts as the number of years of education increases. For women with TVET, the women from slums are likely to spend 96.2 percentage points more time at work than women living in nonslum areas. Lastly, cultural norms such as those that expect women to have permission to go outside appear to play a larger role in slum areas when it comes to the time spent at work: women from slums are likely to spend 79.2 percentage points less time working than their nonslum counterparts.

Next we examine the correlation of cognitive and noncognitive skills and labor market outcomes using a specification similar to the one used earlier; the results are presented in Tables 19, 20, and 21. This is assessed separately, since the information on cognitive and noncognitive skills was collected from a subset of participants (593 women and 507 men). The results suggest that while traits such as being able to adapt to change, persistence and grit, self-discipline, and/or seeking knowledge are not strongly correlated to whether an individual chooses to engage in the labor market, they *are* significantly correlated to whether the woman chooses wage earning or self-employment (see Table 20, Column 1). Women who are better at adapting to change are 6.3 percentage points—and those who are self-disciplined are 5.7 percentage points—more likely to engage in wage employment. Alternately, women who are persistent and willing to "grit things out" are 10.2 percentage points more likely to be engaged in self-employment. None of these factors are significantly correlated with the type of employment that men undertake.

Overall, these regressions highlight the fact that the correlates of FLFP are distinct from those of men. First of all, LFP is ubiquitous among the male population in our sample. Delving deeper into the characteristics of men that are correlated with the choice to engage in wage earning or self-employment, in most instances, men seem to be affected very little by demographic, socioeconomic, or societal norms and attitudes. However, these factors are significantly correlated with female LFP. While unmarried women who have no children and who do have TVET are the most likely to be engaged in the labor market, the opposite holds true for married women living in a conservative male-headed household. Businesses in urban spaces are often run from home: this allows for more flexibility, especially for women with young children who require care. Similarly, women from conservative households[13]are more engaged with self-employment, most likely from within their homes.

Table 16 Correlates of Labor Force Participation

	Economic Activity	
	Coef.	**Std Err**
	(1)	**(2)**
Age of respondent (completed years)	-0.005**	0.002
Age of marriage	0.002	0.007
Marital status: never married (1/0)	0.350**	0.148
Household size	0.000	0.012
Years of completed education	-0.042**	0.017
Years of completed education (squared)	0.002	0.001
Respondent received TVET (1/0)	0.231***	0.069
Has child (<=5yrs) requiring care	-0.150***	0.042
Lives in male-headed household (1/0)	-0.208***	0.055
Duration in community: continuous years	-0.002	0.003
Born in the community	-0.039	0.070
Needs permission to go outside	-0.005	0.042
Feels safe outside home	0.096**	0.041
Wears burqa whenever outside the home (1/0)	-0.081**	0.040
Education of spouse (for women)	0.008	0.011
Respondent is depressed (CESD Score > 10) (1/0)	0.105**	0.049
R2	0.21	
N	1,247	

Note: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. As 97 percent of men participate in the labor force, they are excluded from this model. * p<0.1; ** p<0.05; *** p<0.01.

[13] A conservative household is defined as a household in which women are required to ask permission to go outside the community, or are required to wear a burqa when stepping outside the home.

Table 17 Correlates of Wage Earning versus Self-Employment

	Female		Male	
	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)
Age of respondent (completed years)	-0.005*	0.003	-0.008***	0.002
Age of marriage	-0.004	0.008	-0.003	0.005
Mar status member: never married (1/0)	0.177	0.229	-0.391	0.316
Household size	0.003	0.012	-0.018	0.012
Years of completed education	-0.035*	0.020	-0.021	0.013
Years of completed education (squared)	0.003	0.002	0.001	0.001
Respondent received TVET (1/0)	-0.279***	0.086	0.034	0.065
Has child (<=5yrs) requiring care	-0.165***	0.050	-0.056	0.040
Live in male headed household (1/0)	0.018	0.053	-0.019	0.073
Duration in community: continuous years	-0.003	0.003	0.000	0.003
Born in the community	0.036	0.078	-0.092	0.059
Needs permission to go outside	-0.084*	0.051		
Feels safe outside home	0.013	0.048		
Wears burqa whenever outside the home (1/0)	-0.173***	0.046		
Education of spouse (for women)	-0.005	0.013		
Respondent is depressed (CESD Score > 10) (1/0)	0.058	0.053	-0.033	0.062
R2	0.31		0.22	
N	742		1,001	

Note: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. The dependent variable takes on the value of 1 if the person engages in wage employment, and the value of 0 for the self-employed. Sample is restricted to individuals who report being in the labor force in the past 30 days. Questions such as the need to ask for permission to go outside, perceptions of safety, and burqa wearing are asked of female respondents only, and as such are left out of the male- specific model. * p<0.1; ** p<0.05; *** p<0.01.

Table 18 Correlates of Hours Spent at Work (log-linear outcome)

	Female		Male	
	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)
Age of respondent (completed years)	-0.010	0.008	-0.011**	0.005
Age of marriage	0.006	0.025	-0.002	0.010
Marital status: never married (1/0)	0.040	0.627	-0.341	0.653
Household size	-0.018	0.046	0.034*	0.021
Years of completed education	-0.158**	0.063	-0.003	0.025
Years of completed education (squared)	0.014***	0.005	0.001	0.002
Respondent received TVET (1/0)	-0.696**	0.271	-0.027	0.127
Has child (<=5yrs) requiring care	-0.496***	0.158	-0.066	0.077
Lives in male-headed household (1/0)	-0.131	0.169	-0.127	0.096
Duration in community: continuous years	0.005	0.010	-0.009	0.006
Born in the community	0.262	0.298	-0.244*	0.137
Needs permission to go outside	-0.152	0.160		
Feels safe outside home	0.151	0.150		
Wears burqa whenever outside the home (1/0)	-0.219	0.173		
Education of spouse (for women)	-0.002	0.042		
Respondent is depressed (CESD Score > 10) (1/0)	-0.227	0.175	-0.199	0.145
R2	0.26		0.12	
N	742		1,001	

Note: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. Sample restricted to individuals who report being in the labor force in the past 30 days. Questions concerning the need to ask for permission to go outside, perceptions of safety and, burqa wearing are asked only of female respondents, and as such are left out of the male-specific model. * p<0.1; ** p<0.05; *** p<0.01.

Table 19 Correlation between Cognitive and Noncognitive Skills and Female Economic Activity

	Female	
	Coef.	Std Err
	(1)	(2)
(Ln) Knack 1: Adapting to change	0.007	0.030
(Ln) Knack 2: Gritting things out	0.038	0.031
(Ln) Knack 9: Being self-disciplined	0.026	0.022
(Ln) Knack 17: Seeking knowledge	-0.044	0.033
Age of respondent (completed years)	-0.003	0.003
Age of marriage	-0.002	0.009
Household size	0.003	0.016
Years of completed education	-0.036	0.023
Years of completed education (squared)	0.001	0.002
Respondent received TVET (1/0)	0.293***	0.087
Has child (<=5yrs) requiring care	-0.193***	0.051
Lives in male-headed household (1/0)	-0.169**	0.074
Duration in community: continuous years	-0.004	0.004
Born in the community	-0.058	0.094
Needs permission to go outside	-0.022	0.053
Feels safe outside home	0.099*	0.053
Wears burqa whenever outside the home (1/0)	-0.082	0.053
Education of spouse (for women)	0.007	0.014
Respondent is depressed (CESD Score > 10) (1/0)	0.073	0.063
R2	0.25	
N	593	

Note: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. As 97 percent of men participate in the labor force, they are excluded from this mode. * p<0.1; ** p<0.05; *** p<0.01.

Table 20 Correlation between Cognitive and Noncognitive Skills and Type of Employment (Wage or Self- Employment)

	Female		Male	
	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)
(Ln) Knack 1: Adapting to change	0.063*	0.035	0.005	0.031
(Ln) Knack 2: Gritting things out	-0.102***	0.039	-0.026	0.027
(Ln) Knack 9: Being self-disciplined	0.057**	0.025	-0.032	0.020
(Ln) Knack 17: Seeking knowledge	-0.012	0.042	-0.032	0.032
Age of respondent (completed years)	-0.003	0.004	-0.006**	0.002
Age of marriage	-0.001	0.009	-0.003	0.006
Household size	0.011	0.016	-0.021	0.015
Years of completed education	-0.017	0.026	-0.005	0.017
Years of completed education (squared)	0.002	0.002	0.000	0.002
Respondent received TVET (1/0)	-0.356***	0.088	0.021	0.083
Has child (<=5yrs) requiring care	-0.151**	0.064	-0.038	0.052
Live in male-headed household (1/0)	-0.014	0.072	-0.067	0.077
Duration in community: continu-ous years	-0.006	0.004	0.001	0.003
Born in the community	0.059	0.109	-0.108	0.076
Needs permission to go outside	-0.042	0.063		
Feels safe outside home	0.003	0.061		
Wears burqa whenever outside the home (1/0)	-0.170***	0.058		
Education of spouse (for women)	-0.015	0.018		
Respondent is depressed (CESD Score > 10) (1/0)	0.071	0.062	0.012	0.076
R2	0.36		0.23	
N	351		507	

Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. The dependent variable takes on the value of 1 if the person engages in wage employment and the value of 0 for the self-employed. Sample restricted to individuals who report being in the labor force in the past 30 days. Questions concerning the need to ask for permission to go outside, perceptions of safety, and burqa wearing are asked of female respondents only, and as such, are left out of the male-specific model. * p<0.1; ** p<0.05; *** p<0.01.

Table 21 Correlation between Cognitive and Noncognitive Skills on the Hours Spent at Work

	Female		Male	
	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)
(Ln) Knack 1: Adapting to change	0.149	0.125	0.033	0.057
(Ln) Knack 2: Gritting things out	0.039	0.108	-0.001	0.060
(Ln) Knack 9: Being self-disciplined	0.121	0.087	0.010	0.055
(Ln) Knack 17: Seeking knowledge	-0.051	0.126	-0.046	0.057
Age of respondent (completed years)	-0.010	0.011	-0.010**	0.005
Age of marriage	0.007	0.031	0.007	0.012
Household size	0.037	0.058	0.039	0.028
Years of completed education	-0.237***	0.077	-0.002	0.029
Years of completed education (squared)	0.019***	0.006	0.001	0.003
Respondent received TVET (1/0)	-0.801***	0.305	-0.084	0.167
Has child (<=5yrs) requiring care	-0.504**	0.205	-0.042	0.093
Lives in male-headed household (1/0)	-0.335	0.229	-0.156	0.097
Duration in community: continuous years	-0.005	0.014	-0.008	0.008
Born in the community	0.039	0.426	-0.192	0.187
Needs permission to go outside	-0.124	0.209		
Feels safe outside home	0.129	0.194		
Wears burqa whenever outside the home (1/0)	-0.282	0.206		
Education of spouse (for women)	0.065	0.054		
Respondent is depressed (CESD Score > 10) (1/0)	-0.303	0.219	-0.219	0.189
R2	0.34		0.16	
N	351		507	

Note: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. Sample restricted to individuals who report being in the labor force in the past 30 days. Questions concerning the need to ask for permission to go outside, perceptions of safety, and burqa wearing are asked of female respondents only, and as such are left out of the male-specific model. * p<0.1; ** p<0.05; *** p<0.01.

VI. Conclusion

Labor income growth has been the fundamental driver of poverty reduction in Bangladesh in recent years (Joliffe *et al* 2013, Hill and Genoni 2018). However, during the past five years, urban poverty reduction has stagnated and, perhaps without coincidence, this has also been a period in which FLFP rates have fallen. As Bangladesh continues to urbanize, understanding the factors that constrain FLFP in urban areas is increasingly important in order to understand how urban income growth and poverty reduction can be ensured.

Although the decline in FLFP may be driven in part by changes in the demand for female labor in the RMG sector in recent years, it is also possible that it is driven by supply-side factors—for example, norms around women's work and travel outside the home, and factors that determine the cognitive and noncognitive skills of women as they contemplate entering the workforce. This paper has explored the factors that constrain women from engaging in the labor market. It uses a unique new dataset to provide individual-level data on labor market participation, time use, norms, and both cognitive and noncognitive skills.

The paper highlights the fact that FLFP is higher in low-income neighborhoods and slums than in the city as a whole, showing again that FLFP tends to be lower at higher levels of income. At the individual level we also find that women with more education are less likely to work, another indicator of the same relationship. The results also show the well-known finding that, although nearly all men work, FLFP is strongly determined by demographics—for example, by whether a woman is married or not, and by her age.

However, the unique dataset used in this paper also allows us to quantify other important correlates of the labor force participation (LFP) decision. Access to childcare was shown to be strongly correlated with FLFP, and is perhaps one of the main drivers of demographic patterns of female employment found in the data. Women with children less than five years old are 15 percentage points less likely to be engaged in work than women with no children, or with older children. In addition, women reported that access to childcare was a main constraint, and detailed time-use data show that women are often looking after children even when they are engaged in other activities, something that would be impossible to do if working away from home. This points to the need to consider childcare when thinking about how to increase labor income for women in urban areas. This is a challenge that does not exist to the same extent in rural areas, where work is more often in and around the house or farm.

Soft skills were also shown to be an important correlate of the nature of work that women engage in. Women who showed stronger skills in "being disciplined" were more likely to be employees; those with less discipline but more determination were more likely to be self-employed. This could point to the value of soft-skill training, and/or mentorship programs to help women find jobs that they are better suited to, or to help them learn the soft skills that emerging employment opportunities require.

However, perhaps the strongest finding from the data was the importance of mobility, the fear about safety in public spaces, and the implications of these factors for FLFP. The survey revealed that public spaces in Dhaka are often male-dominated spaces, and that this is correlated with women's decisions about employment. Men spend four times more time outside of their communities than women do. A quarter of women only leave their community once a month, and one in ten never leaves her community at all. This means that there are many women in Dhaka that live life as if they were in a remote village, even though they live in one of the biggest cities in the world.

The notion that social norms play an important role in determining FLFP is not new, but this survey has provided a unique ability to quantify the strength of the correlation between these norms, perceptions, and labor participation. About 50 percent of the women interviewed wear a burqa outside of their community, and 30 percent report not feeling safe in their communities. Not surprisingly, women who do not feel that the environment outside of their house is safe are ten percentage points less likely to participate in the labor market. Also, those who wear burqas are eight percentage points less likely to engage in the labor market. The data showed that many women in Dhaka are in both categories. The analysis does not point to a causal relationship between these norms and participation in the labor market, but it does highlight the fact that norms are very different between women who work and those who do not. Finally, the evidence is consistent with the notion that, for many women, working is not deemed desirable, and is something that is not associated with feeling happy about life.

New data and findings from this report could provide evidence for novel interventions to boost female labor force participation in urban areas. The report shows that many families do not have access to childcare, while very few use formal childcare centers. In this regard, community-based childcare, like Guatemala's Community Day Care Centers Program, could be an option. Such programs usually organize parents in poor urban areas in to a small group and choose a woman from the group to be the care provider. The provider will care for the children, while the cost will be covered by the parents and the government (Ruel et al. 2002). An impact evaluation by Hallman et al. (2005) suggests that interventions to make formal day care in poor urban areas more affordable may increase the labor hours of mothers living in the neighborhoods. Public childcare programs, like Rio de Janeiro's public day-care program in Brazil, could be another option. The program provides a childhood development program for infants and children from 0-3 years living in low-income neighborhoods. Barros et al. (2013) finds that access to the program led to a very high utilization rate and a substantial increase in mothers' employment (from 36 to 46 percent). In terms of safety in the community, programs like UN-HABITAT's global Safer Cities Programme could be a useful starting point in reassessing the earlier initiative to address crime and violence activities in low-income communities (UN-HABITAT 2011).

In future research, it will be important to continue to explore the relationship between social norms and participation in the labor market in order to identify interventions that could help encourage FLFP. The evidence indicates that making public spaces more female-friendly, travel safer for women, and female work more socially acceptable may be important in order to increase the ability of women to grow their families' incomes happily, and free of fear. Policy goals and actions should support women who choose to work in urban areas of Bangladesh, as opposed to simply being compelled to work due to economic necessity. Otherwise, the country's gain in FLFP may start to erode, as urban households move out of extreme poverty. Ideally, women's work should be rooted in economic empowerment, and viewed as a means for gaining prosperity and progression to a middle-class society.

Annex

Sampling weights and probability of selection

The probability of selection of the sample was calculated separately for each stage and enumeration area (EA) using the following specification:

$$P_{ij}^{1} = n_j \frac{M_{ij}}{\sum M_{ij}}$$

where the probability of the i^{th} EA being selected from the j^{th} stratum is presented by P_{ij}^{1}. n_j represents the number of selected EAs within each stratum. The number of households in the i^{th} EA in the j^{th} stratum is represented by M_{ij} while $\sum M_{ij}$ represents the total number of households in the stratum.

The probability of the second stage of the selection process is estimated using the following specification:

$$P_{ij}^{2} = \frac{h_{tij}}{H_{tij}}$$

where the probability of a household being selected for the sample is represented by P_{ij}^{2}. h_{tij} is the number of households of type *t* in EA *i* in stratum *j* selected to be surveyed from a total number of households (H_{tij}) within each EA and the particular category.

The overall likelihood of a particular household being selected from a particular stratum is therefore represented as the product of the two aforementioned probabilities, calculated as follows:

$$P_{ij} = P_{ij}^{1} \times P_{ij}^{2}$$

The weight is subsequently constructed as the inverse of the likelihood of a particular household being selected ($1/P_{ij}$).

Annex Table 1: Heterogeneity of Employment Dynamics across Slum and Nonslum Areas

	Labor force participation		Wage vs self-employment		Time spent at work	
	Coef.	Std Err	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)	(5)	(6)
Slum X Age of respondent	-0.002	0.004	0.009*	0.005	-0.006	0.018
Slum X Age of marriage	-0.007	0.012	0.016	0.013	0.041	0.043
Slum X Never married	0.324	0.301	-0.134	0.380	-0.379	1.067
Slum X Household size	0.052**	0.020	-0.035	0.025	0.014	0.102
Slum X Years of completed education	0.037	0.037	0.022	0.045	0.305**	0.142
Slum X Years of completed education (sq)	-0.007**	0.003	0.000	0.004	-0.022*	0.012
Slum X Respondent received TVET	0.209*	0.126	0.046	0.151	0.962**	0.479
Slum X Has child (<=5yrs) requiring care	-0.189**	0.077	0.065	0.109	0.135	0.341
Slum X Male-headed household	-0.138	0.102	-0.030	0.108	0.115	0.398
Slum X Duration in community (continuous years)	-0.002	0.005	-0.011	0.007	-0.002	0.020
Slum X Born in the community	0.060	0.121	-0.173	0.171	-0.883	0.545
Slum X Needs permission to go outside	-0.071	0.077	-0.047	0.106	-0.792**	0.310
Slum X Feels safe outside home	-0.025	0.073	-0.133	0.094	0.095	0.291
Slum X Wears burqa whenever outside the home	-0.037	0.076	0.113	0.103	0.168	0.323
Slum X Education of spouse (for women)	0.012	0.024	-0.013	0.025	-0.117	0.082
Slum X Respondent is depressed	0.018	0.085	-0.168	0.117	0.175	0.352
Slum (1/0)	0.569*	0.322	-0.190	0.383	-0.351	1.068
Age of respondent (completed years)	-0.005**	0.002	-0.006**	0.003	-0.007	0.009
Age of marriage (continuous years)	0.004	0.008	-0.006	0.009	-0.002	0.030

	Labor force participation		Wage vs self-employment		Time spent at work	
	Coef.	Std Err	Coef.	Std Err	Coef.	Std Err
	(1)	(2)	(3)	(4)	(5)	(6)
Marital. status: never married (1/0)	0.337**	0.171	0.147	0.248	0.187	0.733
Household size	-0.013	0.015	0.012	0.015	-0.008	0.056
Years of completed education	-0.046**	0.020	-0.040*	0.022	-0.185**	0.074
Years of completed education (squared)	0.003*	0.002	0.003	0.002	0.016***	0.006
Respondent received TVET (1/0)	0.206**	0.080	-0.290***	0.099	-0.794**	0.317
Has child (<=5yrs) requiring care	-0.114**	0.049	-0.174***	0.057	-0.503***	0.178
Live in male-headed household (1/0)	-0.191***	0.064	0.037	0.062	-0.165	0.196
Duration in community: continuous years	-0.002	0.003	-0.001	0.003	0.003	0.012
Born in the community	-0.063	0.084	0.056	0.097	0.420	0.375
Needs permission to go outside	0.009	0.049	-0.080	0.059	-0.040	0.184
Feels safe outside home	0.102**	0.049	0.034	0.057	0.126	0.182
Wears burqa whenever outside the home (1/0)	-0.075	0.046	-0.185***	0.050	-0.238	0.199
Education of spouse (for women)	0.006	0.012	-0.004	0.015	0.007	0.048
Respondent is depressed (CESD Score > 10) (1/0)	0.105*	0.055	0.080	0.060	-0.262	0.194
R2	0.23		0.32		0.28	
N	1,247		742		742	

Notes: Table shows coefficients of a linear model with neighborhood fixed effects and robust standard errors. Sample is restricted to women. * p<0.1; ** p<0.05; *** p<0.01.

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Acronyms and Abbreviations

BDT	Bangladesh Taka
CESD	Center for Epidemiologic Studies Depression Scale
Dhaka CC	Dhaka City Corporation
DIGNITY	Dhaka low Income area GeNder, Inclusion, and povertY
EA	Enumeration Area
FLFP	Female Labor Force Participation
GBV	Gender-Based Violence
HIES	Household Income and Expenditures Survey
IFPRI	International Food Policy Research Institute
LFP	Labor Force Participation
LFS	Labor Force Survey
PPS	Probability Proportional to Size
PSU	Primary Sampling Unit
PVC	Polyvinyl Chloride
RMG	Ready-Made Garment
SMA	Statistical Metropolitan Area
TVET	Technical and Vocational Education and Training

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CHAPTER IX.

A Model of Entrepreneurship and Employment in Bangladesh: Simulating the Impact of Employment Regulations [1]

Abstract

This paper analyzes the likely effects of the introduction of a government-run employment injury insurance (EII) scheme in Bangladesh. For this, it builds a general equilibrium model with heterogeneous individuals and heterogeneous firms, where individuals choose their type of occupation (wage employment, own-account work, being an employer), and firms choose whether to employ any workers and, if so, how many. The model is calibrated to the Bangladeshi economy and then used for a quantitative policy analysis. The proposed benchmark EII scheme would have small effects on wages and occupational choices because the proposed tax rate is low, and because the true cost would be shared between workers and firms, if wages adjust to the new tax. The strength of quantitative results depends on assumptions about the probability of accidents, on which only limited information is available. Should accidents be significantly more common than assumed in the main scenario, the value of the scheme would be larger, and it could attract some low-skill workers from own-account work to wage employment. The model is also used to analyze the effects of stricter enforcement of labor regulations. Again, part of this cost is passed on to workers, in particular if they value enforcement. If workers strongly value enforcement, they benefit from it, and enforcement can attract individuals from own-account work to wage employment.

1. Introduction

This paper analyzes the likely effects of the introduction of a government-run employment injury insurance (EII) scheme in Bangladesh. The scheme is intended to provide workers with insurance against serious workplace accidents, which is currently lacking. The proposed scheme would pay a lump sum to accident victims, and would be financed by a tax on the payroll of employers.

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[1] This paper was written by Markus Poschke, McGill University.

Such a scheme would of course have benefits for covered workers, and impose costs on employers. If wages adjust in response to the wage tax, part of the costs could be passed on and ultimately be borne by workers. Workers would thus benefit, since they bear only part of the cost, but how much they benefit may depend on their occupational choice and their skill level. In response to the higher cost of labor, firms can be expected to adjust their employment and hiring choices. Going a step further, the scheme can also be expected to affect individuals' choices regarding whether to pursue wage employment, engage in own-account work, or run an employer firm. This margin may be important, given the large role of self-employment in Bangladesh, and in poor countries more generally.

Evaluating these potential effects requires a general equilibrium model with heterogeneous individuals and heterogeneous firms, where individuals choose their type of occupation (wage employment, own-account work, being an employer), and firms choose whether to employ any workers and, if so, how many. This paper thus builds such a model, and uses it to quantitatively evaluate the effects of the proposed EII scheme. The model would also be useful for evaluating other policy interventions that affect the labor market.

The starting point for the model is Poschke (2018b), which introduced endogenous self-employment, with a choice between own-account work and being an employer, into a Diamond-Mortensen-Pissarides (DMP) type model of frictional labor markets. The model used here extends that work by including two types of workers (high and low skill) and taste heterogeneity with respect to self-employment. The calibrated model captures key features of the Bangladeshi economy. In particular, it reproduces its high rate of self-employment, notably low-income own-account work, as well as a preponderance of small firms, combined with a very small number of very large employers. It also captures differences in wages and occupational choices across skill groups.

The main EII policy proposal considered involves a benefit of 24 months' wages, financed by a 0.3 percent tax on wages levied on firms. The model suggests that this scheme would have small effects on wages and occupational choices, simply because the tax rate used to finance benefits is fairly low. The scheme would raise welfare of low-skill workers, since it effectively involves redistribution from high- to low-skill workers. This redistribution is not visible in relative wages, but comes from the larger value of the scheme to low-skill workers.

However, the analysis also shows that effects could be larger if accidents are more common than assumed in the benchmark scenario. This is important, because to the best of my knowledge, information on the prevalence of serious workplace accidents in Bangladesh is scarce. It appears likely that currently reported numbers understate how common accidents are, and an insurance scheme would lead to more accidents being reported.[2] In this case, the insurance value of the scheme, and thus its contribution to welfare, would be larger. This would attract some low-skill workers from own-account work to wage employment.

The paper also analyzes the effect of stricter enforcement of other labor regulations. Since implementing these rules is costly to firms, this is also modeled as a tax on wages, paid by firms. The value of enforcement to workers is probably positive, but uncertain, so the analysis considers several scenarios. The main result of this part is that again, part of the cost is passed on to workers. The more workers value the enforcement of regulation, the more of the cost they bear. In spite of this, worker welfare may well increase if they value enforcement sufficiently highly. This is because they reap the full benefit of enforcement, while bearing only part of the cost. If enforcement is very valuable to workers, this can attract a significant number of workers out of own-account work and into wage employment. In some scenarios, this can result in a small increase in unemployment due to the higher cost of labor and more workers searching for jobs.

The paper is structured as follows. Section 2 sets out some key features of the Bangladeshi labor market that are important for the analysis. Section 3 describes the model. Section 4 shows the calibration of the model. Section 5 contains all the results of policy analysis. An appendix contains technical details.

2. The setting

This paper analyzes the effect of introducing EII, financed by taxes. In doing so, several potential effects of EII and taxes need to be taken into account. For this, it is important to note that, in Bangladesh, wage employment is not the only option for employment, but self-employment is also very widespread, with many of the self-employed being own-account workers. Taking this into consideration is important, because the introduction of EII and taxes changes the relative attractiveness of wage employment (affected by both EII and taxes), own-account work (not directly affected), and employing others (affected by taxes). This section thus gives a brief overview of some relevant features of the Bangladeshi economy.

[2] Without experience rating, an individual employer does not bear the cost of payouts from the scheme, so there is no a priori reason to expect accidents to become less common with the scheme in place.

In doing so, it draws on data from the Quarterly Labor Force Survey (LFS) for Bangladesh for quarters 3 and 4 of 2015 and quarter 1 of 2016, as well as the 2013 Economic Census.

Table 1 shows the composition of the labor force, overall and by skill level. For this, the labor force is split into two skill levels, high and low, where high is defined as having completed at least 12 years of schooling. By this definition, 17 percent of the labor force are high-skilled.[3]

About three-quarters of those who are employed are in wage employment. Almost one-quarter is self-employed. Out of these, about 9 out of 10 are own-account workers, and only 1 in 10 employs others. These values are fairly typical for developing economies. In high-income economies, in contrast, self-employment rates typically are around 10 percent, split roughly evenly between employers and own-account workers. (See Poschke (2018b) for more information.)

The self-employment rate in Bangladesh is particularly high for low-skill workers. The same is true for the rate of own-account work. The fraction of employers is much higher for high-skill workers. In fact, although high-skill workers account for only 17 percent of the labor force, they account for about 40 percent of employers.[4]

The rate of unemployment is very low, at just 2 percent. It is twice as high for high-skill compared to low-skill workers. These rates are very low by international standards. One reason unemployment is low is that unemployment outflow rates are quite high, at 17 percent per month on average, and 20 percent for low-skill workers. These rates are half the level of rates in the United States (which are very high by international standards), but much higher than rates in Continental Europe, and fairly high for developing countries (Donovan, Lu & Schoellman 2017).

Finally, the table reveals that the skill premium is large, with high-skill workers earning more than twice as much as low-skill workers on average.

Table 2 gives information on employer firms, by skill of the owner and the workers. Since there are hardly any firms with low-skill owners in the high-

[3] The sample consists of urban residents aged 16 to 64.

[4] The fraction of employers among low-skill workers from the LFS aligns well with information from the Economic Census. According to the LFS, 2 percent of low-skill workers are employers. The Census contains about 1.9 million firms with low-skill owners, which corresponds to roughly 2 percent of the population between 15 and 65 of 108 million. For high-skill workers, the LFS might overstate the fraction of employers. The Census contains 520,000 firms with high-skill owners, which amounts to 2.8 percent of high-skill workers – much less than 5.8 percent.

skill sector, I omit that group, and focus on low-skill owners employing low-skill workers, as well as high-skill owners employing low-skill or high-skill workers. For the purposes of this table and the quantitative analysis below, firms are classified as high-skill if more than half the workers in a firm's industry are high-skill in LFS data.

Table 1: Composition of the labor force

	All	High skill	Low skill
Labor force share		17.3	82.7
Share employees	76.2	79.7	75.3
Self-employment rate	23.8	20.3	24.5
Own-account workers	21.1	14.5	22.5
Fraction employers	2.7	5.8	2
U rate	2.2	3.7	1.8
U outflow rate	17.3	11.2	20.3
Relative earnings		2.43	1

Source, LFS, 2015Q3-2016Q1. High skill: 12 years of schooling or more. U outflow rate is monthly, to any other state.

The table shows that most firms are run by low-skill owners, and employ low-skill workers. However, although these firms account for more than three-quarters of all firms, they account for significantly less than half of all employment. This is because firms run by low-skill owners are significantly smaller. Almost 90 percent of firms from this group have fewer than five employees (conditional on having employees).

Firms run by high-skill workers are significantly larger. Among these, the ones also employing high-skill workers are overall slightly larger. However, the largest firms are run by high-skill workers, and employ low-skill workers. In this segment, there is a small set of firms with more than 1,000 employees that account for only 0.16 percent of all firms in that group, but employ almost 40 percent of workers in that group, or almost 15 percent of all workers.

3. Model

This section sets out a model of entrepreneurship and employment in frictional labor markets. Policies, like an EII scheme financed by taxes on firms, can affect not only labor demand, but also occupational choices. Effects may also differ by worker skill. Therefore, a key part of the model consists in the choices of heterogeneous individuals between job search and entrepreneurship (with a further choice between own-account work or being an employer). The results of these choices, as well as rates of unemployment, employment, and wages by skill level, are all endogenous outcomes of the model. They are in turn functions of fundamentals of the economy and of economic policies, like taxes. The model can thus be used to simulate the responses of the endogenous outcomes to changes in the environment, like the EII scheme and the taxes used to finance it.

