The Impact of Ready Made Garments on Labor Force Participation and Fertility Among Bangladeshi Women

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Abstract

In this paper, I analyze of the impact of Ready Made Garments (RMG) factories on Bangladeshi women in two ways. First, I use datasets with a broader range of geographic and temporal coverage relative to previous literature. Second, I exploit spatial variation in Knit and Woven exports to estimate the Female Labor Force Participation (FLFP) response, ameliorating some of the concerns related to unobserved location characteristics. I find strong evidence of increases in FLFP, and changes in composition of FLFP due to exposure to RMG factories. However, I find no impact on fertility.

1 Introduction

Since its inception in the 1980s, the Ready Made Garments (RMG) industry rapidly came to dominate the export earnings of Bangladesh. In Fiscal Year 2016-2017, 81 percent of the Bangladeshi exports originated from the RMG industry – employing about 4 million people, and contributing to 0.0657895 percent and 0.3267974 percent of overall and industrial labor force participation (Bangladesh Burea of Statistics 2020). According to Matsuura and Teng (2020), about 61 percent of the workers in RMG sector are women.[1] The growth of the RMG industry has resulted in a steady increase in the Female Labor Force Participation (FLFP) from about 24.6 percent in 1990 to about 36 percent in 2019. This contrasts the South Asian experience where FLFP was at 29 percent in 1990 and dropped to 23.6 percent in 2019 (The World Bank 2021).[2]

Over the same period, the fertility rate of Bangladeshi women has decreased from 4.49 in 1990 to about 2.20 in 2016.[3] This change occurred concurrently with an increase in women's literacy rates from about 27 percent in 1981 to over 94 percent in 2018. The corresponding increase for men was less dramatic, from 40 percent to 91 percent (The World Bank 2021). This paved the way for Bangladesh to meet many of the Millennium Development Goals including reducing poverty gap ratio, attaining gender parity at primary and secondary education and under-five mortality rate reduction ahead of the 2015 deadline (United Nations Development Program). By my calculation, the RMG industry accounted for about 12-16 percent of female employment in Bangladesh in 2017.[4] Possibilities of employment in RMG factories changes the economic value of women. Heath and Mobarak (2015) argue that exposure to RMG factories also increases returns to education and skills. Thus, there is a possibility of a direct impact of RMG factories on education attainment of women. I will explore this in future. In addition, this also implies a possibility of reduction in fertility and desired fertility due to increasing opportunity cost of child bearing (Aaronson, Lange, and Mazumder 2014). Another possibility is that this decreases fertility at younger ages when women are more employable (Matsuura and Teng 2020) but keeps the overall fertility same by delaying child birth. Additionally, Anderson and Eswaran (2009) find that the increased outside employment is positively associated with female empowerment in Bangladesh. In addition, Matsuura and Teng (2020) reports a greater incidence of divorces among female RMG workers than what my sample suggests.

In this paper, I estimate the impact of RMG factories on FLFP and fertility of women in Bangladesh. As an update to this research, I will explore the impact of RMG factories on

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[1]Matsuura and Teng (2020) also note that the estimates from different sources range from 58-80 percent.

[2]See Appendix 1 for a comparison of the Bangladeshi evolution of FLFP relative to other country groups.

[3]See