Table 2: The firm size distribution

Worker skill/owner skill:	L/L	L/H	H/H
Fraction of firms	77	15	6
Fraction of total employment	40	37	21
Mean size (n>0)	2.7	9.6	11.1
Fraction of firms with...			
n<5	55.9	15.6	10
n<20	84.9	28.8	44.3
n<100	92.9	36.7	71.1
n<1000	95.9	61.2	90.5
Fraction of employment in firms with…			
n<5	55.9	15.6	10
n<20	84.9	28.8	44.3
n<100	92.9	36.7	71.1
n<1000	95.9	61.2	90.5

The model economy consists of a measure one of individuals, and an endogenous measure of firms, which are created and operated by individuals who choose to do so. Individuals who choose self-employment may be employers, and employ other individuals as workers, or they may be own-account workers.

There are two types of individuals, H and L, with high and low skills respectively, present in the population in proportions p_H and p_L, $p_H + p_L = 1$. When working as employees in a firm, they have productivity a_H and a_L, respectively. That is, high-skill workers supply a_H efficiency units of labor per period, and low-skill workers a_L efficiency units. In addition, individuals differ in their taste for entrepreneurship, τ .[5]

[5] It is well documented that tastes with respect to entrepreneurship differ widely in the population and have a strong effect on the choice to pursue entrepreneurship (see e.g. Hamilton (2000), Hurst & Pugsley (2011)). While taste heterogeneity in itself does not play an important role in the model, it helps generate realistic rates of entrepreneurship across the

Individuals who enter self-employment differ in the productivity z of their enterprise. Based on its value, they decide whether to be own-account workers or to employ others. Productivity in own-account work is in line with an individual's productivity as a worker. In equilibrium, those with highly productive enterprises decide to be employers. There are two types of employer firms. Firms can operate either a high-skill technology, using only high-skill workers, or a low-skill technology, using only low-skill workers. Low-skill employers can only operate the low-skill technology, and thus hire only L-type workers. High-skill employers can choose whether to operate the high- or the low-skill technology. That is, they may run a firm employing only high-skill workers, or only low-skill workers.[6]

Finding a job as an employee requires job search in a frictional labor market, analogous to other large-firm versions of the canonical Diamond-Mortensen-Pissarides (DMP) model like Cahuc, Marque & Wasmer (2008) or Elsby & Michaels (2013). That is, the unemployed who do not become self-employed have to search for a job, and may or may not find one in a given period. As a result, some of them remain unemployed. In addition, the model also captures the important reality of casual work in a simple way. Those in casual work earn income, but cannot find a longer-lasting job. Once an unemployed worker finds a job, wages are bargained between the worker and the employer.

The model builds closely on Poschke (2018b), which adds self-employment, a choice between own-account work and being an employer, and firm size heterogeneity to the DMP model.[7] The setting here goes beyond this by featuring two types of workers and firms, as well as taste heterogeneity. This setting allows analyzing how the regulation of employment affects not only employment and wages, but also unemployment, self-employment, and differences between high- and low-skill individuals. To capture these margins, it is obviously essential to allow for two skill types, and it is also necessary to allow for endogenous entry into self-employment, a choice between own-account work and being an employer, and endogenous firm size and labor market outcomes. Labor market frictions may play an important role in how regulation affects wages, unemployment, and self-employment.

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firm size distribution, as also discussed in Poschke (2018a). Without it, only entrants above a specific, endogenous threshold of productivity would run firms, resulting in an unrealistically stark firm size distribution. With taste heterogeneity, this threshold is smoothed out, as it depends on both productivity and taste. Then some firms will operate despite low productivity because their owners like the activity.

[6] In practice, of course, firms combine both types of workers. Still, this setting is a good approximation of different
types of technologies.

[7] See Pissarides (2000) for an overview of the canonical DMP model.

3.1 States, flows, and the labor market

Time in the model economy is discrete. The economy consists of a measure one of individuals of the two skill types. Each individual also has a permanent taste parameter τ , which governs her taste for self-employment compared to wage work. This parameter is drawn from a distribution $\mathcal{T}_j$ at labor market entry, where j indexes worker skill type ($j \in \{H, L\}$). In each period, any individual leaves the labor market through death or retirement with a fixed probability ϕ. At the same time, a measure ϕ of new-born individuals (with the same skill composition as the general population) newly enter the labor market via unemployment. As a result, the population and its skill and taste composition are constant.

At any point in time, an individual can be in exactly one of five states: unemployment, employment, own-account work, being an employer, or post-accident. Let their measures be u_j, n_j, e_{sj}, e_{fj} and d_j . A fraction of the unemployed engages in casual work in any period.

Flows. Individuals flow between the five states. Some of the flows occur exogenously (like retirement and job destruction), while other flows are endogenously determined in the model (like job finding and self-employment entry). All flow rates can vary between firms using the high-skill and the low-skill technology.

The exogenous flows occur with fixed rates, and are as follows. Employees face a probability χ_i per period of having an accident. If this occurs, they leave their job and enter a permanent disability state.[8] Moreover, existing matches dissolve with a probability ξ_j. Own-account workers and employers need to close their business with probabilities λ_{sj} and λ_{fj} , respectively. All of these flows move the affected individuals into the unemployment pool. For firm closures, employees also lose their jobs and move to unemployment. To simplify notation, denote the total job separation rate for workers by $s_j \equiv 1-(1-\phi)^2(1-\xi_j)(1-\lambda_{fj})$, and the exit rates for firms by $\widetilde{\lambda_{sj}} \equiv \lambda_{sj}+(1-\lambda_{sj})\phi$ and $\widetilde{\lambda_{fj}} \equiv \lambda_{fj}+(1-\lambda_{fj})\phi$, respectively. Separations can be caused by death of either the worker or the employer, by firm shutdown, or by an exogenous match separation.

In any period, a fraction δ of individuals in the unemployment pool needs to engage in casual work. I model this state as a result of a shock instead of a choice to keep the model simple. Modeling it as a choice would require

[8] The focus here is on serious accidents. It would be easy to extend the model and assume that individuals leave the disability state with some fixed probability, which could vary by skill.

introducing saving, which would substantially complicate the model. While engaged in casual work, individuals cannot search for jobs. In the following period, they return to the unemployment pool and again face the defined probability of casual work. Given its exogenous nature, income from casual work does not affect equilibrium outcomes unless it is so high that individuals would voluntarily choose it over job search. Hence, to save on notation, I assume that both the unemployed and individuals in casual work enjoy an income flow of b.

The flows from unemployment into jobs and into self-employment are endogenous. The job finding rate for job searchers f is an equilibrium object, and I discuss its determination below. The entry rate into self-employment, h, depends on choices of the unemployed. Its determination is described when their occupational choice problem is discussed below.

The labor market. The labor market is as in a standard random search and matching model: The creation of new job matches is governed by a matching function, which transforms its inputs – job searchers and job vacancies – into successful matches. This process is segmented along skill lines. Unemployed workers decide whether to search or become self-employed. With a self-employment entry rate h_j , this implies a measure of job searchers $\overline{u_j} = (1-\delta_j)(1-h_j)(1-\phi)u_j$. (Those who retire or take a casual job cannot search.) Firms aiming to hire an employee post vacancies, at a cost of k_{vj} per vacancy and period. Define labor market tightness for skill level j as $\theta_j \equiv v_j/\overline{u_j}$. Then, assuming a standard Cobb-Douglas matching function, the probability that a vacancy is filled in any given period is$q_j = q(\theta_j) \equiv A\,\theta_j^{-\mu}$, and the probability that a job seeker finds a job is $\theta_j\, q_j$, where μ is the exponent on vacancies in the matching function, and A parameterizes the efficiency of the matching process. Both probabilities depend only on labor market tightness in the relevant market segment. Since both the number of vacancies and that of searchers arise from choices, labor market tightness in each segment is an equilibrium outcome of the model, and so are the job finding and vacancy filling probabilities.

The distribution of employment states. These flows generate a partition of individuals in the economy into the five states. I will focus on stationary equilibria of this economy. In a stationary equilibrium, the measure of agents in each state is constant. Each measure can be derived by equating flows into and out of a state. In this way, the equilibrium measures of own-account workers and employers can be obtained as

$$e_s = \frac{(1-\delta)h(1-\phi)}{\widetilde{\lambda_s}}\, u \qquad (1)$$

and

$$e_f = \frac{(1-\delta)h(1-\phi)p_f}{\widetilde{\lambda_f}} u, \qquad (2)$$

where p_s and p_f denote the probability that an entrant chooses to become an own-account worker or an employer, respectively, and skill subscripts have been omitted for conciseness. These two endogenous objects are described below.

The unemployment rate in a stationary equilibrium is given by the modified Beveridge curve
(MBC)

$$u = \frac{(1-e_f-e_s)s/(1+\chi/\phi) + e_f\,\widetilde{\lambda_f} + e_s\,\widetilde{\lambda_s}}{s/(1+\chi/\phi) + (1-\delta)(1-h)(1-\phi)\theta\,q + (1-\delta)\,(1-\phi)\,h(p_f+p_s)}\,. \qquad (3)$$

For $\lambda_f = \lambda_s$, this simplifies to

$$u = \frac{s}{s + (1-\delta)(1-h)(1-\phi)(1+\chi/\phi)\theta\,q + (1-\delta)\,(1-\phi)\,h(p_f+p_s)s/\widetilde{\lambda_f}}. \qquad (4)$$

This expression is analogous to the usual Beveridge curve, with three differences. First, accidents cause flows out of employment at a rate χ, which slightly affects the unemployment rate. Second, unemployment outflows occur not only to employment (at a rate θq for searchers), but also to self-employment. As a result, the job finding rate and the unemployment outflow rate are different in this economy. Third, employees and entrepreneurs have different flow rates into unemployment. This is captured in the different terms in the numerator of equation (3), and results in the final fraction in the denominator in equation (4). Intuitively, if the flow rate into unemployment is lower for entrepreneurs than for employees, then a larger entrepreneurship rate tends to reduce unemployment.

Finally, the measure of employees follows as

$$n = 1 - u - e_s - e_f - d, \qquad (5)$$

and the measure of individuals in the disability state is

$$d = \frac{\chi}{\phi} \qquad (6)$$

Next, I describe the values and optimal behavior for firms, employees, and the unemployed.

3.2 Agents' problems, value functions, and occupational choice

Firms. Firms produce a homogeneous good and sell it in a perfectly competitive market. The price of output is normalized to 1. Recall that there are two types of firms, employing a high-skill technology with high-skill workers, or a low-skill technology with low-skill workers. Firms differ in their productivity z. Starting a firm requires paying a fixed cost k_{fj} . After this, entrants learn about the productivity of their venture. (They draw it from a known distribution with mean and variance that can differ by the owner's skill.) For simplicity, productivity is constant throughout a firm's life. Depending on their realized productivity, entrants choose whether to hire employees and which technology to operate, whether to become an own-account worker, or whether to return to unemployment.

Taste τ affects how much an individual enjoys net income from self-employment relative to that from other sources. A taste value larger than 1 implies that the individual enjoys self-employment. This modeling features captures the well-known fact that the taste for self-employment varies broadly in the population, and is an important determinant of being self-employed. The parameter can capture a variety of motives, for example the desire to be one's own boss, or stand in in a simple way for variation in risk aversion.

Own-account workers produce with the production function $y = a_j z$. Employer firms use a production function $y = z\left(a_j n_j\right)^{\gamma j}$, where j indicates the skill type used in the firm, and n_j is employment of workers of type j. (Recall that only a single skill type can be used in a firm.) The parameter $\gamma_j \in (0,1)$ captures the degree of decreasing returns to scale in production. In addition, employer firms pay a fixed cost ζ_j every period. They may also face a tax at rate t_j on their wage bill.

In this setting, a firm's employment is an endogenous object that depends on a firm's productivity, technology, and the cost of labor and hiring. As a result, the model generates firms of different sizes (in addition to own-account workers), and has a well-defined firm size distribution for any distribution of productivity. Firms of the two types differ in the productivity of their employees, in their returns to scale, and in their distribution of productivity. All of these lead to differences in size between the two types of firm. Taste does not affect firm size because it applies to net income, i.e. both revenue and cost. It only affects which firms are active.

Entrants can choose between own-account work and becoming an employer, and high-skill entrants can choose between operating a high- or low-skill firm. The relative attractiveness of these options depends on the wages for the two types of workers (w_j), the cost k_{vj} and difficulty q_j of hiring them, and the cost ζ_j of being an employer.

The cost parameter ζ_j governs the relative attractiveness of being an employer. It could be either positive or negative. It could be positive if running an employer firm requires stronger compliance with rules and regulations compared to own-account work, which is a typical presumption in the literature (see e.g. Albrecht, Navarro & Vroman 2009). Tastes, as modeled here, do not affect the choice between being an employer and an own-account worker, but affect the entry decision.

Let a firm's optimal employment choice given prices be $n_j(z)$. Then the value of own-account work for an individual of type j and with taste τ is given by

$$F_{sj}(\tau, z) = \tau\, a_j\, z \; + \; \frac{(1-\phi)\left(1-\lambda_{sj}\right)}{1+r} F_{sj}(\tau, z) + \frac{(1-\phi)\lambda_{sj}}{1+r} U_j. \tag{7}$$

The value of being an employer with technology j for an individual of type i is

$$F_{fij}(\tau, z) = -\zeta + \tau \left[z \left(a_j\, n_j(z) \right)^{\gamma_j} - (1+t_j) w_j\, n_j(z) - \frac{k_{vj}}{q_j\left(\theta_j\right)}\; \hat{\xi}_j\, n_j(z) \right] + \frac{(1-\phi)\left(1-\lambda_{fj}\right)}{1+r} F_{fij}(\tau, z) + \frac{(1-\phi)\lambda_{fj}}{1+r} U_i,$$

where $\hat{\xi}_j = \xi_j \; + \; \left(1-\xi_j\right)\phi \; + \; (1-\xi_i)(1-\phi)\chi_j$ is the rate of attrition of workers that a firm faces due to exogenous separations, death/retirement, and accidents.

The value of each activity consists in the utility value of flow profits plus the expected, discounted continuation value. For own-account workers, flow profits are simply equal to output. For employers, they equal output minus the wage bill, minus the cost of rehiring workers who depart, either due to match destruction or due to death.

Firm entry and type decision. The unemployed can decide to start a firm instead of searching for a job. Doing so involves first paying an entry cost k_{fj} . They then draw their productivity z from a known distribution $G_j(z)$.[9] Based on the realization of z, they decide whether to become an employer and of which type, whether to continue as own-account workers, or whether to return to unemployment. The following description is for high-skilled individuals, who can choose to operate either the high- or the low-

[9] The assumption of uncertainty about post-entry productivity is in line with the literature on firm dynamics, and is motivated by the large rates of turnover of young firms.

skill technology. The problem for low-skill individuals is analogous but simpler, since the low-skill technology is not available to them.

For a high-skill entrant with taste τ and productivity z, four choices are available: return to unemployment (yielding U_H), own-account work (yielding $F_{sH}(\tau, z)$) being an employer with the low-skill technology (yielding $F_{fHL}(\tau, z) - \frac{k_{vL}}{q_L(\theta_L)}\, n_L(z)$), or being an employer with the high-skill technology (yielding $F_{fHH}(\tau, z) - \frac{k_{vH}}{q_H\,(\theta_H)}\, n_H(z)$). In the latter two options, the term that is subtracted accounts for the cost of hiring that is incurred to bring the firm to its optimal scale.

The optimal choice is characterized by three thresholds, $z_{sH}(\tau)$, $z_{fH}(\tau)$ and $z_{fHH}(\tau)$. (See Figure 1.) It is clear that the value of unemployment, U_H, is independent of z. It is also clear from equation (7) that the value of own-account work increases linearly in productivity z. Finally, given optimal employment choices discussed below, the net value of operating an employer firm at optimal employment, net of the cost $n_j(z)k_{vj}/q_j$ of reaching that level, is increasing and convex in z.[10] As a result, continuation values as a function of z are as depicted in Figure 1. Entrants with productivity above $z_{fH}(\tau)$ become employers. Those with productivity below $z_{sH}(\tau)$ exit to unemployment, and those with z between $z_{sH}(\tau)$ and $z_{fH}(\tau)$ z become own-account workers. The third threshold $z_{fHH}(\tau)$ separates the levels of productivity where it is optimal to be a low-tech employer from those where the optimal choice is to be a high-tech employer. (This structure is analogous to that in Gollin (2007), except for the third threshold.) In general, it is not clear whether the most productive employers choose the high- or the low-skill technology. But one can show that they will choose the one that is closer to constant returns to scale (i.e. the one with the higher level of γ_j).

[10] Convexity reflects the ability of employers to leverage their own productivity z by hiring workers accordingly. Given constant firm-level productivity and constant, linear hiring costs due to labor market frictions, it is optimal for firms to move to optimal employment directly upon entry.

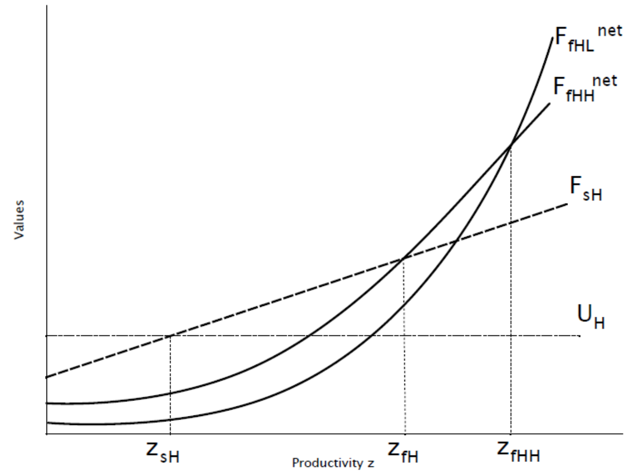

Figure 1: The values of unemployment (U_H), self-employment (F_{sH}), and the value of being an employer net of hiring costs at entry for firms employing low-skill ($F_{sHL}^{net}(z) = F_{fHL}(z) - n_{HL}(z)k_{vL}/q_L$) and high-skill workers, respectively, with associated productivity cutoffs.

Combining these possibilities, the value of entry for high-skill individuals with taste parameter τ is given by the following equation and analogously for low-skill individuals, with the difference that they can only run firms with the low-skill technology.

$$Q_H(\tau) = \frac{1-\phi}{1+r}\left[-k_{fH} + \max \int F_{fHH}(\tau,z) - \frac{k_{vH}}{q_H(\theta_H)} n_H(z)\, F_{fHL}(\tau,z) - \frac{k_{vL}}{q_L(\theta_L)} \;\; n_L(z), F_{sH}(\tau,z), U_H)\, dG_H(z)\right], \tag{9}$$

I now turn to workers and the unemployed.

Workers. Employed workers receive a wage w_j per period. They lose their job with the combined separation probability s_j, and keep it otherwise. Wage determination is discussed below. Since wages are common across jobs in a sector, workers have no incentive to leave a job voluntarily. As a result, the value of employment is given by

$$W_j = w_j + \frac{1 - s_j - \chi_j}{1+r} W_j + \frac{s_j - \phi}{1+r} U_j + \frac{\chi_j}{1+r} D_j, \tag{10}$$

where U_j is the value of the unemployment state, and D_j the value of the post-accident disability state for an individual of skill j.

Accidents. Workers who have an accident enter a permanent disability state, with utility flow b_{dj} equivalent to $\rho j w_j$ (including the flow value of any transfer payment the agent may receive). In practice, the policy proposal involves payment of a lump sum. The flow value here can be chosen to be equivalent to the lump sum. Moreover, it can be set so that benefits paid equal tax revenue, and the budget for the scheme breaks even, or it can be set to be larger, capturing that workers may value the insurance they receive at more than its cost, or to be lower, capturing that workers do not value the insurance, or do not take it into account in their choices.[11]

Let the value of the disability state be D_j. Then

$$D_j \;=\; \frac{\rho_j w_j (1+r)}{r+\phi} \qquad (11)$$

so

$$W_j \;=\; w_j \left(1 + \chi_j \frac{\rho_j}{r+\phi}\right) \;+\; \frac{1 - s_j - \chi_j}{1+r}\, W_j \;+\; \frac{s_j - \phi}{1+r} U_j \qquad (12)$$

In steady state, the mass of people receiving benefits is $n_j \chi_j / \phi$, where n_j is total employment of type j.

Unemployment and occupational choice. In any period, the unemployed need to engage in casual work with probability δ_j . Otherwise, they choose between job search and self-employment entry. These choices determine the self-employment entry rate h_j .

Job search yields a per period flow value of b_j , and results in success with probability $\theta_j q_j$. As a result, the values of search, S_j , and that of casual employment, U_j, are given by

$$S_j \;=\; b_j + \frac{1-\phi}{1+r}\left[\theta_j\, q_j\, W_j \;+\; \left(1 - \theta_j\, q_j\right) U_j\right] \qquad (13)$$

$$\underline{U_j} \;=\; b_j \;+\; \frac{1-\phi}{1+r}\, U_j \qquad (14)$$

With occupational choice, the value of unemployment for an individual of skill j is given by[12]

$$U_j \;= \delta_j\, \underline{U_j} \;+\; \left(1 - \delta_j\right) max\{S_j, Q_j(\tau)\} \qquad (15)$$

[11] We assume that employers or own-account workers are not at risk of accidents, because they are not covered by the compensation scheme. However, one could think of the calibrated payoffs of these activities as including the risk of accidents.

[12] Note that via $Q_j(\tau)$, the other worker values also depend on τ . This is suppressed in the equation for conciseness.

With probability δ_j , the unemployed need to engage in casual work and cannot search. With the complementary probability, they can either search, or choose to start a firm. Since individuals differ in taste, only those with $Q_j(\tau) > S_j$ enter self-employment. Those with τ such that $Q_j(\tau) = S_j$ are indifferent between the two choices. Let the value of τ that satisfies this condition be $\bar{\tau}$. Then, those individuals with $\tau > \bar{\tau}$ enter self-employment. Since $\bar{\tau}$ is endogenous and depends on equilibrium objects, this implies that an endogenous fraction h_j of the unemployed with skill j start a firm, where $h_j \equiv \int_{\bar{\tau}_j}^{\infty} u_j(\tau)\, d\tau / u_j$,where $u_j(\tau)$ is the taste distribution of the unemployed with skill j.

3.3 Wage determination and vacancy posting

When a firm and a worker meet and a match is created, the two parties bargain over the wage. Because of frictions in match creation, each match involves some surplus. The wage determines how this surplus is split between the firm and the worker.

Like Cahuc et al. (2008) and Elsby & Michaels (2013), I assume that sector j workers and firms split the surplus from a match, with workers receiving a fixed share proportional to their bargaining weight η_j .[13] Wages are bargained upon hiring, and remain constant thereafter. That is, wages solve the surplus sharing equation

$$(1 - \eta_j)(W_j - U_j) = \eta_j \, \frac{\partial F_f^{ij}(\tau, z, n_j)}{\partial\, n_j} \qquad (16)$$

where the last term on the right-hand side denotes the marginal value of an additional worker to a j-tech firm with productivity z and employment n_j operated by an owner with skill i and taste τ .

For simplicity, I assume that when a worker and a firm bargain over the wage, neither of them can observe the other's taste τ , and that they instead assume that the other has the population average taste.[14]

In this setting, it can be shown (see Appendix A.3 for a detailed derivation) that

[13] See Stole & Zwiebel (1996) and Bruegemann, Gautier & Menzio (forthcoming) for the game-theoretic foundations of this assumption.

[14] This implies that workers ignore some information at their disposal, like the effect of taste on entry, and that both parties ignore selection patterns. Taking these issues into account would complicate the analysis without obvious added benefit or realism.

$$w = \frac{1 - \tilde{\eta}\, t\, (\gamma - 1)}{1 - \tilde{\eta}\, (1 + t\, \gamma)} \frac{r + \phi + \chi}{1 + r} \frac{1 - \eta}{\eta} \frac{\tilde{\eta}}{1 + t}\, U + \frac{\tilde{\eta}}{1 - \tilde{\eta}\, (1 + t\, \gamma)} \left[1 - \frac{(1 - \phi)(1 - \lambda_f)}{1 + r} + \hat{\xi} \right] \frac{k_v}{q(\theta)}, \tag{17}$$

where $\tilde{\eta} = (1 + t)\eta\, \frac{r+\phi}{(1+\eta\, t)(r+\phi)+(1-\eta)\chi\, \rho}$, and j subscripts are omitted for conciseness. Four remarks are in order. First, the wage curve given by equation (17) is analogous to the wage curve in a standard DMP model, with the exception of the values of the constants. In particular, wages increase with labor market tightness θ, reflecting the fact that match surplus is larger when the expected hiring cost k_v/q is larger. Wages also increase with the value of the worker's outside option U. Second, although firms vary in productivity, all workers in a market segment are paid the same wage. This is because, upon hiring, any worker is marginal, and the relevant surplus to consider in bargaining is that of a marginal job. When firms are at their optimal employment, the marginal surplus is equalized across firms. As a consequence, wages are also equalized across firms of heterogeneous productivity. More productive firms then do not pay higher wages, but instead have more employees. (See Appendix A.3 for more detail on this point.) Third, self-employment opportunities enter bargaining workers' outside option U, and can affect wages in this way.

Finally, the possibility of accidents, and benefits paid in case of accidents, enter the wage via χ and ρ. They affect workers' effective bargaining power (the equation contains $\tilde{\eta}$ instead of η, reflecting the effect of taxes as well as benefits) as well as the value of the outside option. With accidents and benefits, $\tilde{\eta} < \eta$. This captures that the additional benefit effectively reduces workers' bargaining power. The separation rate now takes into account the possibility of accidents, both for the weight on U and that on firms' (re)hiring cost. If workers do not value the benefit ($\rho = 0$), but accidents still occur ($\chi > 0$), the wage setting process still takes the more frequent separations into account.

A firm's optimal employment is given by

$$n(z) = (\, z\, \gamma\, a^{\gamma})^{\frac{1}{1-\gamma}} \left\{ \frac{1 + \tilde{\eta}(\gamma - 1)}{1 - \tilde{\eta}(\gamma - 1)} \left[(1 + t)w\, + \left(1 - \frac{(1 - \phi)(1 - \lambda_f)}{1 + r} + \hat{\xi} \right) \frac{k_v}{q} \right] \right\}^{\frac{1}{(1-\gamma)}}. \tag{18}$$

(Again, see Appendix A.3 for a detailed derivation.) Optimal firm size increases with productivity, and decreases with the cost of employing a worker, which comprises both the wage and the expected cost of replacing departing workers. The taste for entrepreneurship does not affect optimal employment, because it applies to profits.

Continuing employer firms face departures of workers at a rate of $\hat{\xi}$ per period, and thus need to post $\hat{\xi} n(z)/q$ vacancies per period to replace them. New entrants find it optimal to hire $n(z)$ workers all at once, and therefore post n(z)=q vacancies. From equation (2), new entrants account for a fraction $\tilde{\lambda}_f$ of employers. As a result, total vacancies in a sector are given by

$$v = \frac{\tilde{\lambda}_f + (1 - \tilde{\lambda}_{fj})\hat{\xi}}{q} e_{fj} \int n(z)\tilde{g}(z)\ dz. \tag{19}$$

Individuals make choices taking labor-market tightness θ in both market segments as given. In equilibrium, tightness generated by individuals' actions in terms of occupational choice and hiring needs to be consistent with this, that is

$$\theta = \frac{v}{(1-\delta)(1-h)(1-\phi)u}, \tag{20}$$

where the denominator on the right-hand side results from entry choices, and the numerator results from entry, firm type, and hiring choices.

3.4 Equilibrium

Taxes, benefits, and the government budget. EII benefits and taxes enter the government's budget.[15] Worker's utility flow in the disability state is $b_{dj} = \rho_j w_j$. Suppose that part of this, $\hat{b}_{dj}$, is an endowment (pure utility), whereas the remainder, $b_{dj} = \hat{b}_{dj}$ is a transfer from the government. The government raises revenue for this transfer from taxes on the wage bill charged to firms.

In this case, aggregate tax revenue is

$$T_j = a_j^{\gamma_j} \left[\frac{\gamma_j a_j}{\eta_j\,(\gamma_j - 1) + 1} \frac{1}{c_{1j} k_{vj}/q_j + w_j} \right]^{\frac{\gamma_j}{1-\gamma_j}} e_{fj}\, z_{\tau j}^{*}\,, \tag{21}$$

where

$$z_{\tau j}^{*} \equiv \int \tau(z) \left[\left(1 - \tau(z)\right) z \right]^{\frac{1}{1-\gamma_j}} dG_j(z) \tag{22}$$

and $c_{1j} \equiv 1 - \frac{(1-\phi)(1-\lambda_{fj})}{1+r} + \xi_j + (1-\xi_j)\phi$. (Recall that e_{fj} is the measure of employers hiring j type workers.) Suppose that a fraction $\hat{\rho}$ of aggregate tax revenue is paid out as benefits. Then flow payments per recipient can be

[15]In practice, the scheme may be administered by a different entity. Here, I refer to it as the "government."

$$b_{dj} - \hat{b}_{dj} = \frac{\rho\, T_j}{d_j} = \frac{\hat{\rho} T_j}{n_j \frac{\chi_j}{\phi}} = \frac{\phi\, \hat{\rho}}{\chi_j} \frac{z^*_{\tau j}}{z^*_j} \frac{Y_j}{n_j} \tag{23}$$

$$= \frac{\phi\, \hat{\rho}}{\chi_j}\, a_j^{\gamma_j} \left(\frac{\gamma_j a_j}{\eta_j \left(\gamma_j - 1\right) + 1} \right)^{\frac{\gamma}{1-\gamma_j}} \left(c_1 \frac{k_{vj}}{q_j} + w_j \right)_j^{-\frac{\gamma}{1-\gamma_j}} z^*_{\tau j} \frac{e_{fj}}{n_j}, \tag{24}$$

where

$$z_j^* = \int \left[\left(1 - \tau(z)\right) z\right]^{\frac{1}{1-\gamma_j}} dG_j(z). \tag{25}$$

(Note that, of course, z^*, z^*_τ, Y, q, e_f and n are all endogenous and change with the tax system.) From the first line, payouts are a (endogenous) fraction of output per worker.

Since the scheme is only a small part of the Bangladeshi government's budget, it may or may not break even. In the quantitative exercise, several scenarios are considered.

Stationary equilibrium. A stationary equilibrium consists in values $W_j, U_j, S_j, \underline{U_j}, F_f^{ij}(\tau, z)$, $F_s^{ij}(\tau, z), Q_j(\tau)$, a distribution described by u_j, n_j, e_s^j, e_f^j, and d_j, probabilities h_j, functions $n_j(z)$, and numbers \$ $\bar{\tau}_j, v_j, \theta_j, w_j$ for $i, j \in \{H, L\}$ such that

1. The values $W_j, U_j, S_j, \underline{U_j}, F_f^{ij}(\tau, z)$, $F_s^{ij}(\tau, z), Q_j(\tau)$ are given by equations (7) to (8) and (9) to (15),
2. The unemployed choose optimally whether to enter self-employment ($\tau > \bar{\tau}_j$) or to search,
3. Wages fulfill equation (17),
4. The equilibrium distributions are generated by household choices and are stationary, according to equations (1) to (5),
5. Firms post vacancies optimally (equations (18) and (19)), and
6. Labor market tightness in each segment j (given by equation (20)) is generated by unemployment in- and outflows and by firms' vacancy posting decisions.

The key equilibrium objects are θ_H and θ_L. Given the assumptions on bargaining, θ_j is sufficient for computing value functions and thus optimal choices (entry, firm type, hiring) for individuals and firms of different taste in a market segment. These choices imply flow rates, which in turn determine rates of unemployment, self-employment, and other states in a stationary state of the economy. The combination of these states and choices imply segment-level vacancies and the number of searchers, and thus tightness.

The two sectors of the economy are linked because high-skill employers can run firms employing low-skill workers. This implies that opportunities for high-skill workers, which affect how many of them choose to become employers, can affect demand for hiring low-skill workers. At the same time, opportunities for low-skill workers, which affect how many of them search for wage employment, affect how many high-skill workers choose to run firms with the low-skill technologies.

4. Calibration

To be able to conduct a quantitative evaluation of various policy proposals, I calibrate the model to the economy of Bangladesh. This requires choosing an empirical definition of high versus low skills, choosing distributions for productivity z and taste τ , and setting parameter values. A model period corresponds to one month.

High skill is defined as having completed 12 years of schooling or more. This implies that the fraction of the labor force with high skills, p_H, is 17.3 percent (Labor Force Survey, 2015Q3 to 2016Q1).

The taste distribution is assumed to be log-normal. Log tastes have standard deviation σ_τ and mean $-\sigma_\tau^2/2$ implying that tastes have mean 1. This distribution is assumed to be identical for both skill groups.[16]

The productivity distribution is assumed to be log-normal, augmented by an atom at a high level of productivity. This is important for capturing the fact that some very large employers, with more than 1,000 employees, account for a large fraction of employment, in particular for low-skill workers. This would not be possible with a log-normal distribution alone. Thus, I assume that with probability $1-\iota_j$ an entrant draws her productivity from a log-normal distribution, where log z has mean μ_j and standard deviation σ_z^j. With probability ι_j , her log productivity is $\mu_j + \kappa_j\sigma_z^j$. Since in practice, large firms mostly have high-skill owners (although they may mostly employ low-skill workers), I set ι_L to zero, and only allow ι_H to be positive.

With these choices made, it remains to choose parameter values. Three of these can be normalized: I set the productivity of low-skill workers, a_L, mean productivity of low-skill entrants, $\exp(\mu_L + \sigma_z^{L2}/2)$, and the productivity parameter in the matching function, A, to 1. Furthermore, I set the exponent on vacancies in the matching function to the commonly used

[16] Ideally, all parameters would vary by skill. However, the challenge is to find identifying information in the data. Therefore, I let as many parameters as possible vary by skill, but am restricted to assume that some are common.

value of 0.5. The annual discount rate is set to 4 percent, and the death/retirement probability ϕ is set such that the expected duration of a working life is 40 years. Absent direct information from Bangladesh, the firm exit rates λ_f^j and λ_s^j are set to be equal, and to generate an annual exit rate of 11.9 percent, as in Mexico (Bartelsman, Haltiwanger & Scarpetta 2004).

This leaves 23 parameters to calibrate: $a^H, k_f^j, k_v^j, \zeta_j, \xi_j, \eta_j, b_j, \gamma_j, \mu_H, \sigma_z^j, \iota_H, \kappa_H, \sigma_\tau$, and δ_j. These are mostly set to match target statistics describing the Bangladeshi economy, with only five parameter values taken from the related literature. That is, the remaining 18 parameter values are set to match 18 targets describing the Bangladeshi economy. Because of the non-linearity of the model, it is not possible to match these targets exactly. Therefore, I set parameter values to minimize the sum of squared distances between target moments and model equivalents.

Next, I discuss what information is used to calibrate the model. In general, because of the complexity of the model, all parameters affect all calibration targets to some extent. However, each parameter has a particularly strong effect on one or a few target moments. I therefore next discuss which information is useful for identifying which parameter. I begin with firms and the distribution of productivity. The parameters describing the distribution of productivity are calibrated to match information on the distribution of firm sizes, by skill, computed from the Economic Census for Bangladesh. Concretely, I calibrate $\sigma_z^L,\ \sigma_z^H,\ \mu_H,\ \sigma_\tau^L,\ \sigma_\tau^H$, and γ_H to match the shares of employment in low-skill and high-skill firms with over 20 employees and over 100 employees, respectively, as well as the shares of firms with less than five employees. Because a very large share of low-skill employment (20.6 percent) is in firms with more than 1,000 employees, I calibrate ι_H to match this number.[17] The degree of returns to scale in low-tech firms, γ_L, is set to 0.85, a value common in the literature (Atkeson & Kehoe 2005).

The costs of entry, k_f^j , are set to match self-employment rates by skill. The costs of being an employer rather than an own-account worker, ζ_j, are set to match the fraction of employers by skill type.

The cost of hiring is one of the main determinants of firms' employment choices, as shown in equation (18). As a result, it directly feeds into vacancy creation by firms (equation 19). Given an unemployment rate and

[17] The target identifies a set of combinations of ι_H and κ_H. In practice, it does not matter much which of these combinations is chosen. In principle, additional information on employment at the top of the firm size distribution could be used to choose one of these combinations. I thus set κ_H to 4.66. This implies that the top firms are roughly 60 percent more productive than those just below, and employ two and a half times as many workers.

occupational choices, vacancy creation directly determines labor market tightness and thereby a searcher's probability of finding a job (equation 20). Thus, the vacancy posting cost k_v^j is set to match unemployment outflow rates by skill group.[18]

The unemployment rate at a point in time depends on unemployment outflows and inflows. In practice, unemployment in Bangladesh is so low that matching it in the model requires no destruction of ongoing matches except when firms close, i.e. ξ_j = 0. Given this, the probability of casual employment by sector, δ_j, can be set to match the unemployment rate.

Finally, the relative productivity of high-skill workers, a_H, is set to match their relative wage. The bargaining power of workers, η_j, is set to match a labor share in national income of approximately two-thirds (Gollin 2002). The utility flow in unemployment is set at 40 percent of the wage.

Table 3: Calibration: model fit

	model		data	
	skill group		skill group	
Moment	L	H	L	H
% share of employment in firms with …				
n>20	45.9	75.1	41.7	55.7
n>100	18.9	30.4	33.8	28.9
n>1000	18.9		20.6	
Rate of own-account work (%)	23.6	22.9	22.5	14.5
Fraction employers (%)	3	4.2	2	4
Unemployment outflow rate (%)	19.8	10.9	20.3	11.2
Unemployment rate (%)	1.8	3.3	1.8	3.7
Skill premium (w_H/w_L)	2.43		2.43	
Labor income share	67.2	57.1	67	67
b/w	0.389	0.392	0.4	0.4

[18] This is computed from unemployment durations reported in the LFS using the method from Shimer (2012).

Table 3 shows the fit of the model. Key statistics are matched very closely. Matching the firm size distribution well turns out to be quite difficult. The model does very well at the top of the distribution. This is important, because a very small number of very large employers account for a large share of employment, and it is desirable to capture this correctly in the model. The model does somewhat less well in the middle. In particular, it does not generate enough small employer firms.

The model also obtains a good fit to the distribution of employment states. It matches the fraction of employers fairly closely, which is important, since these will react to the policies analyzed below. The model overstates the rate of own-account work among high-skilled workers.

Finally, the model also obtains a reasonable fit to other labor market statistics, related to both unemployment and incomes, except for the fact that it understates the labor income share in high-skill employment. Ideally, it would be desirable to evaluate the fit of the model along further dimensions. However, this would require additional analysis of micro data, to compute moments that could be compared to the model.

Table 4: Calibration: parameter values

		Skill group	
Parameter	Interpretation	L	H
σ_z^2	variance log productivity	0.1	0.198
μ_z	mean log productivity	-0.005	-0.073
σ_τ^2	variance log taste	0.1094	0.1104
ι	probability top productivity	0	0.004
κ	level top productivity	--	4.66
γ	returns to scale	0.85	0.835
k_f	entry cost	47	200
ζ	employer fixed cost	40	20
k_v	vacancy posting cost	23.2	72
ξ	match destruction rate	0	0
δ	probability casual work	0.73	0.72
a	worker productivity	1	2.35
η	worker bargaining power	0.0775	0.215
b	utility flow in unemployment	0.155	0.38

Table 4 reports model parameters. A few stand out. The productivity of high-skill entrepreneurs is much more dispersed than that of low-skilled ones. In addition, high-skill entrants benefit from a 0.4 percent probability of drawing a very high level of productivity. These two parameter settings reflect the fact that larger firms are run by high-skill entrepreneurs, whereas low-skill employers mostly run small firms. While mean productivity of the distribution that entrants draw from does not vary greatly by entrepreneur skill, productivity conditional on choices is higher for high-skill entrepreneurs. High-skill individuals are also significantly more productive as workers. This gives them a wage premium of more than 100 percent, in line with the data.

Finally, the calibration assigns higher entry costs to high-skill owners, but lower costs for such an owner to be an employer. If it were not for the former, the attractive productivity distribution faced by high-skill entrants would motivate too many high-skill individuals to start firms. The higher entry cost is, of course, in line with the larger size and (not measured here) capital intensity of businesses run by high-skill employers. The lower cost of being an employer leads more high-skill entrants to become employers, in line with the data. This could be interpreted to reflect choices of industry and production technology of high-skill entrepreneurs, which more naturally imply employing others.

Overall, the model captures key features of the Bangladeshi economy: high rates of self-employment and in particular own-account work, and a preponderance of small firms, combined with a very small number of very large employers. In the following section, I use the calibrated model for policy analysis.

5. Policy analysis

This section presents results evaluating the EII policy under several scenarios. It also presents some results on the implications of stronger enforcement of labor regulation.

5.1 Employment injury insurance

The EII policy involves paying workers a lump sum benefit after they suffer an accident. These benefits would be, partly or fully, financed by taxes on wages levied on employers. Any analysis of such a policy requires three inputs for the model: the accident rate, the size of the benefit paid, and the type and rate of tax used to finance the benefit. The main scenario I analyze consists of a benefit equivalent to 24 months' wages of a low-skill worker paid out after an accident, financed by a payroll tax of 0.3 percent.[19] A

[19] For comparison, Kumar, Mahmud, Nataraj & Cho (2019) report that in a sample of Bangladeshi small and medium-sized enterprises (SMEs), 75 percent of employees report that their employer would cover medical costs after a work-related accident. This is a highly valued job benefit – but much smaller than the benefit studied here.

challenge consists in quantifying the accident rate, on which there is no strong evidence. In the main scenario, I assume that the accident probability is such that the EII budget breaks even. This implies an accident probability per worker of 0.015 percent per month or 0.18 percent per year. While this sounds tiny, it adds up to a probability of 7 percent in a 40-year working life. [20]

In addition to the main scenario, I also analyze several other scenarios. The first one addresses the fact that it is unclear how much workers value EII benefits. It is plausible that workers would like insurance against accidents, and EII provides this. But at the same time, it may also be that workers would not know about the scheme or, due to the relatively low probability of accidents in any given month, not take it into account in their decisions. I therefore explore the implications of introducing an EII scheme for several values of the parameter ρ, which controls how much workers value EII benefits.

Then, I consider the outcomes implied if the true accident probability is higher. This captures uncertainty about the true accident probability, but also allows for the case that there is currently under-reporting, and that more accidents would be reported once an EII policy is in place. Clearly, a higher accident probability implies greater expenditure of the EII scheme. I consider both a case where taxes are increased to balance the budget, and one where they are kept as in the benchmark.

Table 5: The effect of the benchmark EII scheme on wages and choices

	skill group	
Change in...	L	H
w (in %)	-0.18	-0.12
w_H/w_L (in %)	0.06	
Value of being unemployed (U, in %)	0.16	-0.03
Value of wage employment (W, in %)	0.17	-0.01

[20] Officially reported numbers are much lower still, as shown in Khanom (n.d.). For example, in 2005, 1,527 deaths, serious accidents, or minor injuries were reported to the Inspectorate of Factories. However, at that time, only large establishments were required to report accidents, and even for them, the degree of compliance with the reporting requirement is unknown. These numbers thus constitute a lower bound on the number of accidents. An alternative source consists in newspaper reports. Over the period 2005-09, about 3,600 deaths or injuries per year were reported in newspapers. These reports are more likely to capture large events, and may thus also seriously understate true figures. The importance accorded to the issue in public debate suggests that true figures may be significantly higher. The fact that Kumar et al. (2019) find a high willingness of employees to "pay" for accident insurance, defined as employers covering medical costs after a work-related accident, also suggests that the perceived probability of accidents is substantial.

Fraction employees (pct pts)	0.06	-0.07
u rate (pct pts)	0	0.01
Rate of own-account work (pct pts)	-0.08	0.03
Fraction employers (pct pts)	0	0.01
Mean firm size (in %)	0.12	0.3

Table 5 shows the results for the benchmark EII scheme. The introduction of the 0.3 percent tax on wages leads to a reduction in wages. The fact that there is bargaining, and that workers have alternatives to wage employment, imply that wages decline by less than 0.3 percent, and the burden of the tax is shared by workers and employers. Despite lower wages, the value of unemployment and employment both rise for low-skill workers. This is because they value the EII benefit, and only bear part of its cost through the lower wage. High-skill workers, in contrast, are very marginally worse off. This is because they pay the same tax rate, but value the benefit less because it is smaller relative to their (higher) wage.

The EII benefit makes wage employment more attractive for low-skill workers, so their rate of employment rises, and the rate of own-account work falls. For high-skill workers, the opposite change occurs. It should be noted that these changes are small – all rates change by less than one-tenth of a percentage point. This is because the tax and the benefit are small interventions relative to the size of the economy and overall payoffs.

Table 6: The effect of the benchmark EII scheme on wages and choices, alternative assumptions on benefit valuation

	Value to workers			
	Full cost		0.5 x cost	
	Skill group		Skill group	
Change in...	L	H	L	H
w (in %)	-0.1	-0.09	-0.18	-0.09
w_H/w_L (in %)	0.01		0.09	
Value of being unemployed (U, in %)	0.05	-0.07	0.16	-0.14
Value of wage employment (W, in %)	0.06	-0.05	0.17	-0.13
Fraction employees (pct pts)	0.03	-0.05	0.06	-0.12
u (pct pts)	0	0.01	0	0.01
Rate of own-account work (pct pts)	-0.05	0	-0.08	0.07
Employer rate (pct pts)	0	0	0	0.01
Mean firm size (in %)	0.15	0.23	0.12	0.47

Table 6 shows results for alternative assumptions on how workers value benefits. In the main scenario, workers fully value the EII insurance benefits, and correctly anticipate receiving them in case of an accident. Here, I consider two alternative scenarios. In the first one, workers value the benefit only at half its cost. This would occur for example if workers are not fully aware of the benefit, or not certain that they would receive it. In a second scenario, low-skill workers fully value the benefit, but high-skill workers do not value it at all. This could occur if for example high-skill workers do not think that they could be subject to accidents.

In the benchmark scenario, taxes on wages result in lower wages because taxes reduce the firm's surplus, and because the benefit increases workers' surplus. If benefits are valued less, workers' surplus increases less, so that wages fall less. The lower valuation also implies that the value of employment and unemployment increases less than above for low-skill workers, and falls more for high-skill workers. As a result, the movement of low-skill workers from own-account work to self-employment is muted. The same is true for the movement of high-skill workers into own-account work.

If high-skill workers do not value the benefit, but low-skill workers do, outcomes are similar to the main exercise, but slightly strengthened. The value of employment and unemployment for high-skill workers declines more, and these workers shift into own-account work to a larger extent. The fraction of high-skill employers also increases. Since some of them employ low-skill workers, this change could in principle affect outcomes for low-skill workers. However, the change in the fraction of employers is so small that this effect is not visible. Overall, changes in choices are still small, with the largest change barely exceeding one-tenth of a percentage point.

Table 7: The effect of the benchmark EII scheme on wages and choices, five times higher accident probability

	Benchmark taxes Skill group		Taxes such that budget breaks even Skill group	
Change in...	L	H	L	H
w (in %)	-0.72	-0.3	-0.89	-0.67
w_H/w_L (in %)	0.42		0.23	
Value of being unemployed (U, in %)	1.05	0.39	0.76	-0.28
Value of wage employment (W, in %)	1.05	0.41	0.8	-0.15
Fraction employees (pct pts)	0.51	-0.01	0.35	-0.28
u (pct pts)	0	0	0.02	0.11
Rate of own-account work (pct pts)	-0.68	-0.01	-0.53	0.02
Employer rate (pct pts)	-0.01	0.01	-0.04	-0.01
Mean firm size (in %)	0.01	-0.03	0.02	-0.02
Tax rate	0.003		0.019	
Budget deficit/Y (in %)	-1.2		0	

Table 7 shows results for a case where the true accident probability is not 0.015 percent per month, but five times higher, at 0.075 percent per month. This implies a probability of 0.9 percent per year, or 30 percent over 40 years. This may constitute an upper bound on the probability of accidents, about which there is considerable uncertainty.

A higher probability of accidents of course implies more benefit payouts. At the benchmark tax rate of 0.3 percent, this implies that the EII scheme will run a budget deficit. To avoid this, the wage tax would need to be levied at a rate of 1.9 percent. The table shows results for both cases.

A higher probability of accidents raises the value of the EII scheme. The scheme thus significantly raises the welfare of low-skill workers, even at the higher tax rate required for the scheme to break even. High-skill workers benefit if the scheme runs a deficit. At the higher break-even taxes, the EII scheme reduces their welfare, since their tax payments exceed the value of benefits they receive. The combination of taxes and welfare changes leads to lower wages for all groups. The wages of low-skill workers fall particularly strongly, reflecting that their valuation of the insurance scheme enters bargaining. This illustrates that relative wages are not a sufficient statistic for relative welfare of the two groups: they do not take into account the value of the insurance scheme. Because of the value of insurance, the relative welfare of low-skill employees rises, although their relative wage falls.

These changes make it more attractive for low-skill workers to become employees, so the fraction of own-account workers falls, and that of employees increases. In the high-tax case, the higher cost of high-skill workers leads to a small increase in unemployment (by a tenth of a percentage point) for them.

Summarizing, these results show that the benchmark EII scheme should have small effects on wages and occupational choices, simply because the tax rate used to finance benefits is fairly low. In this case, the scheme would slightly raise welfare of low-skill workers. Should it turn out though that accidents are more likely than assumed in the benchmark scenario, effects could be larger. In this case, the insurance value of the scheme, and thus its contribution to welfare, would be much larger. This could attract some low-skill workers into wage employment, despite slightly lower wages. A scheme that is financed by a common proportional tax rate and pays out fixed benefits redistributes from high- to low-wage workers. As a consequence, high-skill workers tend to lose out slightly from a scheme with a balanced budget. Because these losses are small, they should lead only to small changes in occupational choices.

5.2 Enforcement of labor regulation

The model also provides a useful laboratory for analyzing the effects of stronger enforcement of labor regulations. The key implication of stronger enforcement is that it raises costs to firms. This can be captured by modeling stronger enforcement as a wage tax, paid by firms. This captures the fact that stricter enforcement raises the cost of employing workers, for each worker.

Since a large share of regulation consists in health, safety, and other rules intended to benefit workers, workers should in principle value this stronger enforcement. The analysis will thus also allow for workers to value the stricter enforcement. This section shows results for four scenarios, varying in the cost of enforcement to firms and the valuation of enforcement by workers. In the first two scenarios, the cost of enforcement to firms is low, at 1 percent of the wage per worker. In the last two, it is high, at 5 percent of the wage. In each case, I consider two scenarios for the valuation of enforcement by workers. In the first one, they value it at its full cost, whereas in the second one, they only value it at half its cost.

Table 8: The effect of stricter enforcement of regulation on wages and choices, A: cost of regulation equivalent to 1 percent of wages

	Value to workers			
	Full cost		0.5 x cost	
	Skill group		Skill group	
Change in...	L	H	L	H
w (in %)	-0.51	-0.53	-0.3	-0.37
w_H/w_L (in %)	-0.02		-0.07	
Value of being unemployed (U, in %)	0.42	0.28	0.13	-0.05
Value of wage employment (W, in %)	0.44	0.34	0.15	0.01
Fraction employees (pct pts)	0.16	-0.12	0.05	-0.08
u (pct pts)	0.01	0.04	0.02	0.05
Rate of own-account work (pct pts)	-0.22	0	-0.09	-0.06
Employer rate (pct pts)	0	0.01	-0.01	-0.01
Mean firm size (in %)	0	0.01	0	0.01

Table 8 shows results for the first two scenarios, i.e., with a low cost of enforcement, and two values for the valuation by workers. When workers fully value the benefits of the regulation, enforcement raises the value of employment for both groups. When workers value it only partly, the value of employment still rises slightly for the low-skilled. Part of the cost of enforcement is paid by workers, in the form of lower wages. The more workers value it, the more their wages fall. This occurs because when workers value enforcement, it raises their surplus from employment relationships; in bargaining, firms can then extract part of that surplus via lower wages.

As employment becomes more attractive, more low-skill workers choose to search and become wage employees, and their rate of own-account work falls. For high-skill workers, changes in occupational choices are tiny.

Table 9: The effect of stricter enforcement of regulation on wages and choices, B: cost of regulation equivalent to 5 percent of wages

	Value to workers			
	Full cost		0.5 x cost	
	Skill group		Skill group	
Change in...	L	H	L	H
w (in %)	-2.44	-2.57	-1.44	-1.8
w_H/w_L (in %)	-0.13		-0.37	
Value of being unemployed (U, in %)	2.1	1.36	0.67	-0.31
Value of wage employment (W, in %)	2.2	1.67	0.78	0.01
Fraction employees (pct pts)	0.9	-0.49	0.28	-0.34
u (pct pts)	0.07	0.19	0.08	0.25
Rate of own-account work (pct pts)	-1.16	-0.12	-0.49	-0.36
Employer rate (pct pts)	-0.07	0	-0.11	-0.12
Mean firm size (in %)	0.04	-0.02	0.04	-0.03

Results are qualitatively similar when the cost of regulation is larger (see Table 9), but all changes are quantitatively larger. In these scenarios, it becomes evident that the higher cost of labor due to enforcement also leads to a somewhat higher unemployment rate.

Summarizing, the cost of enforcement is shared between firms and workers. When workers value enforcement, it makes wage employment more attractive, and pulls workers out of own-account work. As more workers look for jobs, and the cost of labor is higher, unemployment may rise slightly. Overall, the reaction of unemployment is quantitatively modest even for quite costly regulation. A key factor in this is the assumption of wage bargaining, which allows wages to react to the cost of enforcement.[21]

[21] Wages would also absorb some of the cost of enforcement in a competitive labor market. This might differ if firms have monopsony power, or if some institutional features of the market prevent wages from reacting to changes in the environment.

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Appendix

A. Proofs and derivations

A.1 Summary of model timing

The following summarizes the timing of events in this economy.

1. If individuals chose to enter, they pay the entry cost k_f and their productivity $z \sim f(z)$ is realized.
2. Depending on z, entrants decide whether
(a) to keep the business and post vacancies to reach the optimal employment level,
(b) to be self-employed, or
(c) to exit and go to the unemployment pool.
3. Shocks $\left(\phi, \lambda_f, \lambda_s, \xi, \delta, \theta \cdot\ q(\theta)\right)$ are realized.
4. Value functions are measured and occupational choices take place.
5. Production takes place and payoffs (w; b) are realized.

A.2 Derivation of steady state stocks in the different states

In a stationary equilibrium, inflows and outflows from each state are equal. Moreover, the measure of agents in all states adds up to the total population. This implies

$$e_k = \frac{(1-\delta)(1-\phi)hp_k}{\tilde{\lambda}_k}\, u \tag{26}$$

for k = s; f, as well as

$$n = \frac{(1-\delta)(1-\phi)(1-h)\theta q}{1-\left(1-\lambda_f\right)(1-\xi)(1-\phi)^2(1-\chi)} u \tag{27}$$

Because

$$1 = e_f + e_s + n + d + u = e_f + e_s + n\left(1+\frac{\chi}{\phi}\right) + u, \tag{28}$$

we obtain the MBC (equation 3) in the text. When setting $\lambda_f = \lambda_s$, this simplifies to equation 4.

A.3 Detailed derivation of wage

As stated in the main part of the paper, workers and firms split the surplus according to workers' bargaining weight η. The total surplus is the sum of workers' and firms' surplus, explicit expressions of which are given below. Let j index agent/employee type. Let i index employer type, if needed separately. Let parameters differ, except for ϕ and r.

Worker's Surplus. The value of employment is given by

$$W_j = \left(1+\chi_j\frac{\rho_j}{r+\phi}\right) w_j + \frac{1-s_j-\chi_j}{1+r} W_j + \frac{s_j-\phi}{1+r} U_j$$

Rewrite this to obtain $W_j - U_j$:

$$W_j - U_j = \frac{1+r}{r+s_j+\chi_j}\left(1+\chi_j\frac{\rho_j}{r+\phi}\right) w_j - \frac{r+\phi+\chi_j}{r+s_j+\chi_j} U_j.$$

Firm's Surplus. The value of a firm is given in (8). The marginal value of hiring an additional
worker the firm has just met, and keeping that worker until either the firm shuts down or some type of separation occurs, is given by

$$c_0\left(\varepsilon\, y_j'\left(n_j\right) - w_j - n_j \cdot w_j'\left(n_j\right)\right) \tag{29}$$

where $\hat{c}_0 = (1+r)/(r+\hat{s}_j)$, and $\hat{s} = 1-(1-\phi)^2\,(1-\lambda_{fj})(1-\xi_j)(1-\chi_j)$.

Nash Bargaining. The following is identical for H and L worker firms, so drop j subscripts. The bargaining rule implies that the wage solves

$$(1-\eta)(W-U) = \eta\, \hat{c}_0 \cdot \left(y'(n) - (1+t)w - n \cdot (1+t)w'(n)\right)$$

Using the expressions above, this becomes

$$(1-\eta)\left(\frac{1+r}{r+s+\chi}\left(1+\chi\frac{\rho}{r+\phi}\right) w - \frac{r+\phi+\chi}{r+s+\chi} U\right) = \eta\, \hat{c}_0 \cdot \left(y'(n) - (1+t)w - n \cdot (1+t)w'(n)\right)$$

$$\left[\frac{(1-\eta)(1+r)}{r+s+\chi}\left(1+\frac{\chi\rho}{r+\phi}\right) + \eta\, \hat{c}_0(1+t)\right] w = \frac{(1-\eta)(r+\phi+\chi)}{r+s+\chi} U + \eta\, \hat{c}_0 \cdot \left(y'(n) - n \cdot (1+t)w'(n)\right)$$

$$\frac{(1-\eta)(1+r)\widehat{\left(1+\frac{\chi\rho}{r+\phi}\right)} + \eta\, c_0(1+t)(r+s+\chi)}{r+s+\chi} w = \frac{(1-\eta)(r+\phi+\chi)}{r+s+\chi} U + \eta\, \hat{c}_0\left(y'(n) - n\,(1+t)w'(n)\right)$$

Then, approximating $\hat{c}_0$as $(1+r)/(r+s+\chi)$,

$$\left(1+\eta t + \frac{(1-\eta)\chi\rho}{r+\phi}\right) w = (1-\eta)\, \frac{r+\phi+\chi}{1+r} U + \eta \cdot \left(y'(n) - n \cdot (1+t)w'(n)\right).$$

so that

$$w = \frac{(1-\eta)(r+\phi)}{(1+\eta t)(r+\phi)+(1-\eta)\chi\rho}\frac{r+\phi+\chi}{1+r} U + \frac{\eta(r+\phi)}{(1+\eta t)(r+\phi)+(1-\eta)\chi\,\rho}\left(y'(n) - n\,(1+t)w'(n)\right).$$

Let

$$\hat{\eta} \equiv \eta\, \frac{r+\phi}{(1+\eta t)(r+\phi)+(1-\eta)\chi\rho}; \qquad c_U \equiv (1-\eta)\, \frac{r+\phi}{(1+\eta\, t)(r+\phi)+(1-\eta)\chi\,\rho}\, \frac{r+\phi+\chi}{1+r}. \quad (30)$$

Note that $c_U = \frac{r+\phi+\chi}{1+r}\frac{1-\eta}{\eta}\hat{\eta}$. Then the differential equation is

$$w = c_U\, U + \hat{\eta}\left(y'(n) - n\,(1+t)w'(n)\right) \qquad (31)$$

The solution to the differential equation then is

$$w(n) = n^{-\frac{1}{\tilde{\eta}}} \int_0^n y'(z)\, z^{\frac{1}{\tilde{\eta}}-1} dz + c_U\, U, \qquad (32)$$

Where $\tilde{\eta} \equiv (1-t)\hat{\eta}$. Integrating yields

$$w(n) = c_U\, U + \frac{y'(n)}{\gamma - 1 + \frac{1}{\tilde{\eta}}} \qquad (33)$$

The firm's optimality condition for employment here is

$$y'(n) = (1+t)w + n \cdot (1+t)w'(n) + \left[\frac{1+r-(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right]\frac{k_v}{q} \qquad (34)$$

or, using the solution to the wage equation,

$$y'(n) = \frac{1+\tilde{\eta}\,(\gamma-1)}{1-\tilde{\eta}t(\gamma-1)} - \left\{(1+t)w + \left[\frac{1+r-(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right]\frac{k_v}{q}\right\} \qquad (35)$$

Solving this for n yields labor demand

$$n(z) = \left(z\,\gamma\, a^{\gamma}\right)^{\frac{1}{1-\gamma}} \left\{\frac{1+\tilde{\eta}\,(\gamma-1)}{1-\tilde{\eta}t(\gamma-1)}\left[(1+t)w + \left(1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right)\frac{k_v}{q}\right]\right\}^{-\frac{1}{1-\gamma}} \quad (36)$$

Substituting it into the wage equation yields

$$w = c_U U + \frac{\tilde{\eta}}{1-\tilde{\eta}\,t(\gamma-1)}\left\{(1+t)w + \left[\frac{1+r - (1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right]\frac{k_v}{q}\right\}. \quad (37)$$

That is, the wage at optimal labor demand is

$$w = \frac{\left(1-\tilde{\eta}\,t\,(\gamma-1)\right)}{1-\tilde{\eta}\,(1+t\,\gamma)}\;\frac{r+\phi+\chi}{1+r}\;\frac{1-\eta}{\eta}\frac{\tilde{\eta}}{1+t}U + \frac{\tilde{\eta}}{1-\tilde{\eta}\,(1+t\,\gamma)}\left[1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right]\frac{k_v}{q}, \quad (38)$$

where $\tilde{\eta} = (1+t)\eta\frac{r+\phi}{(1+\eta\,t)(r+\phi)+(1-\eta)\chi\,\rho}$.

Solution of the differential equation for w. Without the constant, the equation is

$$w'(n) + \frac{w}{\hat{\eta}\,(1+t)n} - \frac{y'(n)}{(1+t)n} = 0. \quad (39)$$

Let $\tilde{\eta} \equiv \tilde{\eta}(1+t)$ The solution of the homogeneous equation

$$w'(n) + \frac{w}{\tilde{\eta}n} = 0$$

then is

$$w(n) = Cn^{-\frac{1}{\tilde{\eta}}} \quad (40)$$

C is a function of integration that can be a function of n. So take the derivative of equation (40)
with respect to n:

$$\frac{\partial w}{\partial n} = C'(n)n^{-\frac{1}{\tilde{\eta}}} - \frac{C}{\tilde{\eta}}\,n^{-\frac{1}{\tilde{\eta}}-1}$$

\

Substituting this into (39) yields

$$C'(n) = y'(n)n^{\frac{1}{\tilde{\eta}}-1}\}$$

Integrating this gives $C(n)$as

$$C(n) = \int_0^n y'(z)z^{\frac{1}{\tilde{\eta}}-1}\,dz + D$$

so the wage w is

$$w(n) = n^{-\frac{1}{\tilde{\eta}}} \int_0^n y'(z) z^{\frac{1}{\tilde{\eta}}-1} \, dz + Dn^{-\frac{1}{\tilde{\eta}}}$$

The constant D can be dealt with assuming that the wage bill goes to zero as employment goes to
zero. This implies D = 0. The solution to equation (31) then is

$$w(n) = nn^{-\frac{1}{\tilde{\eta}}} \int_0^n y'(z) z^{\frac{1}{\tilde{\eta}}-1} \, dz + c_U U.$$

Integrating yields

$$w(n) = c_U \, U + \frac{y'(n)}{\gamma - 1 + 1/\tilde{\eta}} \qquad (41)$$

The division in the last term here comes from the overhiring effect. Note that y0 of course is j-specific. But conditional on the type of worker hired, this equation applies to both types of firm, indexing all terms by j as required.

To obtain the wage at the firm's optimal constant level of employment (replacing any workers who leave), use the labor demand condition. To obtain this, equate the marginal value of having an additional employee for the firm's entire life, from (29), to the expected hiring cost. This results in

$$y'(n) = (1+t)w + n \cdot \ (1+t)w'(n) + \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi\right]\frac{k_v}{q}$$

To simplify, take the derivative of (41) with respect to n, multiply by n, and replace the n _ w0 (n)
term in the labor demand condition. This yields

$$y'(n) = (1+t)w + (1+t)\frac{(\gamma-1)y'(n)}{\gamma - 1 + 1/\tilde{\eta}} + \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi\right]\frac{k_v}{q}$$

or

$$y'(n) = \frac{1 + \hat{\eta}(1+t)(\gamma-1)}{1 + \hat{\eta}t(1+t)(\gamma-1)} + \left\{(1+t)w + \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi\right]\frac{k_v}{q}\right\}$$

Again, this holds for each worker type j. Solve this for n to obtain the labor demand condition in (36). Substituting this expression into (41) yields the wage at the optimal employment level given in equation (38).

B. Computation

The algorithm for solving the model is as follows.

1. Guess candidate values of θ_j ; $j = L; H$.

2. Compute the implied sectoral job finding rates and vacancy filling rates using the matching function.

3. For each segment, solve the linear system of equations (12), (13), (15) and (17) for the wage w and the values of employment (W), search (S) and unemployment (U).

4. Compute optimal employment for each type of firm, using equation (18), for a grid of values of productivity. (These depend on θ and w.)

5. For each type of worker, use equations (7) and (8) to compute the values of own-account work and being an employer, for a grid of values of productivity and taste. (These depend on θ and w.)

6. For each value of productivity and taste, obtain the optimal post-entry action (return to unemployment, own-account work, employ low-skill workers, or, for H individuals only, employ high-skill workers). This yields the thresholds z_{sj}, z_{fj} and z_{fHH}.

7. Using the distribution of productivity for each type of worker, compute the probability of each of these outcomes (this yields p_f and p_s) as well as the expected value of entry $Q_j(\tau)$ for each taste value using these optimal choices (equation 9).

8. Compare $Q_j(\tau)$ to S to determine at which taste levels entry is optimal. This implies the probability for entering from unemployment, h_j .

9. Using these probabilities, compute the stationary distribution of productivity and the steady state stocks of individuals in the different labor market states using the expressions in equations (1) to (6).

10. Using these stocks, optimal labor demands and the guess of tightness, compute total vacancies by segment (equation (19)) and implied labor market tightness (equation (20)).

11. If implied labor market tightness equals the initial guess in each segment, the equilibrium has been obtained. Otherwise, update the guesses for θ_j in step 1, and begin again from that step.

CHAPTER X.

Equity in Education Outcomes and Spending in Bangladesh[1]

Abstract

Bangladesh has continued to improve access to education and educational attainment. Gains have been equitable, reducing disparities by gender, wealth, and geography. Yet progress is still needed at higher education levels, and there are still persistent gaps between the poor and rich and across districts. Gains are partly the result of Government of Bangladesh (GoB) efforts to improve education outcomes, but also reflect increased private spending by households. GoB education spending is still low compared to other countries in the region and presents large variation across the territory, which is not correlated with education outcomes and internal efficiency indicators. Only when public spending translates into lower student-to-teacher ratios do outcomes seem to improve, but those ratios remain inadequate compared to other countries and unevenly distributed across districts. Focusing on higher quality spending rather than increasing overall budgets will be a priority for further progress. Stipend programs help with the progressivity of the system at the primary level. However, at the secondary level, there is still significant room to improve the progressivity of these benefits. Finally, addressing norms and expectations around the benefits of schooling can

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be an important avenue to increase school attendance. About four in ten secondary school-age children out of school report lack of interest or being too old to go back as their main reasons for not attending school; three in ten females cite family chores and marriage as reasons for not attending.

Introduction

Investments in education have immense intrinsic and instrumental value. At the individual level, education creates opportunities for better labor market outcomes, higher incomes, reduced poverty, and improved overall welfare. For societies, education is central for development, growth, stronger institutions, and social cohesion. Bangladesh has made remarkable progress in expanding access to education, with sustained expansions in attendance rates for all levels of education. These gains have been an important driver of the substantial poverty reduction observed in the past decades (World Bank 2018).

This note relies on the recently completed Household Income and Expenditure Survey (HIES) 2016/17 to provide an updated picture of education outcomes in Bangladesh. Evidence suggests that improvements in education attainment have been important in explaining gains in welfare levels and poverty reduction across the country. However, as access at the national level becomes widespread, it becomes more relevant to identify lagging areas, in order to then understand their specific challenges and better define policies and interventions. An important feature of the latest HIES survey is that it is representative at district level, which provides a unique opportunity to compare outcomes across the country.

The HIES 2016/17 is combined with its previous three rounds (HIES 2000, 2005, and 2010) to depict the main trends in education attainment and enrollment by gender, income levels, and across regions.[2] Moreover, detailed education expenditure data by households is combined with government budget data processed under the BOOST[3] initiative to analyze the progressivity of public spending.

[2] The Household Income and Expenditure (HIES) cross-sectional survey is the main official source of information about households' consumption, poverty and income. The HIES 2016/17 data was collected from April 2016 until March 2017. The previous rounds of HIES data were collected in 2000, 2005, and 2010. For the rest of this report, we refer to the yearly estimates as from 2000, 2005, 2010, and 2016, respectively.

[3] BOOST (in all caps) is not an acronym. It is the name of a data tool developed by the World Bank to help enhance the analysis of public expenditure data. The BOOST initiative is a World Bank effort launched in 2010 to facilitate access to budget data. Currently deployed in about 40 countries, the BOOST approach provides a user-friendly platform where all expenditure data can be easily accessed. For more information, see: http://boost.worldbank.org/boost-initiative

Finally, the relationship between spending and key outcomes at the district level is analyzed to inform about the effectiveness of public spending. The analysis also relies on information from the Annual Primary School Census (APSC) and from the Bangladesh Bureau of Educational Information and Statistics (BANBEIS).[4]

The analysis shows that Bangladesh has made remarkable progress in expanding access to education, with sustained expansions in attendance rates for all levels of education. The number of out of school children 6-14 years old fell from about 5.5 million to three million children between 2010 and 2016, an impressive 45 percent reduction in six years. The gains in access have recently been accompanied by improvements in the internal efficiency of the education system measured by reductions in drop-out rates and higher survival rates.

The progress has been broad based and has reduced inequality, though more is needed. For instance, gender disparities fell both in terms of access and achievement. Today, at the primary and secondary levels, the focus should be on males, who are lagging in attendance. For females, more emphasis should be put on understanding and addressing constraints to achieve tertiary education. In addition, expansions in access have reduced disparities between poor and non-poor children and across regions. Attendance rates in Sylhet have been increasing rapidly, especially since 2010, reducing its historical disadvantage compared to other divisions. Yet, there are visible gaps in school attendance by poverty status and region, which indicate that human capital disadvantages for the poor and some regions will persist for some time, unless progress accelerates.

The gains are partly the result of expansions in spending on education, led by households. Even though the share of households' spending on education has been relatively constant over time, the amounts spent on education by households grew substantially. The average real annual growth in households' education spending was 9 percent over the 2000-2016 period. GoB spending per student in real terms increased, but mainly at the tertiary level.

More progressive public and private spending supported the reduction in education disparities. GoB spending, particularly at the primary level, has become more progressive. Stipend programs and tuition waivers help to improve the progressivity of public spending, but mainly for the primary subsector. In addition,

[4] The analyses presented below were conducted to inform an ongoing Public Expenditure Review of the education sector. Analyses related to the quality of education, non-educational investments in learning outcomes (e.g., nutrition), or returns to education are not developed in this note, as they are being carried out separately.

households' private spending increased faster for children with fewer resources. Therefore, while in 2000 the top quintile spent 22 times more on education per student than the poorest quintile, in 2016 the richest quintile spent only six times more than the poorest quintile. Yet, poor households still have substantially lower private spending on education than richer households. In 2016, the median household in the poorest quintile spent about Tk. 202 per student per month, compared to Tk. 1,310 per student for the median household in the richest quintile.

Some policy priorities are suggested by this analysis:

1. **Expanding the levels of GoB spending on education**. The level of public spending on education is low by international standards, and the recent increases in spending per student have been concentrated at the tertiary level. Increasing spending on education can contribute to improving both the quality and quantity of education services.
2. **Improving the quality of GoB education spending by strengthening its link with education outcomes.** Increases in spending alone will not be enough to deliver better education services and outcomes. Currently, education spending per student for primary and secondary presents large variation across the territory, which is not correlated with attendance rates and internal efficiency indicators. Only when spending translates into lower student-to-teacher ratios do results seem to improve. However, Bangladesh's student-to-teacher ratios remain inadequate compared to other countries. This suggests that, moving forward, gearing towards higher-quality spending, rather than simply increasing the overall budget, will be a priority for further progress.
3. **Improving the targeting of stipends and tuition waivers.** GoB spending is important to reduce disparities between poorer and richer children. For instance, in 2016, the richest quintile spent about 7.5 times more per student in primary education than the poorest quintile. Once public spending is considered, the gap falls to two times more. Stipend programs and tuition waivers at the primary level help with the progressivity of the system. The size of the Primary Education Stipend Project (PESP) benefit represents about 70 percent of the private spending of households in the poorest quintile. However, even though the PESP is more likely to benefit poor children, many of them do not receive this benefit. Moreover, the benefit of the PESP has been fixed since the beginning of the program, so its importance for households' budgets has been declining in real terms. At the secondary level, there is no relationship between poverty and the receipt of stipends and tuition waivers. Only 20 percent of stipend

recipients belong to the poorest quintile. Given the size of these programs in a context of low spending, better targeting of benefits can be helpful to enhance the progressivity of GoB spending, particularly at the secondary level.

4. **Enhancing the value placed on education investments by households.** Households' spending was a central element behind the higher investments in children's education and the reduction in disparities seen in the past two decades. However, many households do not find value in education investments. About 51 percent of households with primary-age children out of school report lack of interest or the children's age as the main reasons for not attending. Similarly, four in ten secondary-age children out of school report lack of interest or being too old to go back as their main reasons for not attending school. Work reasons follow (cited by one in four children not attending), particularly for males. Moreover, family chores and marriage become an important reason for women to not attend secondary school (30 percent of women not attending). Similar reasons are found at the tertiary level. Thus, beyond supporting households' budgets, addressing norms and expectations around the benefits of schooling can be an important avenue for further progress.

The next section summarizes recent progress in school achievement and attendance rates, with a focus on understanding the extent to which this progress has been broad based and on highlighting remaining disparity challenges. The second section describes public and private spending patterns on education and the results from an incidence analysis of spending. The third section explores the relationship between spending and outcomes. Section four concludes.

I. Equity in outcomes

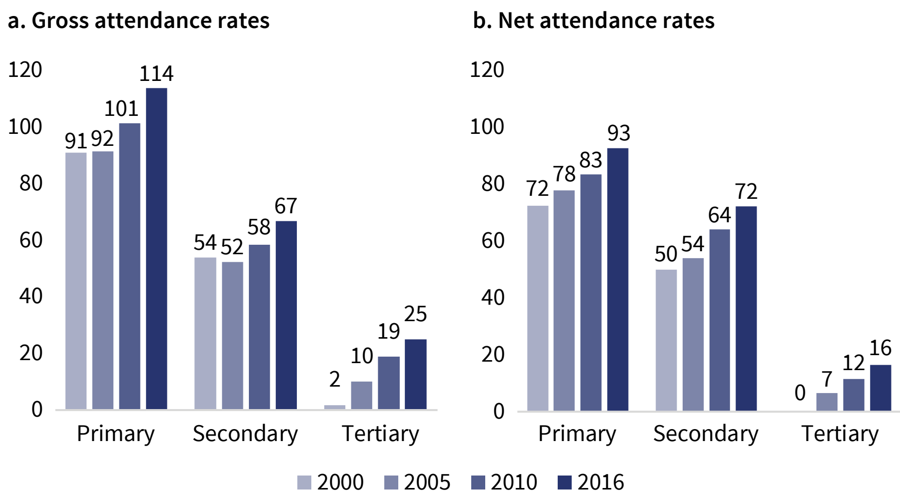
During the past two decades, Bangladesh has made remarkable progress in expanding school attendance. Over the period 2000-2016, the primary gross attendance rate[5] increased from 91 to 114 percent, the secondary gross atten-

[5] The HIES only collects information on whether the person is currently attending school, therefore these figures will be lower than official enrollment rates. We define gross attendance rates in primary as the ratio between the number of students attending primary and the number of students age 6-10. The gross attendance rates in secondary is calculated as the ratio between the number of students attending secondary and the number of students age 11-17. The gross attendance rate in tertiary is calculated as the ratio between the number of students attending a level above secondary and the number of students age 18-22. Net attendance rates for primary are calculated as the percentage of children 6-10 attending primary. For secondary, the net attendance rate considers the population 11-17. For tertiary, the net attendance rate considers the population 18-22.

dance rate rose from 54 to 67 percent, while in tertiary gross attendance increased from 2 to 25 percent (Figure 1). Also, over the same period, net attendance rates expanded by 20 percentage points for primary, 22 points for secondary, and 16 points for tertiary.

As access expanded, the number of out of school children fell significantly. In 2010, about 5.5 million children ages 6-14 years old were out of school. In 2016, this number was about three million children, a 45 percent reduction in six years.

Figure 1. Gross and net attendance rates (%) by education level (2000-2016)



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.

The gains in attendance have also been accompanied by improvements in the internal efficiency of the education system (Table 1). For instance, between 2005 and 2017, for the primary level, repetition rates declined from 10 to 6 percent, the cycle drop-out rate fell from 47 to 19 percent, survival rates increased by more than 50 percent, and the coefficient of efficiency rose by 21 points.[6] At the secondary level, there has also been an overall improvement on the same indicators.

[6] The repetition rate measures the rate at which pupils from a cohort repeat a grade. It is defined as the ratio between the number of repeaters in a given grade in a given school year (t+1) and the number of pupils from the same cohort enrolled in same grade in the previous school year (t). The survival rate is the percentage of a cohort of pupils (or students) enrolled in the first grade of a given level or cycle of education in a given school year expected to reach successive grades, regardless of repetition. This rate is calculated following the UNESCO reconstruction cohort model. The coefficient of efficiency is an indicator of the internal efficiency of an educational system. It summarizes the consequences

Table 1. Internal efficiency indicators

a. Primary level				
	2005	2010	2016	2017
Repetition rate	10	13	6	6
Cycle drop-out rate	47	40	19	19
Survival rate	54	67	82	83
Coefficient of efficiency	61	62	81	82

Source: Annual Primary School Students Census (APSC) and Bangladesh Bureau of Educational Information and Statistics (BANBEIS).

b. Secondary level		
	2010	2016
Repetition rate	4	3
Cycle drop-out rate	57	37
Survival rate	63	65
Coefficient of efficiency	50	73

Source: Bangladesh Bureau of Educational Information and Statistics (BANBEIS).

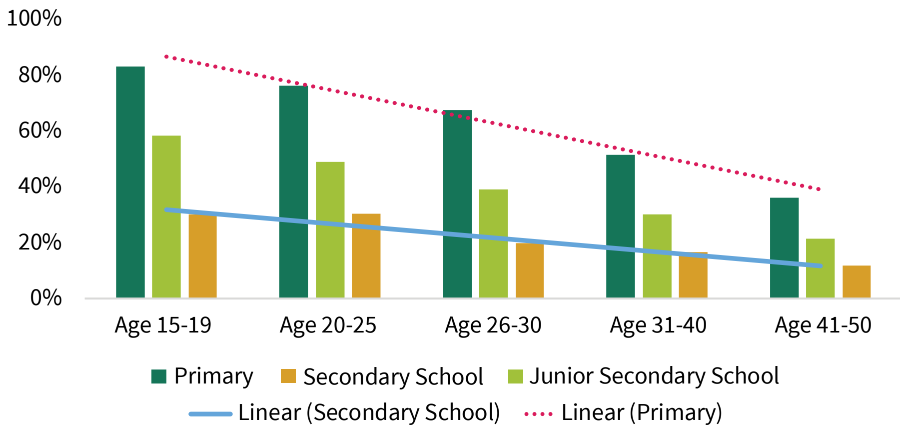
The sustained increase in education attainment over many years is changing the education profile of the adult population. Literacy rates for the adult population 15+ have improved from 46 percent in 2000 to 63 percent in 2016.[7] In addition, completion of at least primary school has increased from 30 percent of adults in 2000 to 43 percent in 2016. Completion of secondary (Grade 10) has expanded from 8 percent in 2000 to 13 percent in 2016. Progress is more evident when comparing across cohorts (Figure 2). While in 2016, 36 percent of the population age 41-50 had completed primary education, 83 percent of the population 15-19 had completed this level. Similarly, while 21 percent of the population 41-50 achieved junior secondary, 58 percent of the population 15-19 achieved this level.

In addition, the expansions in schooling have been broad based and have reduced inequalities by gender, wealth, and across geographic regions. For instance, even though adult females are less educated than males overall, the new generations are reversing this disadvantage. Figure 3 presents the difference between the percentage of adult women and men achieving various levels of education and shows that gender disparities in school achievement have been

of repetition and dropout on the efficiency of the educational process in producing graduates. It is defined as the ideal (optimal) number of pupil years required (i.e., in the absence of repetition and dropout) to produce a number of graduates from a given school cohort expressed as a percentage of the actual number of pupil years spent to produce the same number of graduates.

[7] A person is considered literate if she can write a letter.

Figure 2. Primary and secondary school completion rates across age groups (2016)



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.

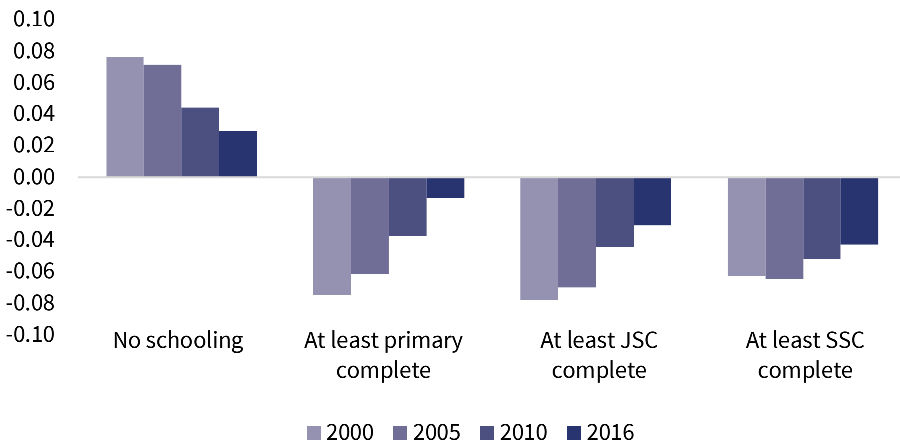
declining with time. In 2000, 67 percent of adult women had no schooling, compared to 60 percent of men (seven percentage points difference); by 2016, this difference was three percentage points. The reduction in the gender gap has been large in terms of completing primary level, from a disadvantage of seven points for women in 2000 to only one point in 2016. The faster progress in women's education achievement shows that young men are now less likely to complete primary or secondary, though they still outperform females in tertiary (Appendix Figure A.1).

The rapid gains in attendance by females have resulted in males' now being the group lagging behind in primary and secondary school attendance. In 2016, girls' primary school attendance was two percentage points higher than that of boys (Figure 4). This gap has not changed much from that observed in 2000. For secondary, attendance is higher for females, but the difference with males has been declining with time.

Moreover, expansions in school attendance have been equalizing at the primary and secondary levels between poorer and richer children (Figure 5). In 2016, 89 percent of children ages 6-10 in the poorest consumption quintile were attending primary school, compared to 97 percent of children in the richest quintile, a 21 percentage point reduction in the gap between the poorest and richest quintiles since 2000. Differences in secondary school attendance across quintiles have also narrowed, though they are much larger than the ones observed at the primary level.

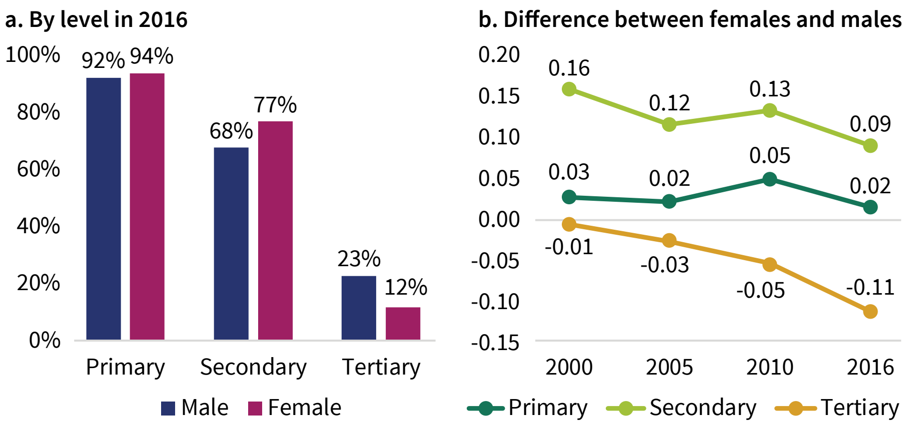
As school attendance has grown more rapidly among the poor, differences in school achievement have shrunk across consumption quintiles. In terms of literacy rates, in 2000, 27 percent of the population 15+ years old living in poverty was literate, compared to 60 percent of the non-poor (a 33 point gap). By 2016, the gap had fallen to 18 percentage points. Comparing across cohorts, there has been a reduction in the primary and secondary completion gaps between poor and non-poor, though the difference is still important (Appendix Figure A.2).

Figure 3. Gap in school achievement between females and males



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: The bars present the difference between the share of women and share of men achieving an education level. JSC: junior secondary school; SSC: senior secondary school.

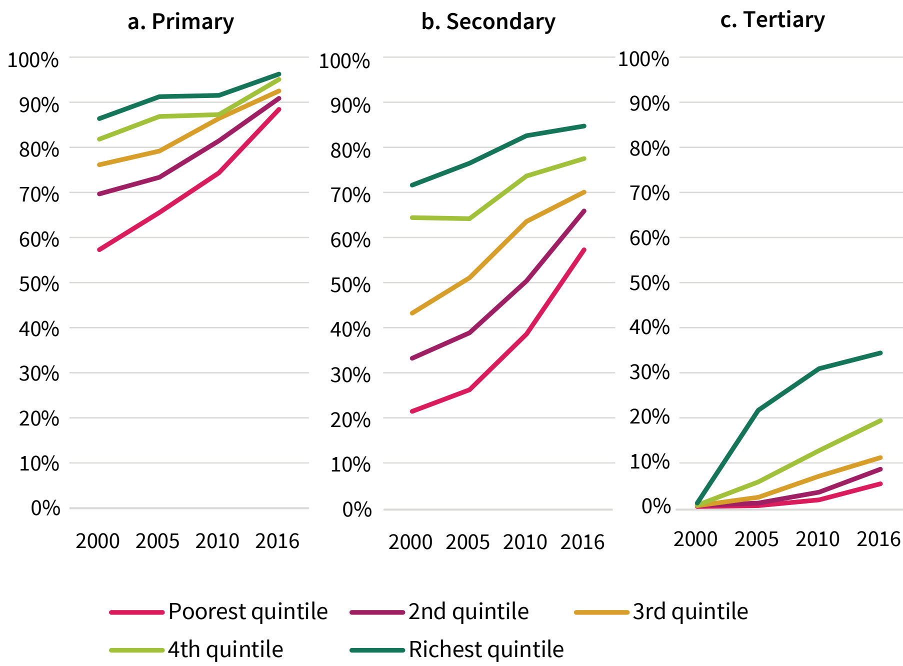
Figure 4. Attendance rates by gender



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: Figures represent net attendance rates.

There have also been faster gains in primary school attendance in lagging regions. In 2000, Dhaka division had the lowest attendance rates (67 percent) followed by Sylhet division (69 percent) (see Figure 6). The two divisions were far behind Khulna and Barisal, with 82 and 80 percent attendance rates, respectively.

Figure 5. Net attendance rates by consumption quintile, 2000-2016



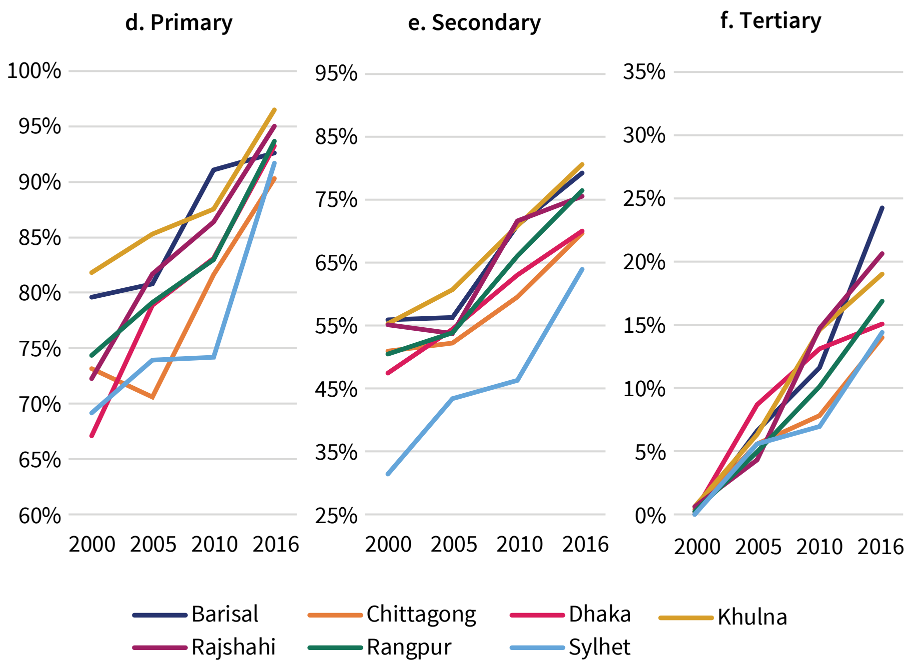
Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: Quintiles are defined based on household per capita consumption, deflated across space to account for differences in the cost of living across 16 different regions.

By 2016, all divisions had net attendance rates above 90 percent, ranging from 90 percent in Chittagong to 97 percent in Khulna. For Sylhet, Rangpur, Rajshahi, and Khulna, gains accelerated after 2010. However, in Barisal, progress slowed between 2010 and 2016. In Chittagong, faster progress started in 2005.

At the secondary level, there has also been substantial expansion in attendance rates accompanied by a reduction in disparities across divisions. Between 2000 and 2016, secondary attendance rates increased by more than 1 percent per year on average across all divisions. Even though the increase in attendance was faster for lagging divisions, in 2016 there were still large gaps in attendance, with Sylhet at 64 percent, compared to Khulna at 81 percent.

Similarly, for the tertiary level, attendance rates have increased across the board, starting from less than 1 percent in 2000. Between 2010 and 2016, Barisal and Sylhet divisions raised attendance rates by more than 50 percent, followed by Chittagong (44 percent) and Rangpur (about 40 percent). Dhaka division showed the slowest increase over the 2010-16 period (13 percent).

Figure 6. Net attendance rates by division, 2000-2016



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.

Despite progress, challenges remain

Roughly one in ten children ages 6-14 is still out of school. Out of school children are more likely to be male, live in urban areas, and come from the poorest households (Table 2). Conditional regressions also highlight that children living in households with fewer resources and with less-educated adults are significantly more likely to be out of school (Appendix Table A.1). The higher likelihood that out of school children will live in an urban area is also reflected in slightly lower attendance rates in urban areas (93 percent versus 91 percent for primary school, and 73 percent versus 70 percent for secondary school).

Table 2. Characteristics of children out of school

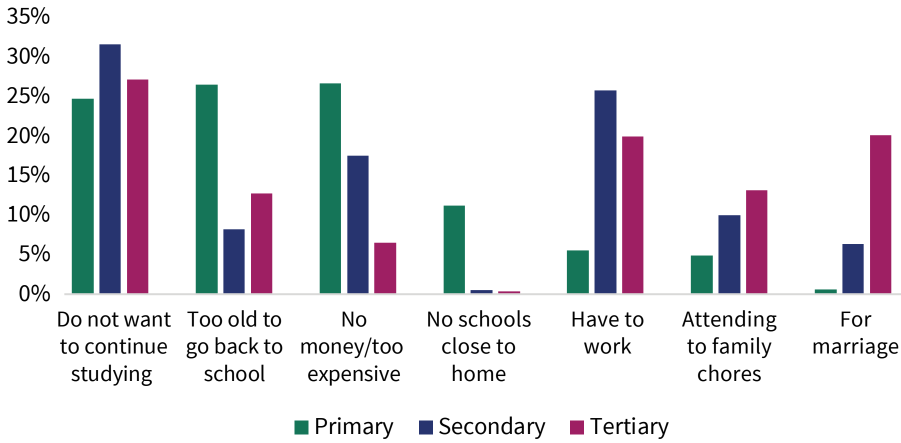
	Children 6-14 years old	
	In school	**Out of school**
All	**91%**	**9%**
Area		
Rural	76%	68%
Urban	24%	32%
Gender		
Female	50%	40%
Male	50%	60%
Quintile		
1	22%	35%
2	21%	26%
3	20%	19%
4	19%	12%
5	17%	8%

Source: Author's calculations using Household Income and Expenditure Survey 2016/17.

Improving primary school attendance will require efforts to increase the perceived value of education, in addition to overcoming resource constraints. Results using the Human Opportunity Index summarized in Appendix B indicate that children living in more educated households with more resources are more likely to attend school. However, according to HIES 2016, 51 percent of households report lack of interest or the children's age as the main reasons for not sending children to primary school (Figure 7). The next most widely cited reason is resource constraints (27 percent of cases). Eleven percent of respondents indicate that there are no schools near their homes. Understanding why households do not see value in education emerges as fundamental for tackling the problem of out of school children.

Moreover, as primary school attendance becomes universal, there is still room for improvement in other internal efficiency indicators. In the case of primary net attendance rates, 56 out of 64 districts in Bangladesh have net attendance rates above 98 percent. However, in terms of repetition, survival, and dropout rates, there is significant variation across the territory, with some districts performing relatively well but many still at levels comparable to 2005 and 2010 national averages. For instance, 25 percent of districts still have repetition rates above 8 percent. Furthermore, survival rates range from 59 to 93 percent, dropout rates range from 8 to 47 percent, and about 14 percent of districts present a dropout rate above 28 (Figure 8).

Figure 7. Reasons for not attending school, by level, 2016

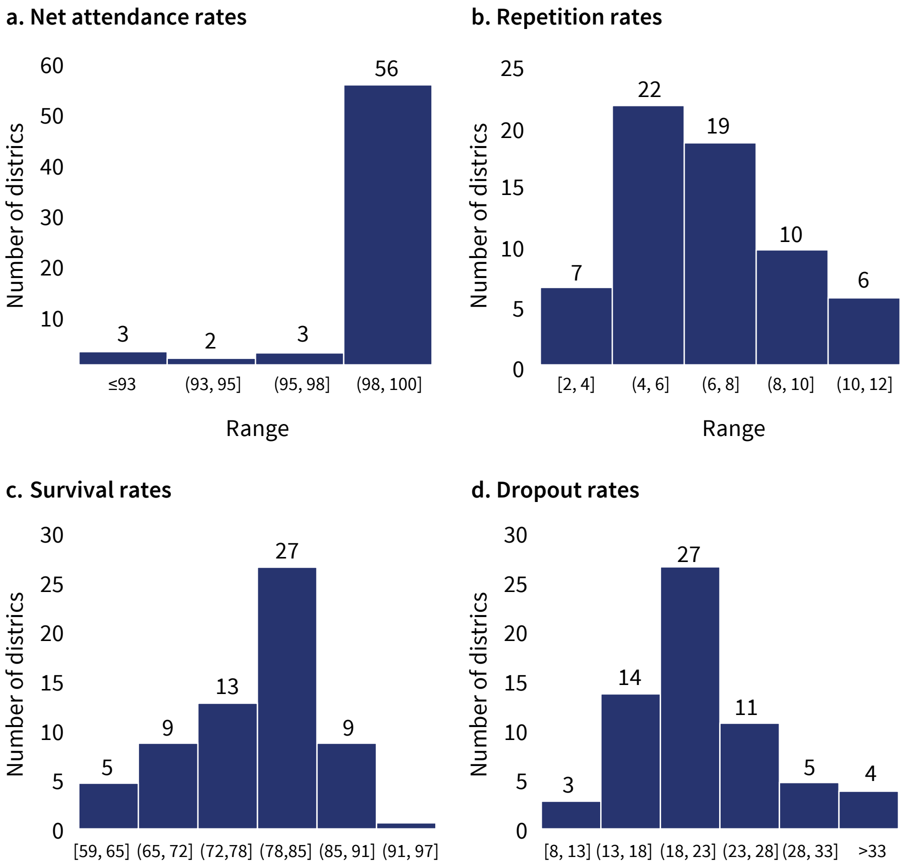


Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.

At the secondary and tertiary levels, higher and more equal access is still a major challenge. Gross attendance rates for tertiary level are about 25 percent and, for the population ages 17-22, attendance rates are about 16 percent. In 2016, only 30 percent of the population 15-25 had completed secondary school. In addition, the rapid expansion in tertiary attendance rates has been led by males, which translates into an increasing difference in attendance by gender. In 2016, the attendance rate of women ages 17-22 was 12 percent, compared to 23 percent for men (Figure 4). Similarly, the gains in tertiary level attendance seen since 2000 have been largely driven by the top consumption quintiles. Across the country's districts, secondary net attendance rates vary widely, ranging from 59 to 87 percent. In addition, about 30 percent of districts present secondary net attendance rates below 71 percent, and 14 percent of them fall below 65 percent. For the tertiary level, attendance rates vary significantly across districts, from 7 to 31 percent (Figure 9).

Again, increasing the value that households see in education arises as an important avenue for greater attendance at higher education levels. For secondary school-aged children, 40 percent of households cite lack of interest or being too old to go back as the main reasons for not attending. Work reasons follow (26 percent), particularly for males (34 percent of males compared to 14 percent of females). Moreover, family chores and marriage become an important reason for women not to attend secondary school (cited by 30 percent of women not attending). For tertiary-aged people not attending school, 40 percent of respondents cite not wanting to go back or being too old. Work (for males) and marriage (for females) follow as main reasons (Appendix Table A.2).

Figure 8. Variation in educational outcome indicators for primary level across districts (2016)



Source: Annual Primary School Students Census (APSC) 2016.

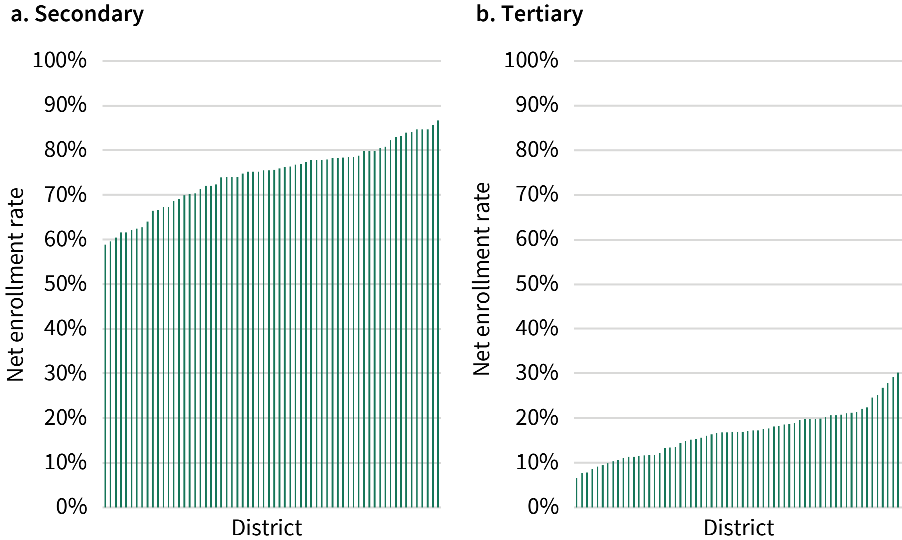
II. Equity in spending

The equity of public spending on education

This sub-section relies on budget data from BOOST for fiscal year 2014 (FY14), the latest available, to study GoB spending patterns across groups and geographic areas. The analysis focuses on spending at the primary and secondary levels, since these are the two levels where the allocation of public spending can be done at the district level with few assumptions.[8] The amounts presented are expressed

[8] The GoB expenditures included in the analysis are those reported by the Ministry of Primary and Mass Education (MPME) and the Ministry of Education (MOE). Only categories related to primary and

Figure 9. Net attendance rates in secondary and tertiary across districts (2016)



Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.

in takas of 2016, unless specified otherwise. It is important to interpret these results with care, as GoB spending on education has been increasing since FY14. The relative comparisons across areas and groups are valid under the assumption that the distribution of spending has not changed significantly since FY14.

The education system in Bangladesh is large and complex. It caters to approximately 17.3 million primary-level students (Grades 1-5), 13.9 million secondary-level students (Grades 6-12), and 4.5 million tertiary-level students. These students are served by 133,904 primary level institutions, 34,036 secondary level institutions, and 5,983 tertiary institutions (Table 3).

secondary education were included. For the expenditure items that could not be disaggregated at the district level, several types of expenditures were allocated uniformly based on either the share of students, teachers or institutions in each district. For instance, for the MPME, about 22 percent of the expenditures did not have a district code, 70 percent of them corresponding to stipends. In this case, the amount was distributed based on the share of students receiving stipends in each district. For MOE, most of the unassigned expenditures correspond to teachers' salaries, which were allocated based of the share of teachers in each district.

Table 3: Number of students and institutions by level of education

Level	No of students	(%)	No. of institutions	(%)
Primary (Gr. 1-5)	17,251,568	(49.8 %)	133,904	(77.0%)
Secondary (Gr. 6-12)	13,878,242	(37.2%)	34,036	(19.6%)
Tertiary	4,513,119	(13.0%)	5,983	(3.4%)
Overall	34,642,929	(100%)	173,923	(100%)

Source: Bangladesh Bureau of Educational Information and Statistics (BANBEIS) Education Statistics Report 2018.
Note: Both secondary and tertiary levels include technical and vocational education (0.89 million students in 5,897 institutions).

There are two ministries responsible for overseeing the education system in the country—the Ministry of Primary and Mass Education (MoPME) and the Ministry of Education (MoE). MoPME handles pre-primary to Grade 5, as well as non-formal education, and MoE is responsible for secondary education (Grades 6-10), higher secondary education (Grades 11-12), technical and vocational education, Madrasah education,[9] and tertiary education. MoE is responsible for policy formulation and allocating funding for tertiary education. The University Grants Commission (UGC) is responsible for coordinating university education, and for quality assurance of both public and private universities. Additionally, the National University (NU) is responsible for overseeing the large number of government and non-government colleges affiliated with it.

GoB education spending per student has been increasing in nominal terms during the past few years, but recent gains in real terms are seen mainly for the tertiary sector. The GoB has shown a strong commitment to the sustained improvement of the education sector with yearly increases in the budgetary allocations in the Medium-Term Macroeconomic Framework (MTMF). The annual budget allocated to the education sector has continuously increased in nominal terms in recent years. This expansion has been accompanied by an increase in spending per student in nominal terms for all levels (Table 4a). In real terms, however, except for a substantial increase at the tertiary level, spending per student has either declined or increased only marginally (Table 4b).

Furthermore, Bangladesh's spending on education is low compared with other countries in the region. Public expenditure on education as a share of the gross domestic product (GDP) was only 2.2 percent in 2015. Apart from Sri Lanka,

[9] Islamic religious education.

all other countries in South Asia spent significantly more on education than Bangladesh in 2015 (UNESCO Institute for Statistics 2018). Similarly, Bangladesh ranked second from the bottom in the region in terms of the share of the national budget devoted to education (11.7 percent). The Incheon Declaration, adopted in May 2015 by many multilateral organizations, including the World Bank, and participants from 160 countries during the World Education Forum, urged countries to devote at least 4 to 6 percent of GDP and/or at least 15 to 20 percent of public expenditure to the education sector to improve educational outcomes. Bangladesh is still far below these targets.[10] At the primary and secondary levels, spending per student as a percentage of GDP per capita is much smaller than the average for OECD countries, and lower than the figures for other countries in the region (Table 5). The low spending on education imposes severe constraints on improving both the quality and quantity of education services.

Table 4: Per student public spending on education by level

a. Annual in nominal terms (takas)					
Level of Education	**2010-11**	**2012-13**	**2013-14**	**2014-15**	**2015-16**
Primary (Gr. 1-5)	4,728	4,676	5,017	7,173	7,213
Junior Secondary (Gr. 6-8)	4,788	5,358	4,781	5,761	6,497
Secondary (Gr. 9-10)	8,578	8,134	7,794	9,155	9,598
Higher Secondary (Gr. 11-12)	17,100	9,826	15,383	16,603	20,872
Tertiary	11,066	13,272	15,186	16,035	20,924
b. Annual in 2016 takas					
Level of Education	**2010-11**	**2012-13**	**2013-14**	**2014-15**	**2015-16**
Primary (Gr. 1-5)	6,468	5,604	5,616	7,572	7,213
Junior Secondary (Gr. 6-8)	6,552	6,420	5,352	6,072	6,497
Secondary (Gr. 9-10)	11,736	9,756	8,736	9,660	9,598
Higher Secondary (Gr. 11-12)	23,400	11,784	17,232	17,520	20,872
Tertiary	15,144	15,912	17,016	16,920	20,924

Source: Authors' calculations using Bangladesh Bureau of Educational Information and Statistics (BANBEIS) for education per student costs and World Development Indicators (WDI) for inflation adjustment

[10] According to the figures from the Bangladesh Ministry of Finance (MoF), the education budget as a share of the total budget has been lower than 15 percent since 2008 and has not exceeded 2.5 percent as a share of GDP since 2000. The seventh five-year plan of GoB envisions increasing the allocation to education to at least 3 percent of GDP, but even this vision falls significantly short of the recommendation made by the Incheon Declaration.

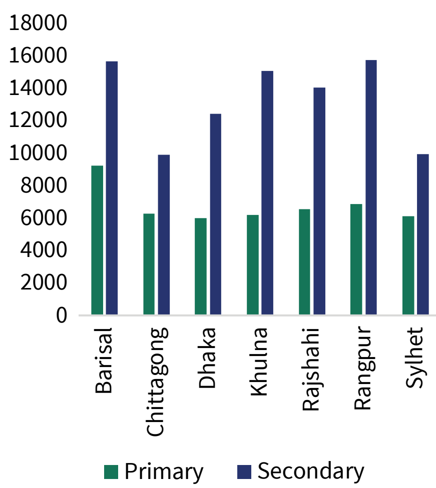
Table 5. Government expenditure per student (% of GDP per capita)

Country	Primary	Secondary	Tertiary
Bangladesh	9	10	25
Bhutan	14	32	55
India	10	17	49
Maldives	15	..	29
Nepal	13	11	25
Pakistan	10	11	27
Sri Lanka	11	11	30
OECD members	20	23	26

Source: World Development Indicators circa 2016.
Note: Government expenditure per student is the average general government expenditure (current, capital, and transfers) per student in the given level of education, expressed as a percentage of GDP per capita.

At the same time, across the country there is large variation in the levels of spending per student. For the primary level in FY14, Barisal division presented the highest levels of public spending per student (approximately Tk. 9,237 in 2016 prices), while Dhaka had the lowest (Tk. 6,014 in 2016 prices). For secondary, the divisions of Barisal and Rangpur received the highest spending per student (about Tk. 15,000), while Sylhet and Chittagong divisions had the lowest spending per student (about Tk. 9,900) (Figure 10). At the district level for primary, Dhaka was the district with lowest spending per student (Tk. 2,114), while districts like Jhalokati in Barisal division and Joypurhat in Rajshahi division had spending per student of more that Tk. 13,000. A similar pattern is found in secondary, with costs per student ranging from about Tk. 7,000 to Tk. 23,000 (Figure 11).

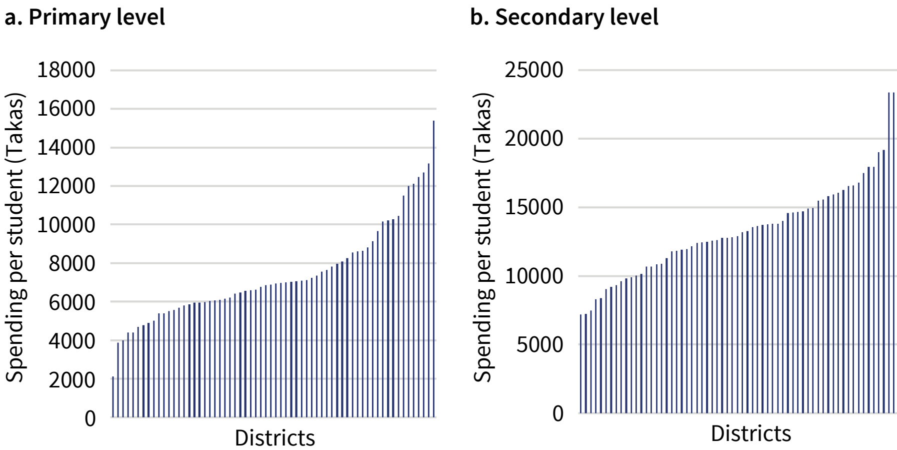
Figure 10. Public spending per student by division



Source: Authors' calculations from BOOST for fiscal year 2014.
Note: Annual amounts in 2016 takas.

GoB spending per student tends to be higher in poorer districts of the country. There is a statistically significant correlation between GoB spending per student and poverty rates at the district level. For primary and secondary, the correlation

Figure 11. Spending per student across districts



Source: Authors' calculations using BOOST for fiscal year 2014.
Note: Annual amounts in 2016 takas.

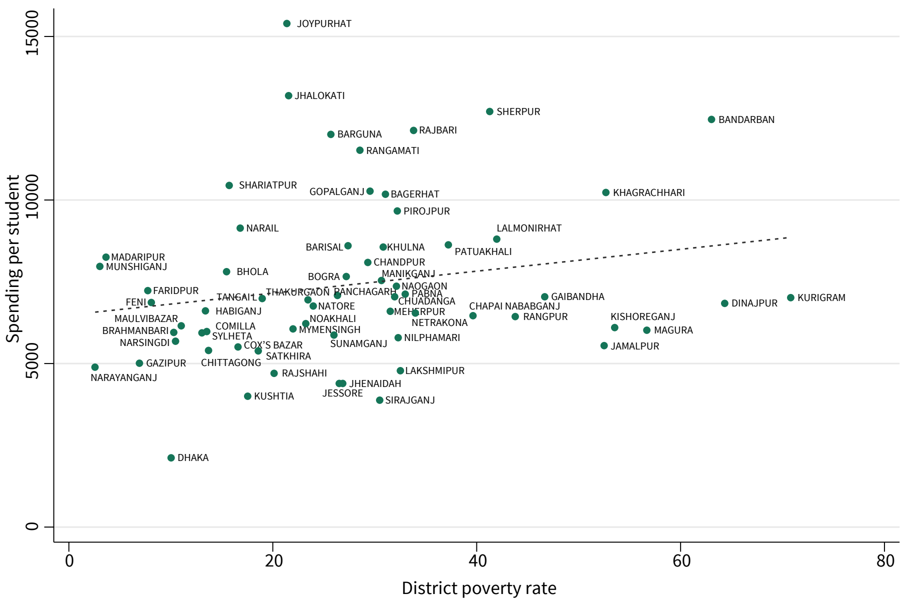
is 22 percent and 30 percent, respectively. However, there are areas with similar levels of poverty and very different levels of spending per student (Figure 12), suggesting that pro-poor targeting is only one element behind budget allocations.

GoB spending for the primary level is pro-poor and has been increasing its progressivity with time. An incidence analysis indicates that the distribution of GoB spending at the primary level is pro-poor. Table 7 shows that the 30.7 percent of primary school age children who are poor receive 35 percent of public primary education expenditures. In 2005, half of the primary school age population was classified as poor, but those students received 47 percent of public primary recurrent expenditures (World Bank 2010). Similar analysis for 2000 showed that 59 percent of primary school age children were living in poverty, but only 56 percent of primary education expenditures accrued to this group (Glinskaya 2005). The gains in progressivity reflect the expansion in primary school attendance in combination with specific cash programs targeted to the poor (i.e., stipends and tuition waivers).

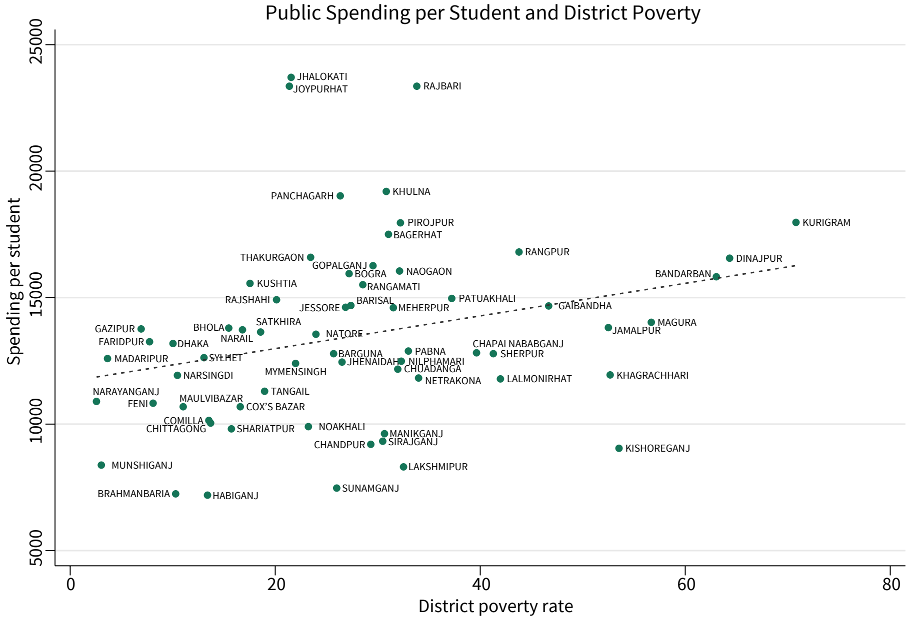
Stipend programs improve the progressivity of public spending at the primary level. The Primary Education Stipends Program (PESP) supports all primary schools by providing stipends to students in Grades 1-5. To qualify for the stipend, students must maintain 85 percent monthly attendance, take all the school examinations, and attain a minimum of 33 percent in exam marks for each of the subjects of a class, with certain exceptions. The program used to target children from poor families, but as of 2015-16, it became universal.

Figure 12. Relationship between spending per student and poverty at the district level

a. Primary level



b. Secondary level



Source: Authors' calculations using Household Income and Expenditure Survey 2016 and BOOST for fiscal year 2014.
Note: District poverty measured using official upper poverty line. Spending in 2016 takas.

Even though the primary stipend program is pro-poor, its coverage is still not universal. At present (2016-17), as many as 11.1 million primary students are being covered by the PESP, about 60 percent of the primary students enrolled in Grades 1-5. There is a positive and statistically significant relationship (β=0.25; T-stat=2.31) with district poverty, indicating that poorer districts tend to have a larger share of primary students receiving stipends. However, according to HIES 2016, even though children in the poorest quintiles are more likely to receive stipends (30 percent of recipients come from the poorest 20 percent of households), about 22 percent of non-recipients belong to the poorest quintile (Table 6).

Table 6. Characteristics of students receiving stipends in 2016

	Primary level		Secondary level	
	Recipient	Non-recipient	Recipient	Non-recipient
Area				
Rural	94%	71%	85%	72%
Urban	6%	29%	15%	28%
Gender				
Female	52%	47%	71%	47%
Male	48%	53%	29%	53%
Quintile				
1	30%	22%	21%	13%
2	25%	21%	21%	17%
3	20%	20%	20%	20%
4	15%	19%	23%	23%
5	9%	17%	16%	27%

Source: Authors' calculations from Household Income and Expenditure Survey 2016/17.

Primary stipends are an important source of funding, compared to the spending of households, though the size of the transfer has been fixed since 2002. The benefit of the PESP stipend has been fixed at Tk.100 per month since the beginning of the program. Still, the size of the benefit represents about a third of the private spending of a median household in 2016, and about 70 percent of the private spending of households in the poorest quintile.

For the secondary education subsector, the distribution of GoB spending lags in terms of reaching the poor, as they are less likely to attend this level (Table 7). For the secondary level, the share of public spending going to the poor and the poorest quintiles is lower than the share of secondary school-age children in those categories. While about 24 percent of the secondary-age children are considered poor, they receive about 22 percent of public spending in secondary education. These patterns result from the fact that children in poorer families are less likely to attend secondary school, therefore they do not benefit from GoB spending. Conditional on attending secondary school, the share across consumption quintiles is very similar to the share of students in each quintile.

In addition, despite an effort to reach the poorest students, there is a weak relationship between poverty and stipends distribution for the secondary level. Secondary stipends are more likely to benefit females (71 percent of recipients are female), and the recipients are more likely to live in rural areas (Table 6). Recipients come from different consumption quintiles, with only 20 percent belonging to the poorest quintile. The higher likelihood of women receiving stipends reflects the previous emphasis of the program on incentivizing female secondary school attendance, though currently the programs have a pro-poor targeting strategy aiming to reach both females and males.

Finally, tuition waivers are distributed in a way comparable to stipends, and there is room to improve their progressivity. According to HIES 2016/17, about 10 percent of students received tuition waivers, more than half of primary school students and a quarter of secondary students (Table 8). About 83 percent of recipients attending primary school live in rural areas, and 52 percent of them are female. Again, tuition waivers tend to benefit the poorest children in primary school, however one in four beneficiaries belongs to the richest 40 percent of the consumption distribution. For secondary, recipients are significantly more likely to be female, and they come from all consumption quintiles.

Table 7. Incidence of public education expenditure

	Primary level		Secondary level	
Group	Share of children	Share of public expenditure	Share of children	Share of public expenditure
Upper poverty				
Non-poor	69.3%	65.1%	76.0%	77.7%
Poor	30.7%	34.9%	24.0%	22.3%
Consumption quintile				
1	25.6%	29.1%	19.5%	17.5%
2	22.2%	24.1%	19.6%	20.0%
3	19.9%	20.3%	20.3%	20.8%
4	17.7%	15.5%	20.2%	21.7%
5	14.7%	11.0%	19.6%	20.0%

Source: Authors' calculations using Household Income and Expenditure Survey 2016 and BOOST for fiscal year 2014.

Table 8. Characteristics of students receiving tuition waivers

	Primary level		Secondary level	
	Recipient	Non-recipient	Recipient	Non-recipient
Area				
Rural	83%	69%	85%	71%
Urban	17%	31%	15%	29%
Gender				
Female	52%	48%	66%	48%
Male	48%	52%	34%	52%
Quintile				
1	28%	21%	21%	13%
2	25%	19%	23%	17%
3	21%	19%	20%	20%
4	16%	21%	21%	23%
5	10%	20%	16%	27%

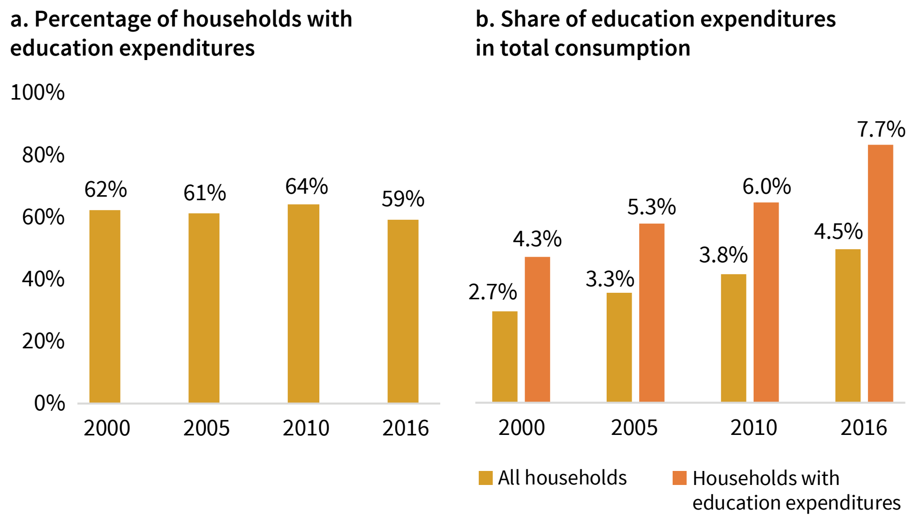
Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.

Households' expenditures on education

The growth in consumption and incomes and the poverty reduction observed in the last two decades have been accompanied by an increased importance of education expenditures in households' budgets. In 2016, about six in ten Bangladeshi households reported incurring education expenditures (Figure 13). The percentage of households with education expenditures has been around 60 percent since 2000, except in 2010, when it was slightly higher (64 percent). Even though the share of households' spending dedicated to education has been relatively constant over time, the amounts spent on education have grown substantially. In 2016, the median household spent Tk. 802 per month on education, about Tk. 516 per child. This represents an increase of more than 148 percent in real terms from the amounts observed in 2000, and a rise of about 47 percent since 2010. The average real annual growth in households' education spending was 9 percent over the 2000-2016 period. Conditional on spending on education, the percentage of education expenditures in households' total consumption has also been rising, from 4.3 percent in 2000, to 6 percent in 2010, reaching 7.7 percent in 2016.

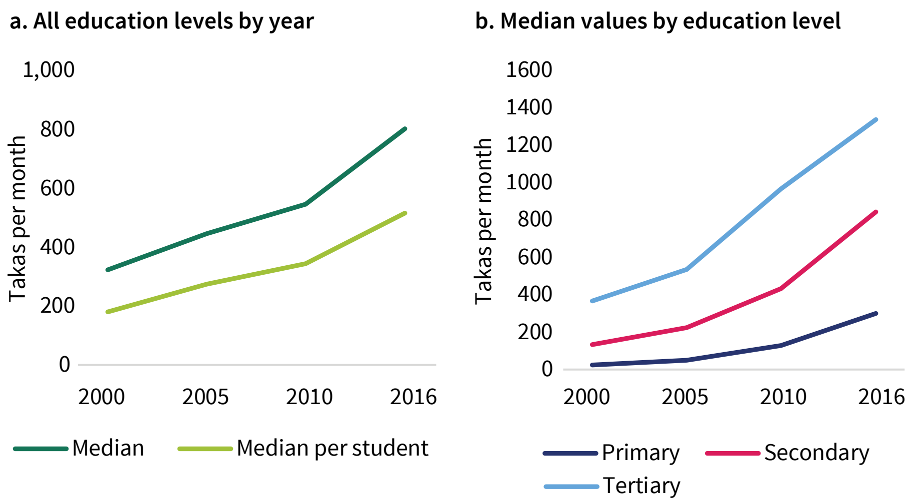
The rise in households' expenditures is observed for all levels of education, with the fastest growth seen for primary. Between 2010 and 2016, median expenditures for primary education increased from Tk. 128 to Tk. 300 per month (135 percent in real terms) (Figure 14). For secondary, the increase was 95 percent, and for tertiary it was 38 percent.

Figure 13. Households' education expenditures, by year



Source: Authors' calculations using Household Income and Expenditure Survey 2000-2016/17.

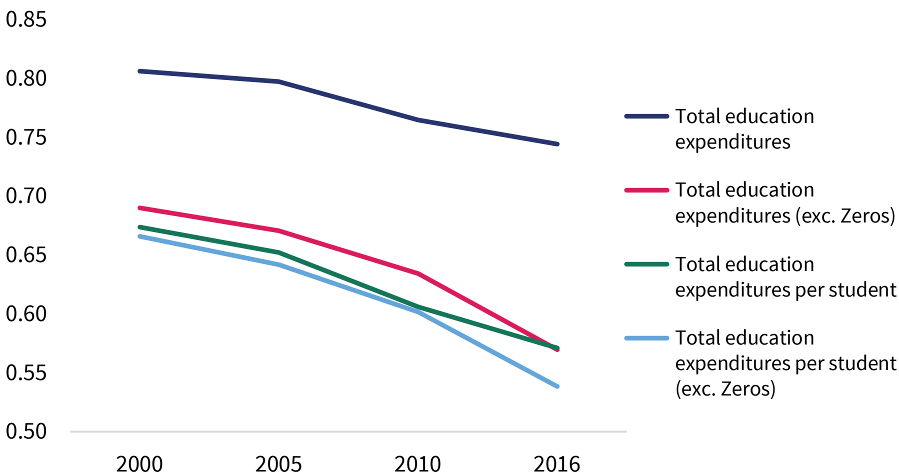
Figure 14. Median expenditures on education per month (in 2016 takas)



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: The figures are calculated for households that report positive education expenditures. Figures in 2016 prices, deflated spatially to account for differences in cost of living across the country.

The expansions in private spending were accompanied by a reduction in the spending gap between poor and richer households. While, in 2000, the top quintile spent 22 times more on education per student than the poorest quintile, in 2016, the richest quintile spent only six times more than the poorest quintile. Therefore, the inequality in the distribution of private education expenditures has been substantially decreasing. The Gini coefficient for education expenditures declined from 0.81 to 0.74 between 2000 and 2016. Considering only households with positive education spending, the fall in inequality measured by the Gini was 12 points, with more than half of the change observed between 2010 and 2016 (Figure 15).

Figure 15. Gini coefficient for household education expenditures, by year



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.

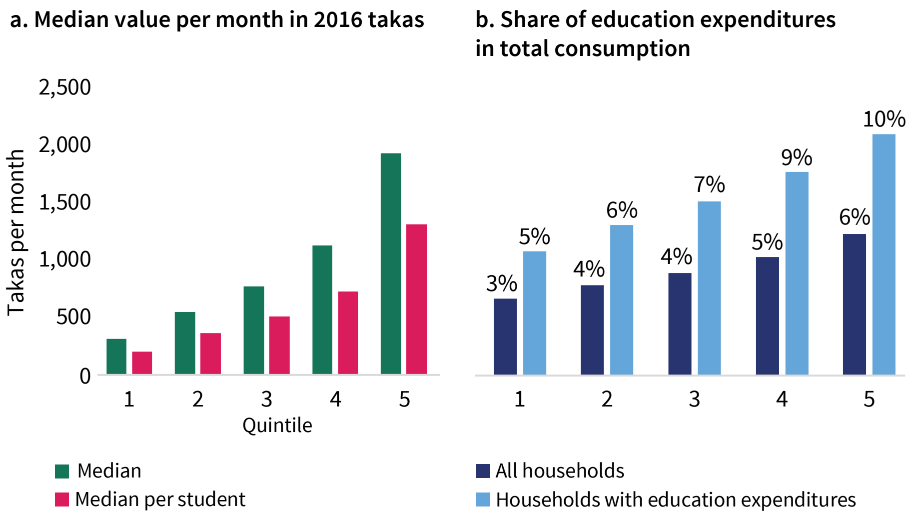
Yet, poor households have substantially lower private spending on education than richer households. Comparing across consumption quintiles, the percentage of households that are spending on education is quite even; in 2016, it ranged from 62 percent of households in the poorest quintile to 59 percent of households in the richest quintile (Figure 16). However, in 2016, the median household in the poorest quintile spent about Tk. 315 per month on education (Tk. 202 per student), compared to Tk. 1,933 (Tk. 1,310 per student) for the median household in the richest quintile. The lower spending of the poor also translates into a lower budget share. While the poorest quintile allocated 5 percent of their total consumption to education, the richest allocated 10 percent of total consumption.[11]

Households' private spending on education is mainly allocated to cover school fees, books, and tutoring. On average, in 2016, households spent about 20 percent on fees, 23 percent on books, 26 percent on private tutoring, 4 percent on transportation, and a remaining 27 percent on miscellaneous items (including

[11] This is conditional on having positive education expenditures.

uniforms, internet, tiffin costs, accommodation, etc.) (Table 9). Across levels, fees gain importance in higher levels of education (16 percent in primary, 19 percent in secondary, rising to 31 percent in tertiary). Tutoring has more importance in secondary (about 31 percent of total spending). In addition, transport costs are most important in tertiary (10 percent of total spending).

Figure 16. Education expenditures by quintile



Source: Authors' calculations using Household Income and Expenditure Survey 2000 to 2016/17.

The share of expenditures allocated to fees, tutoring, and transportation increases for households with more resources, while the share allocated to books decreases for richer households (Figure 17). Across education levels, books comprise about a third of the budget spend on education for the poorest quintile. At the tertiary level, the spending patterns across quintiles becomes more similar, as expected, since this is conditional on attending higher levels of education.

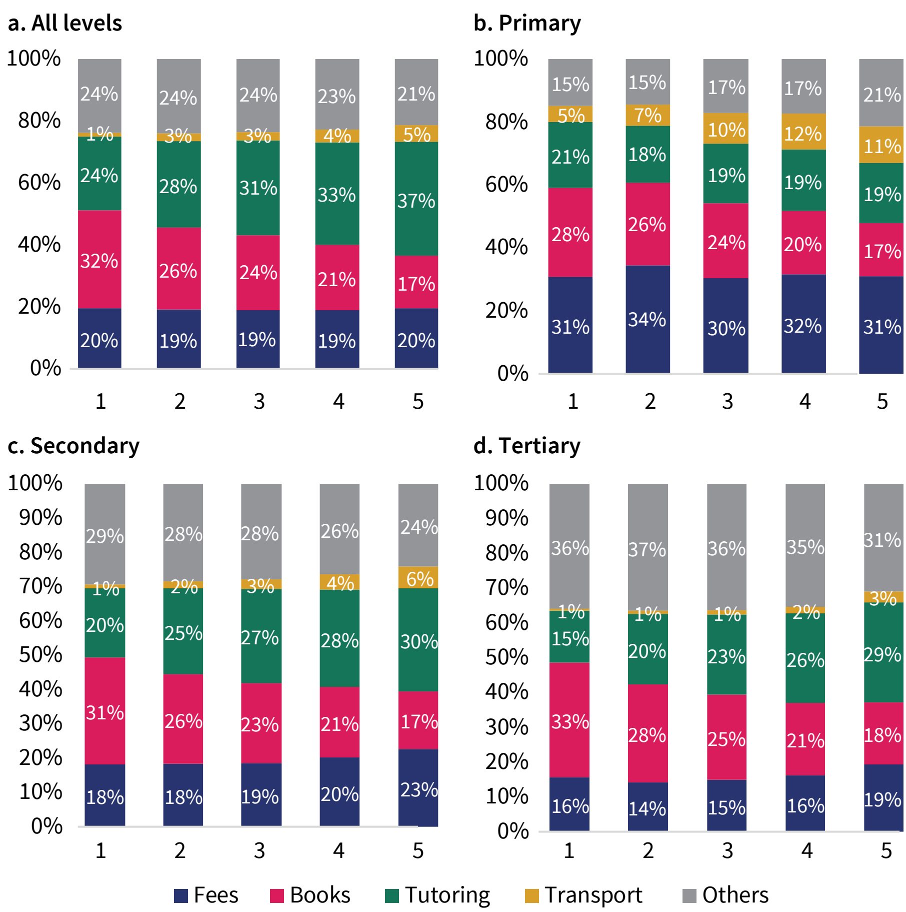
Again, the median amounts spent on fees, books, tutoring, and other items are substantially lower for the poor. For instance, in 2016, the bottom 20 percent spent about Tk. 21 per month in fees, about half what is spent by the next quintile, and about 6 percent of the median household in the richer quintile. These gaps are observed across all three levels of education (Appendix Table A.3).

Table 9. Distribution of expenditures by type

	HIES 2016/17				
	Spending category				
Education level	Fees	Books	Tutoring	Transport	Others
All	20%	23%	26%	4%	27%
Primary	16%	25%	22%	1%	35%
Secondary	19%	24%	31%	3%	23%
Tertiary	31%	21%	19%	10%	18%

Source: Authors' calculations using 2016/17 Household Income and Expenditure Survey.
Note: Fees include expenditures on admission, annual sessions, registration, examination, and tuition. Books include text, note, and exercise books and stationary. Tutoring includes private tutoring and coaching. Other expenditures include uniforms, footwear, hostel, tiffin, internet/e-mail, schooling donation, and others.

Figure 17. Distribution of expenditures by type across consumption quintiles



Source: Authors' calculations using 2016 Household Income and Expenditure Survey.

Part of the difference in private spending patterns between poorer and richer households can be attributed to the type of school attended by children, though government funded institutions are dominant at all education levels. Approximately 57 percent of primary institutions in the country are government schools, fully financed and managed by MoPME (APSC 2017). The remaining primary institutions are mostly non-government funded and privately managed. According to HIES 2016, 84 percent of children of primary-school age attend a government school or a private government-subsidized institution, and about 9 percent of children go to a private non-government-subsidized school (Figure 18). Children in poorer households are more likely to attend government schools. While only 4 percent of children in the poorest consumption quintile attended a private non-government-subsidized school in 2016, this was true for 18 percent of children from the richest quintile (Appendix Table A.4).

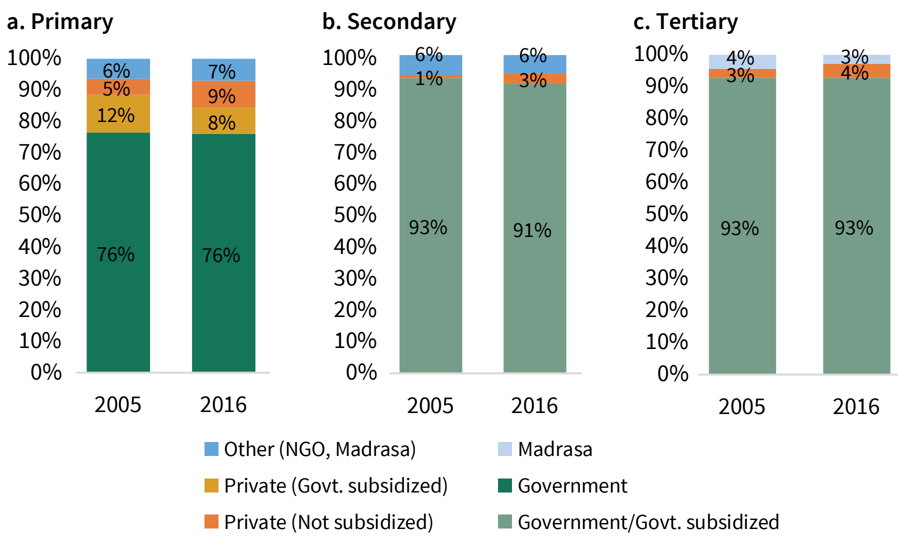
At the secondary level (Grades 6-10), most of the schools are publicly subsidized and privately managed. In 2017, 98 percent of the secondary institutions were under private management, and 82 percent of these non-government secondary schools received Monthly Pay Orders (MPOs) from the government for the payment of teacher salaries (BANBEIS 2018). Therefore, approximately nine in ten secondary-age school children attend a government or government-subsidized private school. Given the dominance of these schools in providing secondary education, there are no major differences in the type of school attended across consumption quintiles. Only children belonging to the richest quintile are more likely to attend private non-government subsidized schools (5 percent compared to 3 percent in the other quintiles).

Similarly, most technical and vocational education and training (TVET) and tertiary institutions receive some government funding or subsidies. Public-sector TVET institutions, which enroll around 22 percent of the TVET student population, are fully financed by the government. In addition, many private TVET institutions receive subsidies from the government, mainly in the form of MPOs for teacher salary payments and through grants from donor-supported government projects. At the tertiary level, public universities, which enroll around 25.5 percent of the total student population, are fully supported by government funds. Government colleges affiliated to the National University (NU), enrolling 37.9 percent of total tertiary level students, also receive full funding from MoE. Non-government colleges, on the other hand, are largely privately funded and generate around 80 percent of their income from student fees. But they also have access to some public funds in the form of MPOs for teacher salaries and through donor-funded government projects. Students are charged nominal tuition and examination fees in government higher secondary schools, government TVET polytechnics, public universities, and NU affiliated government colleges. Private institutions charge substantially higher fees at all levels.

For tertiary, most students attend a government-subsidized private school (55 percent) or government schools (38 percent). Students with more resources are significantly more likely to choose private (not subsidized) schools: 7 percent of students in the richest quintile do so, compared to 1 percent of those in the poorest quintile (Appendix Table A.4).

Compared to a decade ago, there has been an increase in the share of children attending private schools. According to HIES, between 2005 and 2016, the share of students attending private institutions increased by around four percentage points for primary, two percentage points for secondary, and one percentage point for tertiary. The expansions in private schooling have been observed for all consumption quintiles and were faster for the middle quintiles (Appendix Table A.4).

Figure 18. Type of school attended, 2005-2016



Source: Authors' calculations using Household Income and Expenditure Survey 2005 and 2016/17.

The role of public spending in total spending

Public spending contributes a large share of total education expenditures, particularly for the primary level. Estimations combining HIES and BOOST indicate that, for the median child in primary school, about 57 percent of total spending comes from public resources. For secondary, the portion publicly funded is 43 percent.

Consistent with the incidence analysis presented above, public spending has a larger importance for poorer children. For primary, about 76 percent of the education expenditures of the median household in the bottom 20 percent of the consumption distribution come from public resources, compared to 23 percent for the richest 20 percent of the consumption distribution (Figure 19). For secondary, public expenditures represent 60 percent of total expenditures for the median households in the bottom 20 percent, compared to 29 percent for the richest 20 percent.[12]

Therefore, public spending helps reduce the education spending gap between poor and rich households. For instance, in 2016, the richest quintile spent about 7.5 times more per student in primary, compared to the poorest quintile (Table 10). When public spending is added, the richest quintile spends about two times more than the poorest quintile. For secondary, the ratio between mean expenditures per student between the richest and poorest quintiles, declines from 11.4 to 8.4 times, when public spending is added.

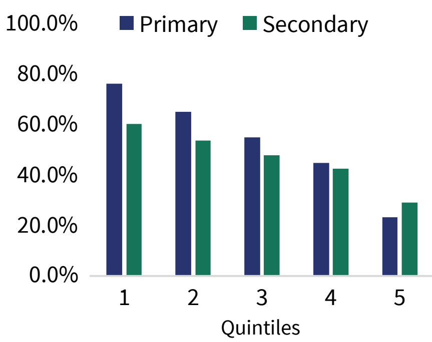
Table 10. Total education expenditures per student, median takas per month

	Primary		Secondary	
Group	**Private**	**Private and public**	**Private**	**Private and public**
All	204	616	417	1183
Consumption quintile				
1	82	494	107	249
2	153	568	279	730
3	246	648	426	1078
4	355	719	669	1485
5	605	942	1225	2090

Source: Authors' calculations using Household Income and Expenditure Survey 2016 and BOOST for fiscal year 2014.
Note: Private denotes the households' expenditures net of stipends which are included in public spending. Private and public also includes the spending from GoB. Amounts in 2016 takas.

[12] Caveat: these shares are slightly underestimated, as the information from BOOST comes from FY14. Yet, the qualitative comparisons across groups should be adequate.

Figure 19. **Share of public expenditure over total education expenditure, by quintile**



Source: Authors' calculations using Household Income and Expenditure Survey 2016 and BOOST for fiscal year 2014.
Note: Total education expenditure includes public and households' private expenditures. The figures presented are medians by group.

III. Relationship between spending and outcomes

The previous section highlights that overall spending has been growing, while inequalities are shrinking between poor and non-poor children. This section explores how strong the cross-sectional relationship between levels of spending and outcomes is. For primary level, the outcomes analyzed are attendance rates and internal efficiency indicators. For secondary, the analysis only focuses on attendance rates, due to other indicators not being readily available at the district level. Even though this analysis is not intended to explain the impact of more resources on education outcomes, the district-level analysis provides a more nuanced picture of their relationship. It should be noted, however, that an analysis of performance within districts, ideally at the school level and across time, would be needed to get a better picture of the challenges in delivering better education outcomes. Unfortunately, the information available does not allow for such detailed analysis.

Despite improving attendance to primary education, Bangladesh's pro-poor spending is not strongly correlated with better overall education outcomes. At the primary level, total public spending per student is not statistically correlated with key performance and internal efficiency outcomes (Figure 20). A district-level analysis shows that total GoB spending per student is not associated with repetition rates, survival rates, efficiency ratio, dropout rates, or gross attendance rates. Only for net attendance rates is the relationship positive and significant at the 10 percent significance level.[13] Appendix Table A.5 presents a series of ordinary least squares (OLS) regressions, where the correlation between outcomes and spending per student for the primary level is

[13] It is important to keep in mind that this analysis presents a cross-sectional correlation between spending and outcomes and cannot inform about the effectiveness of increased spending on outcomes across time. The weak relationship could be explained by the fact that spending is going to groups and areas that are lagging and have relatively worse outcomes. The controls in the multivariate regressions may not completely address this fact.

conditioned by the size of the district population, the share of rural population, the poverty rate, and literacy rates. These multivariate regressions confirm that differences in levels of public spending do not explain variation in outcomes across districts.

However, the student-to-teacher ratio arises as a more significant correlate of these outcomes. Having more students per teacher significantly explains differences in survival rates, dropout rates, and the efficiency ratio across districts. Multivariate regressions also indicate that the ratio of students per teacher emerges as a much stronger correlate of outcomes. In addition, household private education per student correlates with lower repetition rates, a higher efficiency ratio, and lower dropout rates. However, this correlation losses significance, once we control for literacy, poverty, and share of rural population.

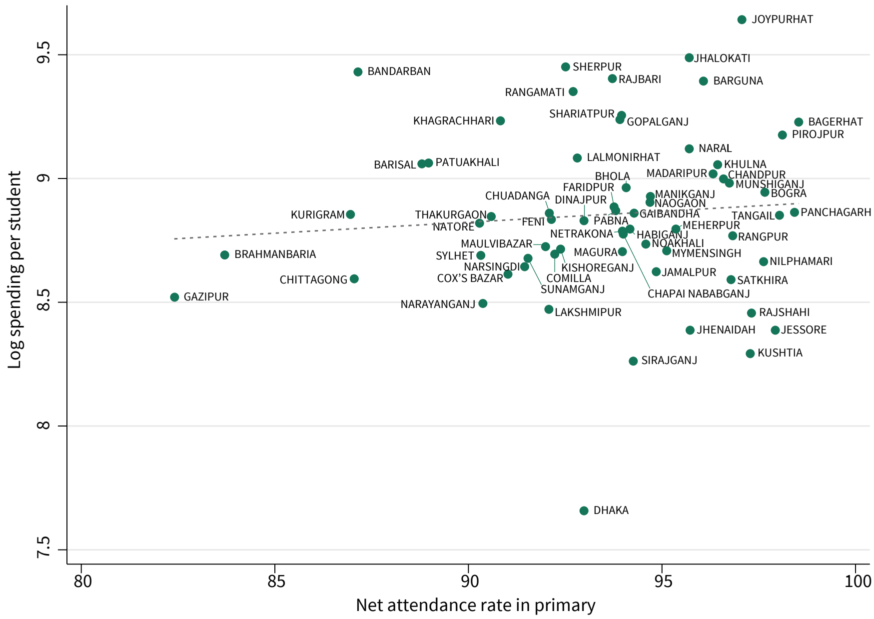
Spending per student at the secondary level is correlated with attendance rates, though the relationship losses significance once other factors are considered (Figure 21). Even though the one-to-one correlation between spending per student and attendance is positive and statistically significant, once basic characteristics of the districts and the student-to-teacher ratio are included in the regression, the correlation becomes insignificant (Appendix Table A.6). However, the student-to-teacher ratio remains correlated with net enrollment once we control for other covariates.

Overall, only when spending translates into lower student-to-teacher ratios do outcomes improve for the primary and secondary levels. This is consistent with previous studies highlighting that higher spending on teachers is a more significant correlate with outcomes for the primary level, and that the effectiveness of other types of spending in improving outcomes is less clear (Steer et al. 2014).

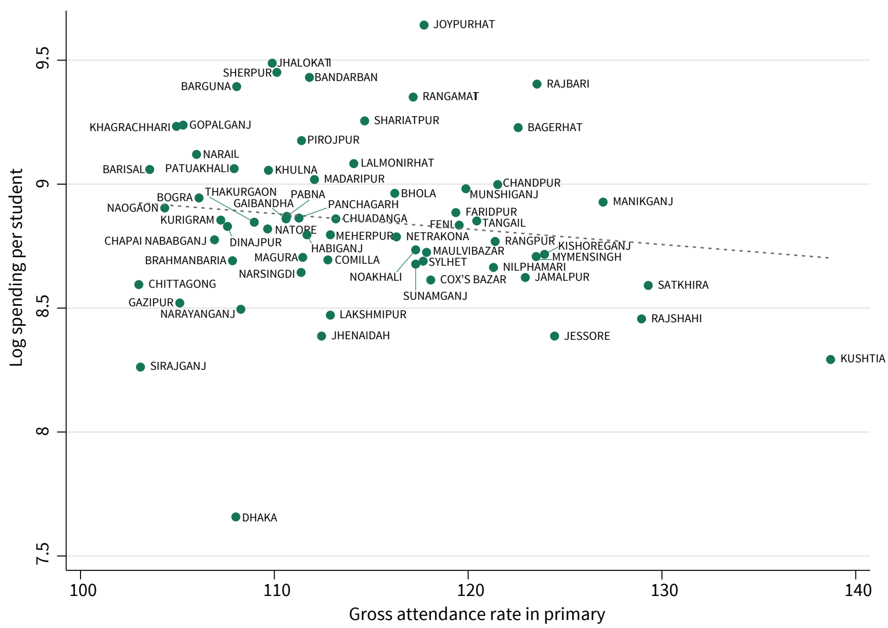
Given their importance for education outcomes, more efforts are needed to improve student-to-teacher ratios in Bangladesh. These ratios are high by international standards (Figure 22). In 2016, the average student-to-teacher ratio was 34 in primary and 36 in secondary. For primary, there has been a reduction in this ratio over time, however for secondary, the ratio has been increasing. Compared to other countries in the region, the primary student-to-teacher ratio is similar to India's, lower than Pakistan's and Bhutan's, but significantly higher than those of other countries in the region and OECD members. For secondary, Bangladesh's ratio is higher than other countries in South Asia.

Figure 20. Relationship between spending per student and outcomes for primary level

a. Net attendance rate

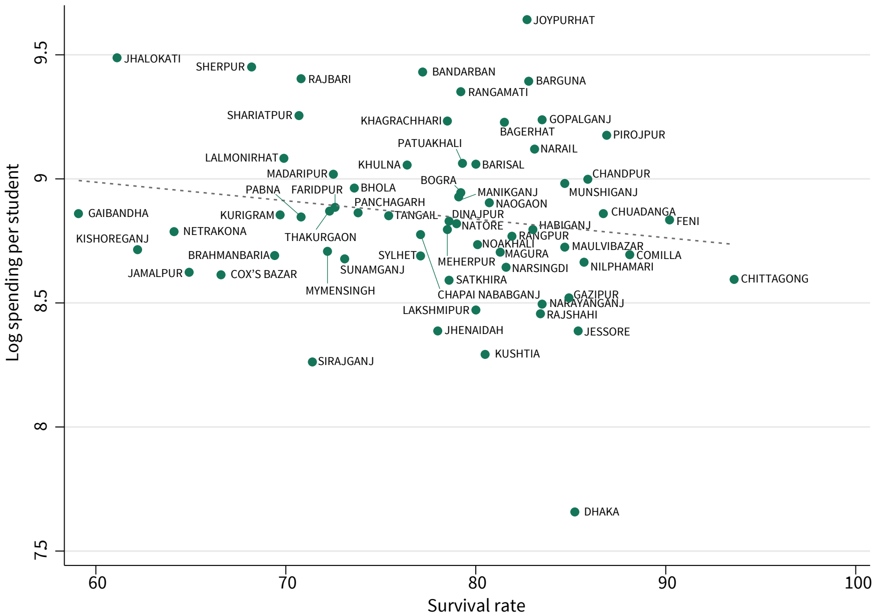


b. Gross attendance rate

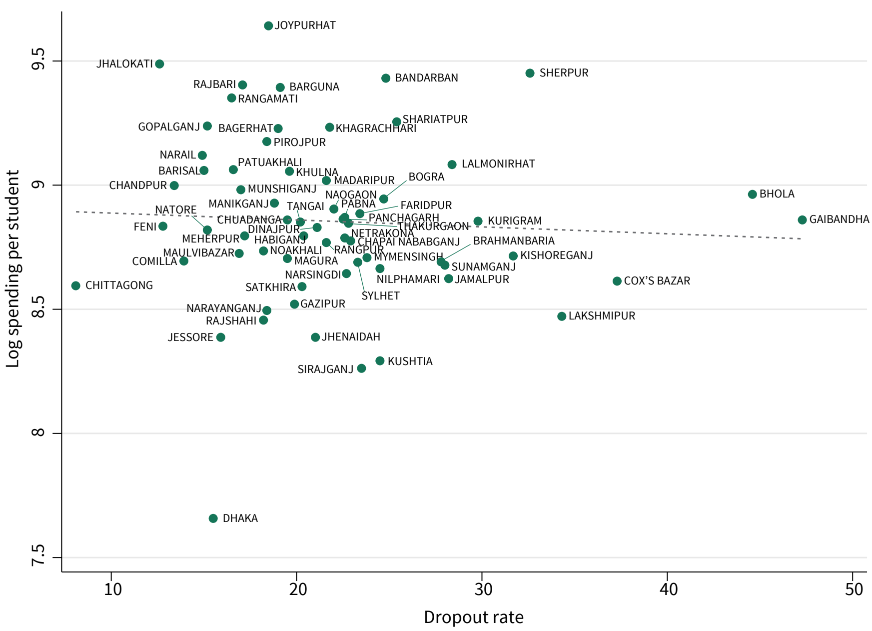


Source: Authors' calculations using BOOST for fiscal year 2014, Household Income and Expenditure Survey, and Annual Primary School Students Census (APSC).

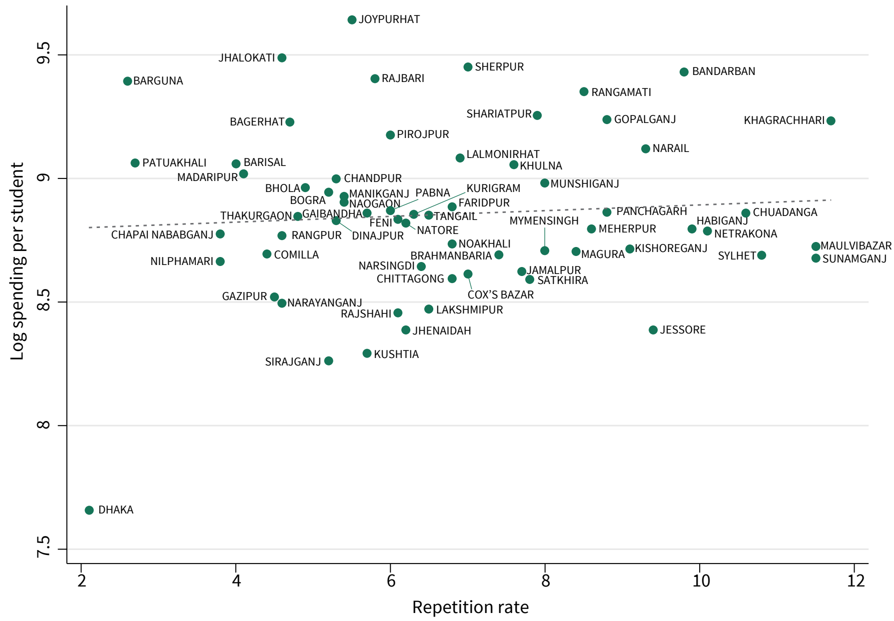
c. Survival rate



d. Dropout rate



e. Repetition rate



f. Efficiency ratio

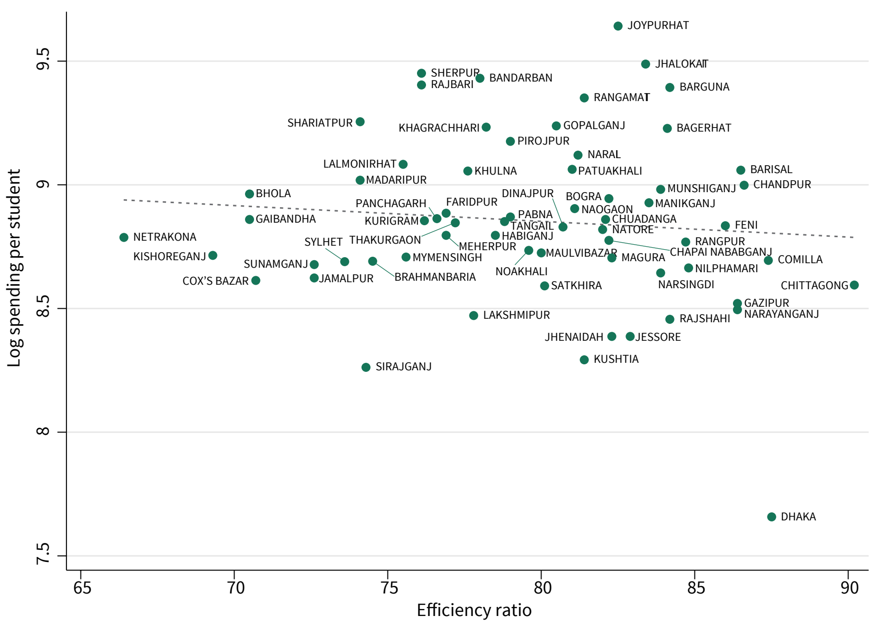
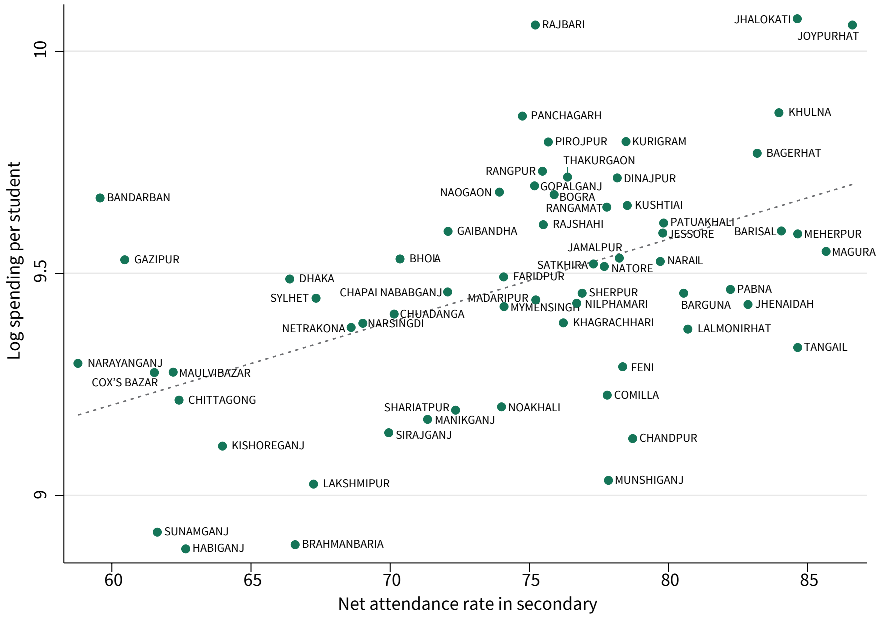
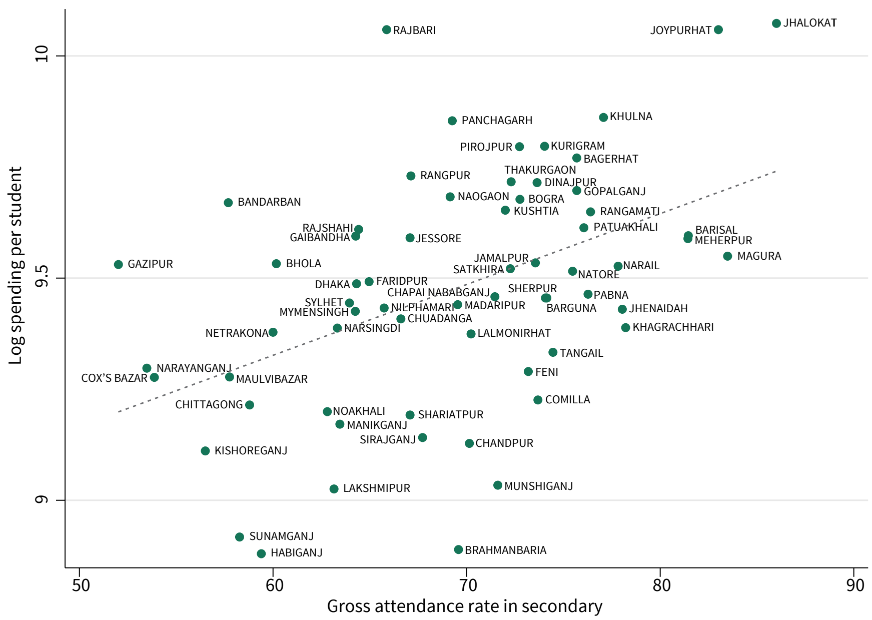


Figure 21. Relationship between spending per student and outcomes for secondary level

a. Net attendance rate



b. Gross attendance rate



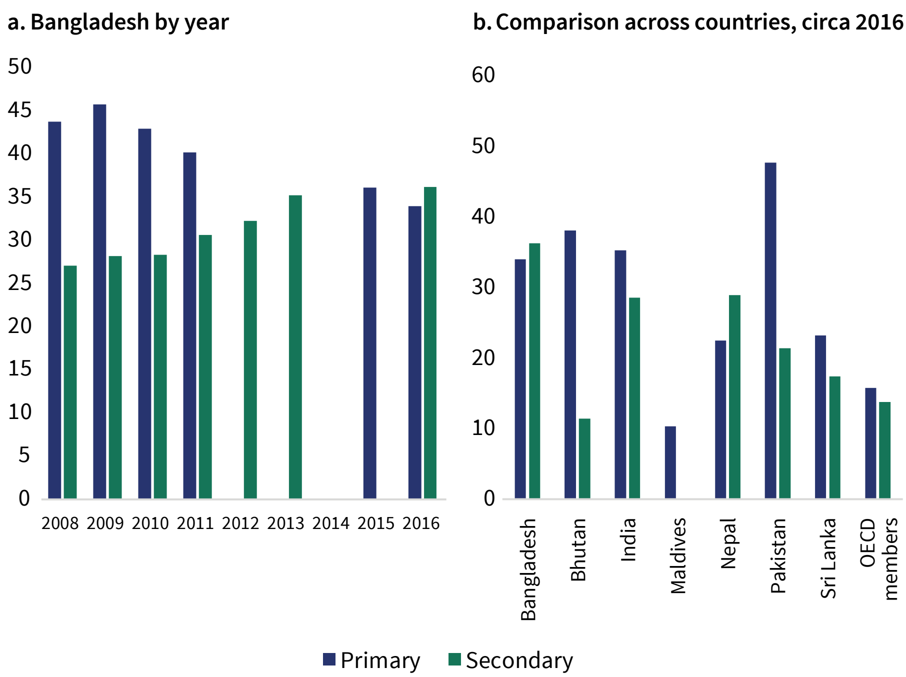
Source: Authors' calculations using BOOST for fiscal year 2014 and Household Income and Expenditure Survey.

Moreover, at the district level, there is significant variation in student-to-teacher ratios, which can partly explain inequalities in performance across the country (Figure 23). For the primary level, the ratio ranges from 21 students per teacher in Rangamati to 53 in Cox's Bazar, both in Chittagong division. At the secondary level, the ratio ranges from 27 in Thakurgaon and Panchagarh in Rangpur division and in Dhaka to 69 in Habiganj in Sylhet division.

IV. Summary

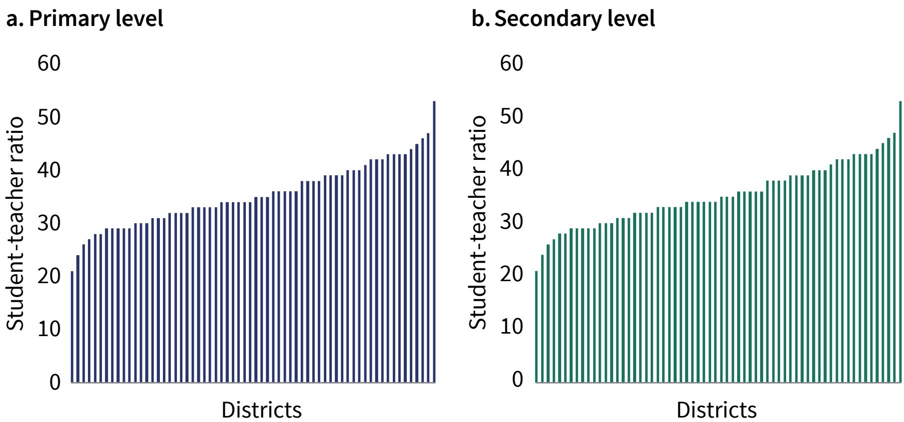
The results presented here show continued improvement in access to education in Bangladesh. The number of out of school children 6-14 years old fell from about 5.5 million to 3 million between 2010 and 2016, an impressive 45 percent reduction in six years. The gains in access have recently been accompanied by improvements in the internal efficiency of the education system measured by reductions in drop-out rates and higher survival rates. In addition, the gains have been equitable, reducing disparities by gender, between the poor and non-poor, and across regions. Yet progress is still needed at higher education levels, and there is still an equity agenda, given persistent gaps between the poor and rich and across divisions and districts.

Figure 22. Student-to-teacher ratio



Source: World Development Indicators.

Figure 23. Student-to-teacher ratios at the district level



Source: Authors' calculations using Household Income and Expenditure Survey 2016 and BOOST for fiscal year 2014.

Progress is partly the result of efforts by the Government of Bangladesh (GoB) to improve education outcomes, but it also reflects increased private spending by households. Education spending per student has been growing in the past few years, and its distribution has become more progressive with time. However, GoB education spending is still low compared to other countries in the region, and it presents large variation across the territory, which is not correlated with education outcomes and internal efficiency indicators. Only when public spending translates into fewer students per teacher do outcomes seem to improve. However, Bangladesh's student-to-teacher ratios remain inadequate compared to other countries and unevenly distributed across districts. Moving forward, this suggests that gearing towards higher-quality spending, in addition to increasing overall budgets, will be a priority to continue improving outcomes.

Stipend programs help with the progressivity of the system at the primary level. The size of the primary stipend program represents about 70 percent of the private spending of households in the poorest quintile, but amounts have been declining in real terms. At the secondary level, there is still significant room to improve the progressivity of these benefits. Improving the targeting of these programs can also help enhance the impact on outcomes and the progressivity of the education system.

Finally, households' private spending had a central role in the achievements seen in the past two decades. However, many Bangladeshis do not see value in investing in education. Addressing norms and expectations around the benefits of schooling can be an important avenue for further progress. About four in ten secondary school-age children out of school report lack of interest or being too old to go back as their main reasons for not attending school. Work reasons follow (one in four children not attending), particularly for males. Moreover, family chores and marriage become an important reason for women not to attend secondary school (cited by 30 percent of women not attending). Similar reasons are found at the tertiary level.

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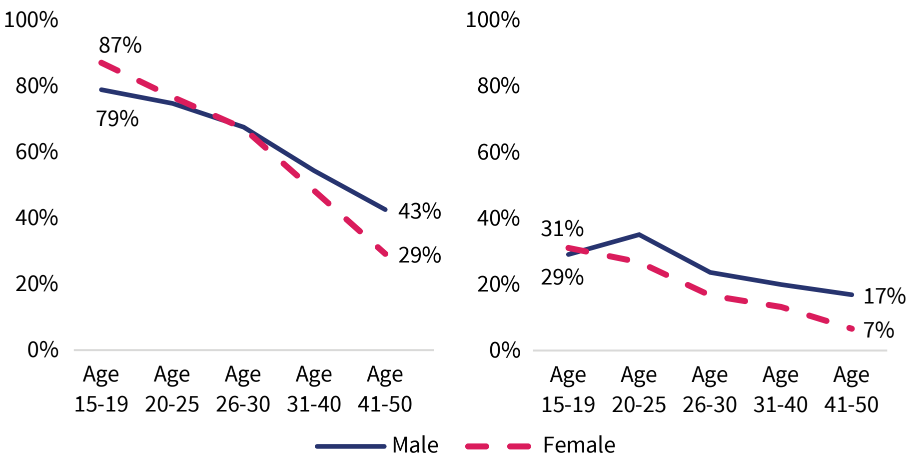
Appendix A: appendix figures and tables

Appendix figures

Figure A1. Primary and secondary school completion rates across age groups by gender (2016)

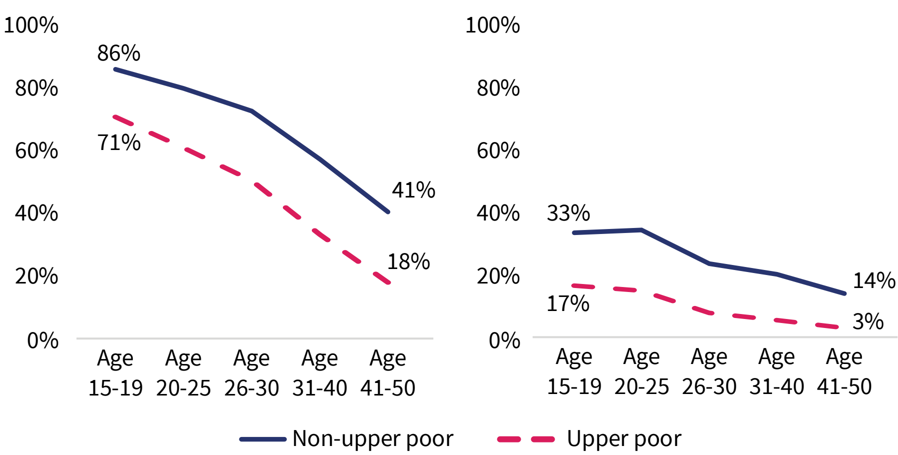
a. Primary school completion **b. Secondary school completion**



Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.
Note: Secondary completion refers to completion of Grade 10.

Figure A2. Primary and secondary school completion rates across age groups by poverty status (2016)

a. Primary school completion **b. Secondary school completion**



Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.
Note: Secondary completion refers to completion of Grade 10.

Appendix tables

Table A.1. Linear probability model for being out of school

	Out of school	Never	Drop out
	(1)	(2)	(3)
Female	-0.036** [0.005]	-0.026** [0.003]	-0.011** [0.002]
Age	0.012** [0.001]	-0.003** [0.001]	0.006** [0.000]
Consumption quintile 1 (1)	0.089** [0.008]	0.062** [0.006]	0.016** [0.005]
Consumption quintile 2	0.059** [0.010]	0.046** [0.008]	0.003 [0.004]
Consumption quintile 3	0.036** [0.007]	0.023** [0.006]	0.005 [0.004]
Consumption quintile 4	0.007 [0.007]	0.004 [0.005]	-0.002 [0.003]
Female-headed household	0.018 [0.014]	0.013 [0.009]	-0.003 [0.006]
Household head's education in years	-0.006** [0.001]	-0.004** [0.001]	-0.001** [0.000]
In urban area	0.053** [0.009]	0.031** [0.007]	0.011** [0.003]
Both parents present in the household	0.003 [0.011]	0.004 [0.007]	-0.006 [0.005]
Total number of children 0-17 years	0.003 [0.003]	0.002 [0.002]	0.002 [0.001]
Constant	-0.051** [0.016]	0.058** [0.012]	-0.035** [0.008]
Observations	**37,211**	**37,211**	**37,211**
R-squared	**0.051**	**0.032**	**0.024**

Source: Author's calculations using Household Income and Expenditure Survey 2016/17.
Note: Regressions include controls for divisions. Standard errors calculated using survey's sampling design.
** p<0.01, * p<0.05, + p<0.1
(1) Omitted is consumption quintile 5.

Table A.2. Reasons for not attending school by group in 2016

	Do not want to study more	Too old to go back	No money/ too expensive	No schools close to home	Have to work	Attending to family chores	For marriage
Primary							
All	25%	26%	27%	11%	6%	5%	1%
Area							
Rural	20%	30%	26%	13%	5%	6%	1%
Urban	37%	17%	28%	8%	7%	2%	1%
Gender							
Female	23%	27%	31%	10%	3%	5%	1%
Male	26%	26%	23%	12%	8%	5%	0%
Quintile							
1	27%	27%	29%	8%	4%	4%	1%
2	25%	20%	24%	15%	9%	7%	0%
3	22%	23%	38%	10%	2%	4%	1%
4	20%	38%	15%	19%	2%	5%	1%
5	26%	44%	4%	7%	14%	4%	1%
Secondary							
All	32%	8%	18%	1%	26%	10%	6%
Area							
Rural	30%	9%	17%	1%	25%	11%	7%
Urban	34%	6%	19%	0%	27%	8%	5%
Gender							
Female	27%	8%	20%	1%	14%	15%	15%
Male	35%	9%	16%	0%	34%	7%	0%
Quintile							
1	28%	10%	22%	1%	23%	11%	6%
2	32%	9%	19%	1%	23%	11%	5%
3	33%	7%	16%	0%	29%	9%	7%
4	31%	6%	14%	0%	30%	10%	8%
5	39%	9%	11%	0%	27%	7%	7%
Tertiary							
All	27%	13%	7%	0%	20%	13%	20%
Area							
Rural	25%	14%	6%	0%	20%	13%	22%
Urban	33%	10%	8%	0%	20%	13%	17%
Gender							
Female	25%	13%	5%	1%	6%	18%	32%
Male	30%	12%	9%	0%	41%	7%	2%
Quintile							
1	26%	15%	6%	0%	20%	10%	22%
2	27%	12%	7%	0%	20%	13%	21%
3	24%	14%	8%	0%	20%	15%	19%
4	27%	11%	7%	0%	20%	16%	18%
5	32%	10%	4%	1%	20%	11%	22%

Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.

Table A3. Median monthly expenditures by type (in takas)

	Fees	Books	Tutoring	Transport	Others	All
All levels						
	Fees	**Books**	**Tutoring**	**Transport**	**Others**	**All**
All	**123**	**150**	**193**	**0**	**158**	**802**
Quintiles						
1	21	73	0	0	73	315
2	61	119	112	0	118	548
3	110	146	202	0	157	773
4	191	192	281	0	209	1127
5	355	258	483	0	311	1933
Primary						
	Fees	**Books**	**Tutoring**	**Transport**	**Others**	**All**
All	**12**	**58**	**0**	**0**	**83**	**300**
Quintiles						
1	8	35	0	0	46	143
2	9	50	0	0	71	232
3	13	58	25	0	100	328
4	18	71	100	0	125	442
5	60	100	200	0	167	730
Secondary						
	Fees	**Books**	**Tutoring**	**Transport**	**Others**	**All**
All	**135**	**167**	**250**	**0**	**158**	**843**
Quintiles						
1	45	92	50	0	71	363
2	88	129	167	0	108	588
3	125	167	250	0	153	827
4	180	192	350	0	200	1100
5	275	250	600	0	292	1817
Tertiary						
	Fees	**Books**	**Tutoring**	**Transport**	**Others**	**All**
All	**350**	**250**	**167**	**75**	**167**	**1338**
Quintiles						
1	192	158	83	0	58	598
2	249	174	67	0	83	758
3	275	208	125	25	123	1004
4	358	233	200	83	158	1363
5	462	300	250	167	300	2117

Source: Authors' calculations using Household Income and Expenditure Survey 2016/17.
Note: In 2016 takas.

Table A.4. Type of school attended by level and consumption quintile, 2005-2016

	Primary											
	2005						2016					
Quintile	Government	Private (Govt. subsidized)	Private (Not subsidized)	NGO run institution	Madrasa (Govt. affiliated)	Madrasa (Kowmi)	Government	Private (Govt. subsidized)	Private (Not subsidized)	NGO run institution	Madrasa (Govt. affiliated)	Madrasa (Kowmi)
1	78%	8%	3%	7%	3%	1%	83%	7%	4%	2%	3%	2%
2	82%	8%	3%	3%	3%	1%	81%	6%	6%	2%	3%	3%
3	84%	6%	2%	3%	4%	1%	78%	8%	7%	1%	4%	2%
4	77%	14%	3%	2%	2%	1%	71%	9%	12%	1%	4%	2%
5	63%	23%	13%	1%	0%	0%	61%	14%	18%	1%	3%	2%
	Secondary											
	2005						2016					
1	30%	55%	1%	1%	12%	2%	24%	66%	3%	1%	5%	1%
2	24%	65%	1%	1%	8%	1%	24%	67%	3%	0%	4%	2%
3	19%	74%	0%	0%	6%	0%	24%	68%	3%	1%	4%	1%
4	18%	76%	1%	0%	5%	0%	23%	69%	3%	0%	4%	1%
5	17%	78%	2%	0%	3%	0%	21%	69%	5%	0%	4%	1%
	Tertiary											
	2005						2016					
1	100%	0%	0%	0%	0%	0%	35%	60%	1%	0%	3%	1%
2	19%	64%	0%	0%	17%	0%	36%	59%	2%	0%	3%	0%
3	29%	37%	2%	0%	21%	10%	35%	58%	3%	0%	1%	2%
4	38%	57%	0%	0%	5%	0%	35%	60%	2%	0%	2%	1%
5	41%	54%	4%	0%	1%	0%	42%	49%	7%	0%	2%	0%

Source: Authors' calculations using Household Income and Expenditure Survey 2005 and 2016/17.

Table A.5. OLS Regression between primary level outcomes and spending

Primary level						
	Repetition rate	**Survival rate**	**Efficiency ratio**	**Dropout rate**	**Net atten-dance rate**	**Gross atten-dance rate**
District variables	**(1)**	**(2)**	**(3)**	**(4)**	**(6)**	**(7)**
Log public education spending per student	-0.77 (1.03)	-5.91+ (3.19)	-1.76 (1.98)	0.58 (3.02)	-2.01 (1.58)	-5.01 (4.94)
Number of students per teacher	0.02 (0.05)	-0.38* (0.14)	-0.36** (0.10)	0.59** (0.20)	-0.15+ (0.08)	0.06 (0.17)
Log private education spending per student	-0.55 (0.56)	-1.74 (1.46)	0.61 (0.71)	-0.19 (1.36)	-0.01 (0.66)	4.06** (1.40)
Log population	-1.19* (0.58)	-0.67 (2.08)	1.14 (1.20)	-1.17 (2.05)	0.01 (0.87)	-0.49 (2.05)
Share of rural population	-0.01 (0.02)	-0.06 (0.07)	-0.04 (0.04)	0.01 (0.06)	0.11* (0.05)	0.23** (0.07)
Poverty rate	-0.01 (0.02)	-0.10+ (0.06)	-0.01 (0.04)	0.08 (0.05)	-0.01 (0.03)	-0.03 (0.06)
Literacy rate for adults	-0.07* (0.03)	0.27* (0.11)	0.20** (0.06)	-0.19* (0.08)	0.06 (0.06)	-0.11 (0.12)
Constant	39.88* (16.27)	159.52** (53.86)	77.53* (33.53)	22.28 (55.32)	104.16** (25.40)	119.34+ (68.15)
Observations	**64**	**64**	**64**	**64**	**64**	**64**
R-squared	**0.17**	**0.35**	**0.47**	**0.42**	**0.20**	**0.21**

Note: Robust standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Table A.6. OLS Regression between net attendance rate in secondary and spending

	Net attendance rate	Gross attendance rate
District variables	**(1)**	**(2)**
Log public education spending per student	4.06 (4.20)	2.94 (4.93)
Number of students per teacher	-0.22* (0.10)	-0.18 (0.12)
Log private education spending per student	1.85 (1.51)	0.45 (1.56)
Log population	-0.61 (1.46)	-2.91+ (1.64)
Share of rural population	0.25** (0.07)	0.17* (0.08)
Poverty rate	0.05 (0.06)	0.07 (0.07)
Literacy rate for adults	0.29** (0.09)	0.33** (0.10)
Constant	-1.57 (50.81)	52.60 (61.59)
Observations	**64**	**64**
R-squared	**0.51**	**0.45**

Note: Robust standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

Appendix B

Human Opportunity Index

The previous sections showed substantial gains in education outcomes and that those gains have been broad-based, reducing disparities across regions and groups. This section explores the relative importance of the expansion in education access and the distribution of that access across children using the Human Opportunity Index (HOI).[14] The HOI, presented in Figure B.1, measures how characteristics such as the area of residence or the gender of a child may affect his/her access to education. For the analysis, we focus on two outcomes: primary and secondary school attendance. The HOI presents an adjusted measure of attendance rates that extracts a penalty for any inequity in attendance observed among children living under various circumstances outside their control.

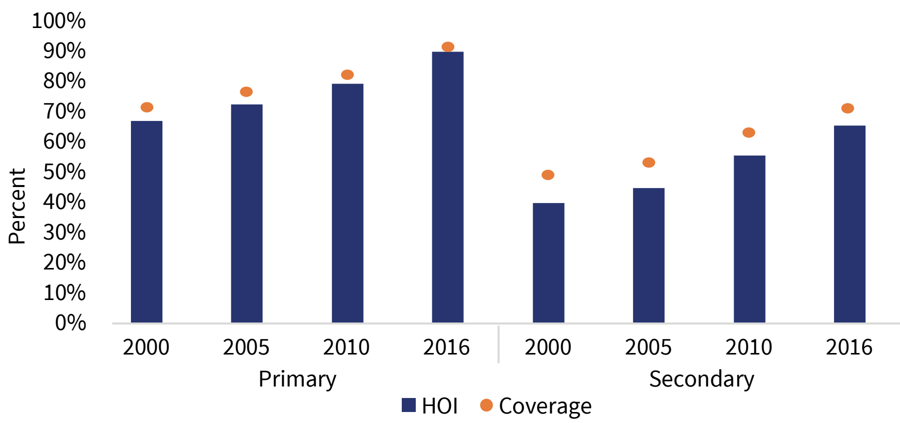
Consistent with the expansions in school attendance presented above, the HOI has increased between 2000 and 2016 for both primary and secondary levels. For primary, the HOI grew from 68 to 91 percent, driven both by a rise in coverage but also a reduction in the inequality of that coverage across children (seen by the shrinking difference between the HOI and the attendance rate). For secondary level, the HOI rose from 40 to 66 percent.

Overall, the increase in the HOI was mainly driven by expansions in attendance rates, but reduction in disparities also played a role (Figure B.2). For primary level, a decomposition of the changes in the HOI across time shows that the expansion in attendance rates explains about 72 percent of the change in the HOI between 2000 and 2016, and 84 percent of the change between 2010 and 2016. For secondary, the rise in attendance explains 76 percent of the change since 2000, and 75 percent of the change since 2010.

[14] The Human Opportunity Index (HOI) measures how individual circumstances (i.e., characteristics such as place of residence, gender, and education of the household head) can affect a child's access to basic opportunities, such as education, electricity, or water and sanitation. It is a synthetic measure of how far a society is from universal access to an essential good or service, and how equitably access is distributed across distinct groups of individuals (circumstances). The HOI is thus an economic indicator that combines coverage rates and equality in a single measure. The HOI is based on discounting a penalty for inequality of opportunity P from the overall coverage rate C so that: HOI=C-P. The penalty is chosen such that it is zero if all circumstance group specific coverage rates are equal, and it is positive and increasing as differences in coverage among circumstance groups increase. For more information about the HOI see Barros et al. 2009; and Barros, Molinas Vega, and Saavedra 2010.

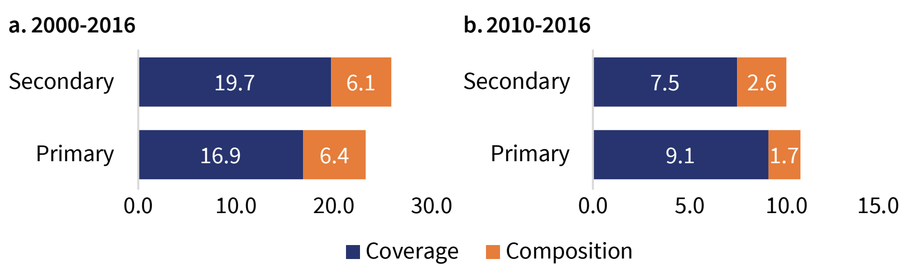
The HOI analysis also highlights that household resources and adults' education are the main circumstances behind disparities in children's school attendance (see Figure B.3). For primary school in 2016, the level of consumption of the household explains 38 percent of the differences in attendance, and the years of education of the household head explain 31 percent of the disparities. For the secondary level, these two factors contribute to 73 percent of the disparities in attendance rates. The next circumstance is the gender of the child, explaining 14 percent of the disparities in secondary attendance.

Figure B1. Human Opportunity Index for attendance rates, 2000-2016



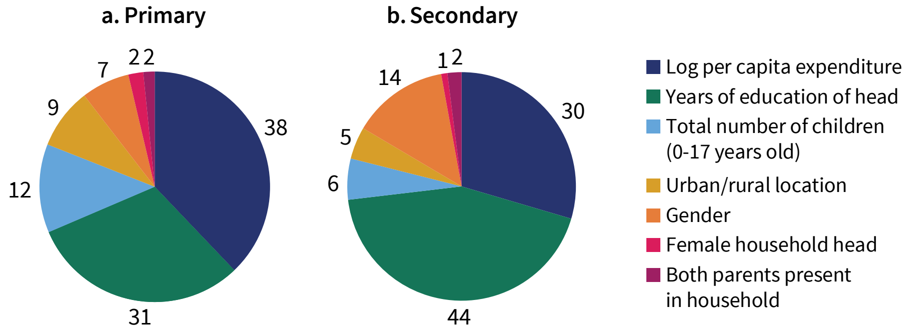
Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: Primary school attendance for children 6-10. Secondary school attendance for children 11-15.

Figure B2. Decomposition of the change in the HOI



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: Primary school attendance for children 6-10. Secondary school attendance for children 11-15. The change in the HOI between two selected years can be decomposable into the composition effect (due to changes in the distribution of circumstances), and the coverage effect (the contribution of changes in the coverage rates of different circumstance groups).

Figure B3. Circumstances that explain disparities in attendance rates, 2016



Source: Authors' calculations using Household Income and Expenditure Survey 2000, 2005, 2010, and 2016/17.
Note: Primary school attendance for children 6-10. Secondary school attendance for children 11-15.

CHAPTER XI.

Short-term Poverty Impacts of the Rohingya Crisis in Cox's Bazar, Bangladesh[1]

September 6, 2018

Abstract

The Rohingya refugee crisis is unprecedented in its scale, speed, and geographic concentration. This paper documents the welfare situation of refugees using data collected three and nine months after the crisis started, in conjunction with the World Food Program. The paper also provides evidence on the economic effects of the localized shock on the host population. High rates of poverty are present among the refugees, but food security has been improving, thanks to an effective humanitarian response. However, the welfare of refugees remains strongly reliant on food aid, with refugees exhausting other coping strategies. The economic effects of the crises have been felt most strongly in markets that were less able to dissipate the shock over space: labor markets and markets for perishable food items. Modest increases in food prices have been observed for most items, but wages have dropped by about a quarter, with large implications for poverty among the host population.

[1] This note was produced by the Poverty and Equity Global Practice as part of the Bangladesh Programmatic Poverty and Equity Work (P165499). The team comprised Jose Joaquin Endara, Maria Eugenia Genoni, Ruth Hill, Laura Maratou-Kolias, Wameq Raza, and Sharad Tandon. The World Food Program (WFP) team included Claudia Ahpoe (Senior Food Security Advisor and Head of the Assessment Team), Takahiro Utsumi (Head of Vulnerability Analysis and Mapping team [VAM]), Seokjin Han (VAM officer). Funding was provided by the State and Peacebuilding Fund (SPF). The SPF is a global fund to finance critical development operations and analysis in situations of fragility, conflict, and violence. The SPF is kindly supported by: Australia, Denmark, Germany, The Netherlands, Norway, Sweden, Switzerland, and The United Kingdom, as well as IBRD.

Introduction

Starting at the end of August 2017, the district of Cox's Bazar in Chittagong division experienced a dramatic increase in the number of refugees arriving from Myanmar. By the end of May 2018, approximately 702,000 Rohingya refugees had settled in the upazilas of Ukhia and Teknaf, bordering Myanmar. Figure 1 shows the dramatic change in landscape around the main settlement area of Kutupalong-Balukhali Expansion Site within three months of the crisis. Three main features make this influx unique: (i) it was extremely sudden, with about 656,000 refugees arriving to the area in less than three months; (ii) it was highly concentrated in a small geographic area and has remained highly localized since then, with the majority of newly arrived refugees, seven out of ten, settling in the Kutupalong-Balukhali Expansion Site; and (iii) as a consequence, the concentration of refugees is now amongst the densest in the world (15 sq. meters per person on average).

This note summarizes a series of just in time analyses to inform about the evolving needs of the refugees and the short-term welfare impact of this crisis on the host community. This work has been done in collaboration with the World Food Program (WFP). The analysis aimed to address three important questions arising as the crisis developed.

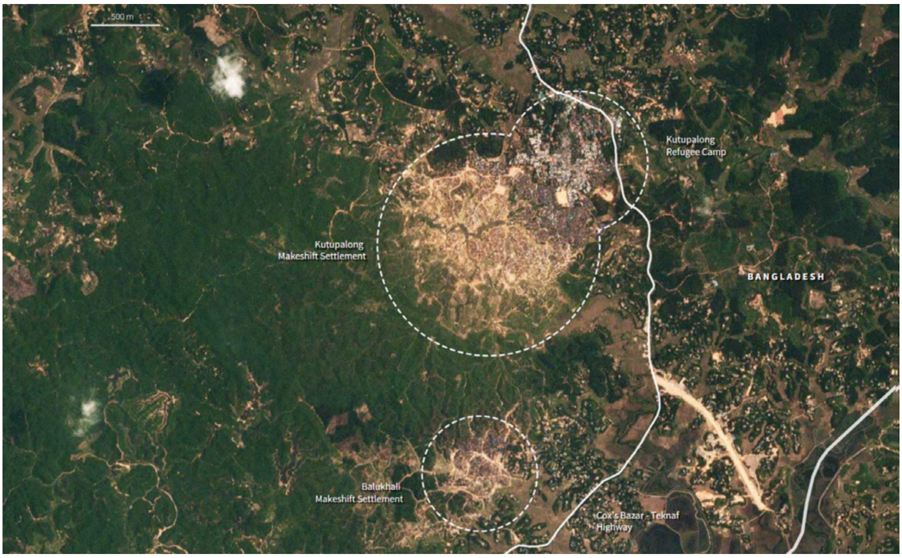
i. First, there was interest in understanding the economic situation of the refugees, to complement existing assessments from humanitarian actors more focused on non-monetary needs and food security. Relatedly, there was a need to understand the evolving welfare situation as the crisis developed, particularly in terms of food security, changes in coping strategies, labor market engagement, and mobility.
ii. Second, anecdotal evidence indicated that the recent influx of refugees significantly reduced daily wages, with large negative impacts on the local community. However, there was no hard information providing an estimate of the wage change and its impact.
iii. Third, reports suggested high food price inflation in the affected area, and there was interest in quantifying the impact on the cost of living for residents.

To shed light on these questions a series of data sources collected before the crisis and as part of the humanitarian response were used:

i. The **Household Income and Expenditure Survey (HIES)** collected by the Bangladesh Bureau of Statistics. This cross-sectional survey is the main official source of information about households' consumption, poverty,

Figure 1. Kutupalong- Balukhali Expansion Site

Before August 2017



3 months later – 656,000 arrivals

Source: http://fingfx.thomsonreuters.com/gfx/rngs/MYANMAR-ROHINGYA/010051VB46G/index.htm and income. The HIES 2016/17 is representative at the district level and was collected from April 2016 until March 2017. The survey covers Bangladeshi households, not refugees. The analysis presented below combines households living in the district of Cox's Bazar and Bandarban to better represent living conditions in the receiving area. However, the results are robust when considering only the district of Cox's Bazar. The sample size for the analysis is 1,440 households.

ii. **The Rohingya Emergency Vulnerability Assessment (REVA)** jointly led by the World Food Programme (WFP) Vulnerability Analysis and Mapping Unit (VAM) and the Food Security Sector (FSS). The objectives of the survey were to assess how many people are food insecure and socio-economically vulnerable, what are their characteristics, and what are the actions required to improve their lives and livelihoods. The assessment covered new arrivals since 25 August 2017, unregistered refugees that arrived prior to 25 August 2017, officially registered refugees, as well as residents in host communities with high prevalence of refugees. Geographically, the following locations were covered across Ukhia and Teknaf districts: registered camps, makeshift camps, new extensions, new settlements, and host communities. A total of 2,046 households were interviewed, including 432 local resident households in host communities with high prevalence of refugees. The survey was conducted in November 2017.

iii. The **first round of the Cox's Bazar Monitoring Survey (CBMS)** collected end of May 2018. The CBMS is a short phone interview with a sample of households that were previously interviewed in the REVA. The CBMS is a joint effort between the World Bank and WFP to monitor the welfare of households as the situation evolves in Cox's Bazar. It is important to note that this survey is not intended to be representative, as it is based on a random sample of refugees with mobile phones who answered the interview (41 percent of refugees in the REVA sample owned a mobile phone, 611 households). The refugee households with phones tend to be smaller, are more likely to have a person working, and report slightly higher wages; thus, they are also less food insecure and less poor than those without mobile phones. However, the differences between refugees with and without phones and are not large enough to compromise the interpretation of the findings. There was also some attrition, as not all refugees that were called could be reached. The information needs to be interpreted with care, but the results are still informative of the evolving situation. The indicators presented below are based on the 153 interviews conducted with recent refugees.

iv. **Daily price information from the Department of Agricultural Marketing** for Cox's Bazar, collected between August 2017 and March 2018. The prices cover 60 food commodities from the main market in Cox's Bazar.
v. **Wage information from the WFP-VAM monitoring survey.** This survey was done with key informants in main markets in the affected area. The occupations for which wage data was collected included agriculture work, house work, semi-skilled construction, and rickshaw/van works, for both refugees and hosts. The period analyzed is December 2017 to May 2018.
vi. **Several rounds from the International Organization for Migration (IOM) Needs and Population Monitoring (NPM) Site Assessment.** The NPM Site Assessment collects information about the Rohingya population in Cox's Bazar, including refugees who arrived before August 2017. The assessment covers all sites where Rohingya refugees have been identified, irrespectively of the location type, including collective and dispersed settlements, locations in host communities, and formal refugee camps. Information is collected through interviews with key informants, particularly majhees (community leaders in collective sites).

Significant efforts were made to make information comparable and as consistent as possible across time and groups. However, caveats remain, as most of the sources were collected at different points in time and with different methodologies. Therefore, the results need to be interpreted with care.

The note is organized in the following way. The first section describes the welfare situation of the Rohingya refugees and how the situation has been evolving. The second section summarizes analysis conducted to estimate the short-term impact of changes in daily wages and the implications for the welfare of the hosts. The third section analyzes the extent to which prices of food have increased and the impact on poverty for hosts. Section four presents some final remarks.

The welfare situation of the refugees

This latest influx of Rohingya refugees poses a considerable welfare challenge. The refugees settled in two very rural sub-districts (Teknaf and Ukhia) with high poverty conditions and more than doubled the host population.[2] The two sub-districts were also home to many Rohingya refugees that migrated prior to 2017.

[2] According to the 2011 poverty map, the upper poverty rate for the upazillas of Teknaf and Ukhia was 38 percent (ranked 382 and 378 out of 544 upazillas), with more than 80 percent of the population living in rural areas. The total estimated host population in the two upazillas was 680,000.

Influxes were recorded in 2003, 2012, and 2016 as well as during the 1970s. It is estimated that about 200,000 refugees already lived in the area. The new refugees arrived with very little, if anything, and their immediate needs for food, water, sanitation, shelter, and health care are substantial. It is estimated that 80 percent of the refugees are women and children.[3] Aid is reaching many refugees, but they are highly vulnerable, and it is estimated that 76 percent of refugees would not be able to meet their basic needs were aid removed.[4]

Congestion and distance complicate access and delivery of services. Approximately three in four refugees live in places only accessible by footpath. According to the CBMS, one of the main problems reported by refugees has been accessing distribution sites and WFP shops; about 23 percent of refugee households are reporting difficulties accessing sites. The main two reported reasons are that the sites are too far away (34 percent) or too crowded (47 percent). The average walking time to food distribution points for recent refugees is 30 minutes.[5] In addition, in 17 percent of the refugee locations, the population has to travel over 30 minutes to reach the nearest health facility on foot. In terms of access to education, in 18 percent of locations formal and non-formal education services were not reachable within 30 minutes on foot.[6]

Moreover, the region hosting displaced Rohingya population camp sites is particularly vulnerable to climatic hazards. Displaced Rohingya families and individuals reside in extremely congested shelters in areas that are highly vulnerable to flooding, landslides and other weather-related hazards. Estimates suggest that between 30,000 (50 percent probability) and nearly 140,000 (1 percent probability) refugees could be affected by cyclones, floods, and landslides.[7]

By the end of May, the monsoon season had started affecting refugees. About 46 percent of recent refugees in the CBMS reported having been affected by floods or heavy rainfall and 8 percent by landslides during May. However, flooding had not affected access to distribution sites. In addition, there was very little mobility reported or anticipated among the interviewed respondents (although it is also more likely that these are the ones the phone survey would have been better placed to track): 92 percent of CBMS respondent households did not change their shelter during May. In addition, 86 percent of households did not

[3] IOM Needs and Population Monitoring Round 10.

[4] Rohingya Emergency Vulnerability Assessment (REVA), December 2017.

[5] Rohingya Emergency Vulnerability Assessment (REVA), November 2017.

[6] IOM Needs and Population Monitoring Round 9.

[7] World Bank (2018). Rapid Impact, Vulnerability and Needs assessment (RIVNA).

intend to leave their current shelter in the next two months. About 11 percent were uncertain about it.

Using consumption as a metric, half of recently arrived refugees consumed less than the minimum expenditure basket (Table 1). In November 2017, half (52 percent) of recently arrived refugees consumed less than the Minimum Expenditure Basket (MEB) used by the Inter Sector Coordinating Group (ISCG) (Tk. 1,458 per month per person). The Minimum Expenditure Basket is very close to the official food poverty line estimated by the Bangladesh Bureau of Statistics. It is hard to compare the consumption aggregate in the HIES with the poverty lines used by the Bangladesh Bureau of Statistics (BBS), as these lines are relevant for a consumption module that is collected for many more items. If these lines were used, however, about 81 percent of recently arrived refugees would be considered lower (extreme) poor and 87 percent upper poor.

For those refugees considered poor, the levels of consumption are also far below the costs of the basic needs baskets. Using information from REVA, the poverty gap for recent refugees was 15 percent of the MEB. An average refugee who cannot afford the MEB would need 423 extra takas per month to afford the MEB.

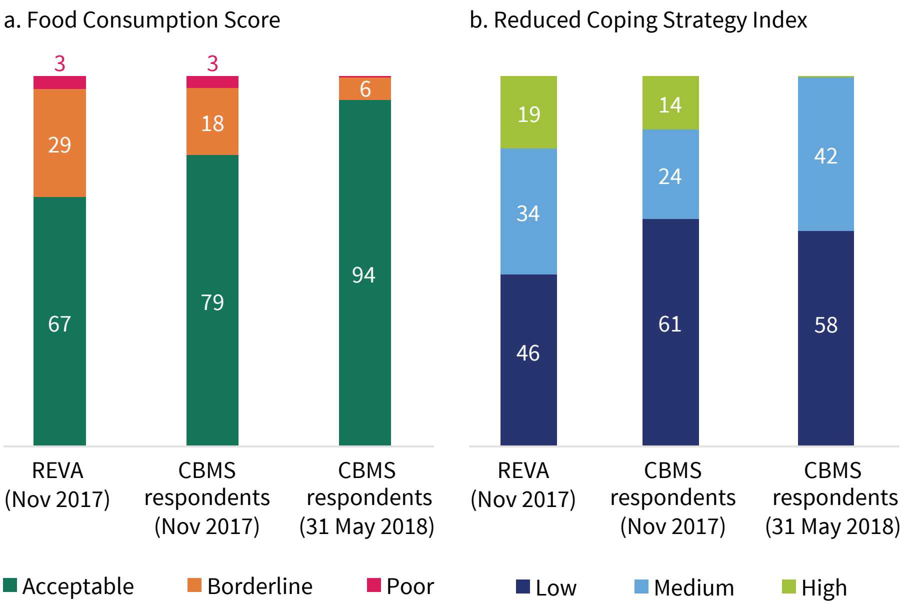
Table 1. Consumption of recently arrived refugees, previous refugees, and hosts relative to cost of basic needs

	Proportion of group living on less than:	
Group	**Food CBN**	**MEB**
Recent refugees	54%	52%
Old refugees	49%	47%
Hosts	32%	30%

Note: Authors' calculations based on REVA. It is important to note that the consumption questions posed to the refugees were fewer than the consumption questions used in defining the Food Consumption Basic Needs (CBN). The Minimum Expenditure Basket (MEB) poverty line is Tk. 1,458. All lines are per person per month in takas of November 2017.

Despite the challenging conditions and the size of needs, food security has been improving (Figure 2). In November 2017, 67 percent of recently arrived refugees were considered food secure based on the food security score, 29 percent had moderate or borderline levels of food consumption and 3 percent were in a severe food insecurity situation. According to the CBMS collected at the end of May 2018, food security has improved. In May 2018, 94 percent of CBMS respondents were food secure, and 6 percent had moderate levels of food consumption. Data for the same respondents in November 2017 indicates that 79 percent of households were food secure, 18 percent were in a moderate or borderline situation, and 3 percent were in a severe food security situation. The Reduced Coping Strategy Index also suggests that households are maintaining food security by using less frequent or costly coping strategies. By May 2018, fewer refugee households were in a severe food security situation proxied by the number or severity of coping strategies they use (0 percent of CBMS households), compared to November 2017 (16 percent of CMBS households). This is also consistent with information documenting reductions in malnutrition rates in camps.[8]

Figure 2. Changes in food security



Note: Authors calculations based on REVA and CBMS. The Food Consumption Score aggregates household-level data on the diversity and frequency of food groups consumed over the previous seven days, which is then weighted according to the relative nutritional value of the consumed food groups. The reduced Coping Strategy Index is based on a list of five food-based coping strategies that households use. The index is calculated as the sum of (i) the *frequency* of each strategy, specifically the number of times that each strategy was used in the last seven days, multiplied by (ii) their *severity* on a scale of 1 (less severe) to 3 (more severe). The coping strategies and their severity (in brackets) are: (i) Rely on less preferred and less expensive foods (1); (ii) Borrow food or rely on help from friends or relatives (2); (iii) Limit portion size at mealtime (1); (iv) Restrict consumption by adults for small children to eat (3); (v) Reduce number of meals eaten in a day (1).

[8] Emergency Nutrition Assessment Round 2, May 2018.

Food assistance has been contributing to minimize food insecurity, but there is also evidence of increased borrowing and selling of food rations and non-food assistance as a coping strategy (Table 2). Despite the importance of assistance in consumption (60 percent of total food consumption), recent refugees rely significantly on purchases and self-consumption. About 55 percent of total consumption and 94 percent of non-food consumption come from purchases or self-consumption (REVA, November 2017). Table 2 shows the percentage of households in the CBMS that engaged in coping strategies due to lack of food or lack of money to buy food. Approximately 58 percent of households are borrowing money to buy food, compared to 32 percent in November. There has also been an increase in the proportion of refugees that report selling food rations or non-food assistance. It may be that this is done to purchase cheaper calories. This has increased from 1 percent in November to 42 percent in May. In November, more households (29 percent compared to 6 percent today) were selling jewelry or gold, or using savings. This suggests that, as assets get depleted, households are switching to borrowing or selling assistance as a coping strategy.

Table 2. Behaviors due to lack of food or money to buy food (% of households)

Coping Strategy	REVA (Nov 2017)	CBMS respondents (Nov 2017)	CBMS respondents (31 May 2018)
Borrowed money to buy food	34%	32%	58%
Selling household goods	4%	4%	1%
Selling jewelry or gold, using savings	33%	29%	6%
Selling productive assets	3%	3%	1%
Collecting firewood for selling	4%	3%	8%
Selling food ration or non-food assistance	4%	1%	42%
Begging	4%	4%	0%
Child work (under 15)	1%	1%	8%
Accepting high-risk, illegal jobs	1%	0%	1%

Note: Authors' calculations based on REVA and CBMS. Households can report multiple strategies.

The impact on the labor market and welfare of hosts

The economy of Cox's Bazar is predominantly agricultural. Approximately 44 percent of land holdings in the district are farms that produce varieties of crops including rice, wheat, vegetables, spices, cash crops, pulses, and betel leaves.

Various fruits like banana, jackfruit, guava, and coconuts are also grown. Prawn farming and salt production in the coastal area of the district are the most important economic activities of the area. Forestry is also important, with various valuable timber and forest trees grown in this district. Finally, the sea beach of Cox's Bazar is an active tourist destination throughout the year.[9]

Host workers in the area are highly reliant on wage employment and daily work. According to the HIES, 99 percent of Bangladeshi households in Cox's Bazar have at least one household member working. Importantly, about 70 percent of the host workers derive income from wage employment and 50 percent from daily work, making changes in daily labor wages of concern for local residents' incomes. Casual/daily labor is a particularly important for poor households, as 80 percent of local workers living in poverty obtain income from daily labor.[10]

Prior to their displacement, refugees had similar livelihood activities to the Bangladeshi living on the other side of the border, which includes engaging in unskilled agricultural and non-agricultural labor, small businesses/petty trade, farming, and fishing. The newly arrived refugees are largely dependent on external support from both formal and informal sources, although they also engage in the local labor market, particularly in unskilled non-agricultural labor.[11] According to the REVA, about 56 percent of the recent refugee households have at least one member working (on average one person per household is working). Moreover, about 90 percent of the recent refugee households with members working are engaged in temporary or seasonal activities.

The participation of refugees in the labor market seems to be more of a coping strategy, but engagement in the labor market has been increasing. According to REVA, refugee households with labor income are as likely to be poor as those not working (52 percent of those working compared to 51 percent of those not working). Overall, total labor income per capita is significantly lower for refugees than hosts (Table 3). Focusing on households with labor income, the median Bangladeshi household earns about four times more than the income of the median refugee household. The lower income is the result of a lower wage received but also fewer days worked by refugees. Estimations using HIES and REVA suggest that the daily wage of refugees is 50 takas lower than for comparable hosts. In addition, the engagement of recent refugees in the labor market

[9] Cox's Bazar District Statistics 2011 (BBS).

[10] Authors' calculations from HIES 2016-2017.

[11] Rohingya Emergency Vulnerability Assessment (REVA), December 2017.

is less intense than that of hosts. While refugees work about 12 days per month on average, hosts work about 29 days on average. In addition, there is evidence that engagement of refugees in the labor market has been rising. According to the CBMS, the percentage of recent refugee households working has increased by about 20 percent.[12]

Table 3. Monthly labor income per capita for hosts and refugees

Group	Average	P25	Median	P75
Recently arrived refugees	769	333	575	900
Hosts	2,829	1,650	2,472	3,600

Note: Authors' calculations using REVA and HIES 2016/17. Figures are for households with positive labor income. Income in monthly takas of November 2017. Recently arrived refugees are those who came to Bangladesh after August 2017.

Given the large share of residents deriving income from daily wage employment, the sudden and large influx of refugees in a relatively small area has impacted the labor market. The estimations combining HIES, REVA, and wage data from WFP-VAM indicate that daily wages have declined by 24 percent on average, compared to averages observed before the influx (Table 4). Such a large fall is plausible, as labor is non-tradable, making the labor supply shock a large shock to the local market.

Table 4. Cox's Bazar daily wages for hosts

	Daily wage	
	Mean	Median
A. Before the crisis (HIES)	402	371
B. Nov 2017 (WFP REVA)	333	300
C. May 2018 (adjusted using WFP VAM)	303	283
Change (%) A vs. C	-24%	-24%

Note: Author's calculations using HIES, REVA, and WFP-VAM monitoring data. Wages include agricultural and non-agricultural workers. About 61 percent of the host daily laborers in HIES are in agriculture.

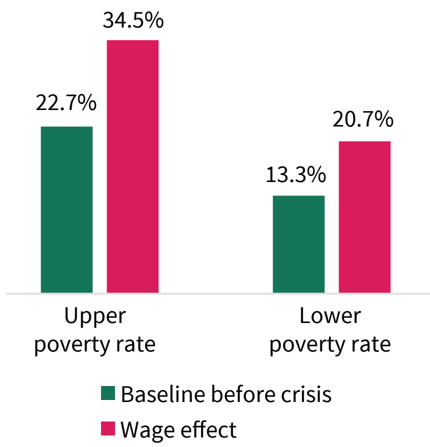
The reduction in daily wages is estimated to have negatively impacted labor incomes and increased poverty for hosts. Poor households save little, if any, of

[12] Note again that this is only based on a sample of refugees with mobile phones, who are more likely to work than are those without phones.

what they earn, and thus the fall in wages has an immediate and large effect on consumption and poverty. The short-term impact of lower wages is negative for those who are working, but there may be positive effects for those who hire labor. Partial equilibrium simulations using HIES indicate that, overall, the impact is negative, with the upper poverty rate for the host community increasing by 12 percentage points (52 percent) and the lower poverty rate increasing by 7 percentage points (56 percent) (Figure 3).

Given that the poor are more likely to be daily laborers, the short-term effect of the daily wage decrease measured as a percentage of per capita consumption is significantly higher for this group (Table 5). For the poorest 20 percent, the impact of a 24 percent drop in daily wages translates into a 15.3 percent reduction in per capita consumption. For the top quintile, there is also a negative impact of the wage drop, but the magnitude is much smaller, about 2.5 percent decline in per capita consumption. The impact of savings due to lower cost of labor for host households hiring labor is estimated to be small (less than 1 percent).

Figure 3. Short-term impacts on poverty due to daily wage decline



Note: Authors' calculation using HIES 2016/17 for host population in Cox's Bazar and Bandarban districts combined. Upper and lower poverty rates estimated following BBS official methodology. Wage effect used the estimated daily wage decline of 24 percent and includes the positive impact of savings for those hiring labor.

Table 5. Impact on per capita consumption due to daily wage decrease across quintiles

	Per capita consumption quintile				
Impact on per capita consumption (%)	1	2	3	4	5
Savings in wages for employers	0.1	0.2	0.4	0.4	0.9
Losses due to lower wages for laborers	-15.5	-10.3	-9.4	-7.6	-3.4
Total change	**-15.3**	**-10.2**	**-9.0**	**-7.2**	**-2.5**

Note: Authors' calculation using HIES 2016/17 for host households in Cox's Bazar and Bandarban districts combined. Estimated impact due to daily wages decreasing by 24 percent. The impact is measured as the percentage change in total household per capita consumption.

The impact on prices of goods and the welfare of hosts

Overall, markets in the affected locations are well connected to the larger markets. The influx area has four main distribution nodes (Court Bazar, Ukhia City Bazar, Nhilla Bazar, and Teknaf Bazar) which are long-stablished markets. Many of the goods sold in smaller markets transit via these four main markets. There are six markets primarily reaching Rohingya refugees which are physically smaller and have fewer wholesalers. These six markets are located along the interior of the Ukhia-Teknaf road and are largely dependent on the flow of goods from the four distribution nodes mentioned above. Market assessments done in the area indicate that these markets are well connected to the larger markets, despite road congestion and logistic challenges after the influx.[13]

The recent refugee influx did not translate into significant price inflation, except for some specific goods with shallow supply chains. Markets serving local and Rohingya customers have good availability of key commodities. Prices of cereals such as rice and wheat have not increased by much, and variation in prices across markets is small.[14] These goods can be sourced easily from other parts of the country, and while the increase in demand is large in the local areas, it is not large in the context of Bangladesh. However, prices of goods that are costlier or challenging to transport, such as vegetables and fresh fish, have increased more substantially.[15] Firewood was most commonly identified as having insufficient availability.[16] Information from the CBMS for May 2018 indicates that price increases have not significantly affected refugees or hosts. Only 3 percent of refugees and 15 percent of the hosts living in areas with high numbers of refugees reported being affected by high food prices.

We estimate the price inflation between August 2017 and March 2018 for different food categories using information on daily prices of 60 food commodities from the Department of Agricultural Marketing (DAM). Prices are collected from the main market in Cox's Bazar. The average price change rate across food categories was 8.5 percent. Overall, this information confirms more anecdotal and qualitative information from market assessments done by humanitarian actors. This type of modest price increase is also consistent with previous studies, which

[13] WFP Market Assessment. 2017.

[14] Market Assessment in Cox's Bazar. Bangladesh Food Security Sector and the United Nations World Food Programme. November 2017.

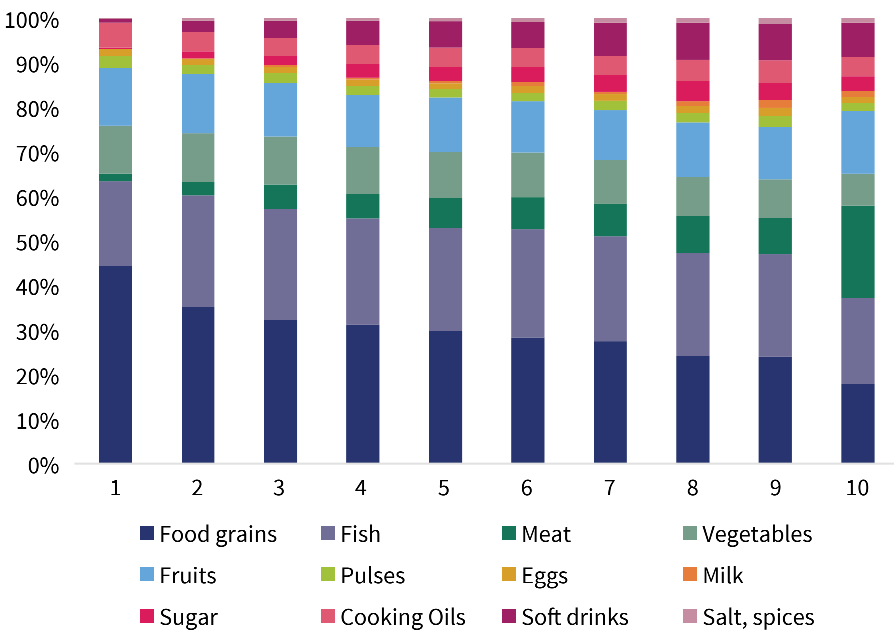
[15] Action Against Hunger Market Assessment in Cox's Bazar. September 2017.

[16] Market Assessment in Cox's Bazar. Bangladesh Food Security Sector and the United Nations World Food Programme. November 2017.

have indicated that food markets are relatively well integrated in Bangladesh. If markets are well integrated, the rapid increase in demand for food can be met by increased supply from other areas. Yet, the relatively low inflation could also reflect the fact that the newly arriving refugees have very little income with which to purchase food and are relying on food aid distribution, which is ongoing in Cox's Bazar.

Price increases will have the largest impact on poverty when they occur for the goods that are most consumed by poor households. Figure 4 shows the pattern of food consumption of households in the area. Grains and fish account for the largest share of consumption. For the poorest decile, food grains account for 39 percent of all food consumption, and fish account for 17 percent of the total food consumption.

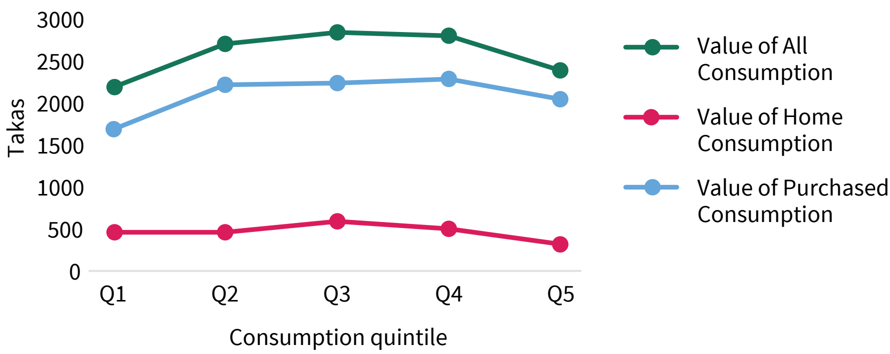
Figure 4. Food consumption patterns by consumption decile



Note: Authors' calculations using HIES 2016/17, Cox's Bazar and Bandarban districts. The figures show the food budget share for each food category.

However, price increases will not universally have an adverse impact on host households, as some households produce some of the food they consume, which lessens the impact. Figure 5 shows the value of food grain consumption that is consumed from households' own produce, compared to the total value of food grains consumed. Across the consumption distribution, nearly a fifth of grain consumption comes from own consumption. When all food items are considered, the share of food consumed from own production is about 10 percent for the two poorest quintiles.

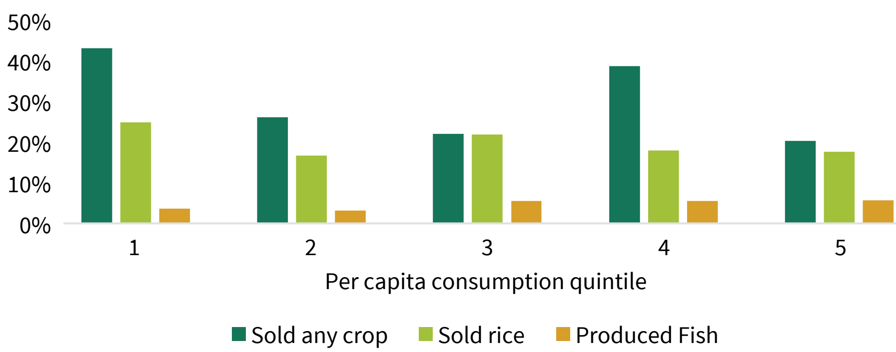
Figure 5. Value of grains purchased and consumed from own production by quintile



Note: Authors' calculations using HIES 2016/17, Cox's Bazar and Bandarban districts.

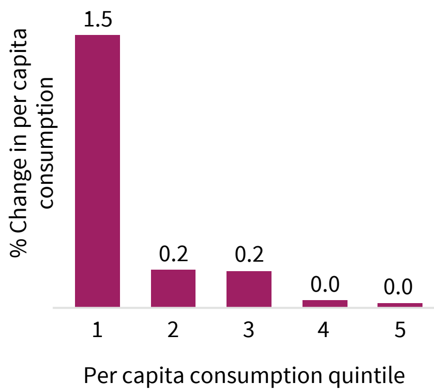
Additionally, some households will benefit, as they sell the items that have seen price increases. Figure 6 indicates that the share of households that sell some crops ranges from 26 to 43 percent among the two poorest quintiles.

Figure 6. The proportion of households that report selling any crop, selling rice, or producing fish



Note: Authors' calculations using HIES 2016/17, Cox's Bazar and Bandarban districts. The figures show the food budget share for each food category.

Figure 7. Changes in per capita consumption due to price increases, by quintile



Note: Authors' calculations using HIES 2016/17, Cox's Bazar and Bandarban districts. The figures show the food budget share for each food category.

Taking these elements into account, the impact of rising prices on poverty for the host community is estimated to be small.[17] Using prices changes between August 2017 and March 2018, there is a less than 1 percentage point increase in both the upper and lower poverty rates. Assuming a more severe scenario, where prices double, the upper and lower poverty rates increase by 3 and 2.5 percentage points, respectively. Comparing across consumption quintiles (from the poorest 20 percent to the richest 20 percent), the impacts measured as the share of per capita consumption are small and concentrated in the bottom 20 percent (Figure 7). One reason for the modest effect is that the impact in prices has been relatively small, on average, particularly for items that have a heavy weight in the consumption basket of the poor (e.g., food grains). Second, nearly 10 percent of all food consumption among the poorest two quintiles of the host community is sourced from own production, and some households also sell the goods for which the price has increased.

[17] This simulation relies on the HIES 2016/17 for the districts of Cox's Bazar and Bandarban combined, to reflect the baseline welfare conditions in the affected upazillas more closely. The simulations consider three effects: (i) the changes in the cost of buying food; (ii) the fact that some households produce food and consume part of that production; and (iii) the income change for those who sell food. In other words, we simulated the impact of the price increase on poverty by re-estimating the cost of basic needs, considering the price increase and assuming that the total amount the household spends on consumption stays constant with two exceptions: (1) the value of consumption increases for those that consume from own production, as the price used to estimate the value of this consumption has increased; (2) the value of consumption increases for those who sell crops, as the price increase increases the income earned from crops sales and allows households to increase their consumption. For this simulation, we also assume a marginal propensity to consume of 0.9. Conservative assumptions have been used in generating these estimates, but estimates are still likely to overestimate the immediate impact on poverty, as households will adapt to changing conditions. Some of the adaptation measures will not have any impact on welfare, for example substituting towards cheaper but still nutrient-rich sources of food given changing relative prices. However, some adaptation strategies will be very costly in the long term. For example, taking children out of school so that they can work, engaging in more risky income-earning activities, or reducing the amount of food consumed.

Final remarks

This note summarizes a series of analyses aiming to understand the short-term welfare consequences of the Rohingya influx in Cox's Bazar. The work combined and harmonized several data sources to inform about the welfare conditions in the area. An important contribution of this analysis was to estimate the impact of changes in wages and food prices for the host community, using a representative baseline for this population.

Overall, the analysis presented indicates that, at least in the short run, the impacts have been highly localized. Short-term negative economic impacts on hosts have been more linked to the deterioration of wages than increases in prices. It is estimated that the average daily wage of hosts decreased by about 24 percent between August 2017 and May 2018, increasing poverty rates for hosts approximately 52 percent. Food inflation has not significantly changed poverty rates. In addition, the impacts have not been large enough to change national poverty rates.

The welfare conditions of refugees are still critical, though food security conditions have been improving. If we consider the poverty lines used by the Bangladesh Bureau of Statistics (BBS), about 81 percent of recently arrived refugees would be considered lower (extreme) poor and 87 percent upper poor. However, monitoring data suggests that food security has been improving. In May 2018, 94 percent of CBMS respondents were food secure, and 6 percent had moderate levels of food consumption. Data for the same respondents in November 2017 indicated that 79 percent of households were food secure, 18 percent were in a moderate or borderline situations, and 3 percent were in a severe food security situation. The Reduced Coping Strategy Index also suggests that households are maintaining food security by using less frequent or costly coping strategies.

As the initial response ends, there is need to start thinking about medium-term support and solutions to increase resiliency. A year into the crisis, the situation remains critical for refugees, who remain highly concentrated and exposed to many risks. There are still large gaps in access to basic services, with many installations (e.g., WASH) of very poor quality. Chronic malnutrition among children under five has been falling but remains near the WHO critical threshold of 40 percent in the main camps.[18] As initial assets become depleted, coping strategies are

[18] Emergency Nutrition Assessment Round 2, May 2018.

also changing. Moreover, goods and labor market dynamics may change as refugees get more settled. The disproportionate share of women and children also poses specific needs and constraints requiring careful attention in the response.

Annex: Estimating the impact of falling wages on poverty

Poor households save little, if any, of what they earn. Thus, a fall in wages has an immediate and large effect on consumption and poverty. The short-term impact of lower wages is negative for those who are working, but there may be positive effects for those who hire labor. To simulate the overall impact of lower wages on poverty, we assume that in the short run there is no other possible response by households, such as changing their labor market participation, the intensity of work, or possible migration. Therefore, these estimates need to be interpreted with care and as very short-term impacts.

The reduction in income from lower wages is thus the number of hours worked in unskilled casual labor multiplied by the reduction in wages estimated.

In order to simulate the impact of lower income on poverty, it is necessary to know how much of its income a household consumes at the margin, in other words, how would we expect a marginal change in income to change consumption. This is the marginal propensity to consume (MPC) out of income. In these estimations and throughout the analysis, we assume that the marginal propensity to consume out of income (MPC) is 0.9. Wolpin estimated the MPC out of income to be between 0.9 and 1 for poor households in India (Wolpin 1982). Similar careful estimates do not exist for Bangladesh, so we use this estimate. Assuming an MPC of 0.9 is a conservative assumption, and assuming a higher MPC would cause wage falls to result in a larger decrease in income.

Savings to the few households who hire labor are included in the analysis by assuming that the reduction in the cost of wages results in increased income, and that households can consume out of that new income, also at an MPC of 0.9.

Reference

Wolpin, Kenneth I. 1982. "A New Test of the Permanent Income Hypothesis: The Impact of Weather on the Income and Consumption of Farm Households in India." *International Economic Review* 23 (October): 583-94.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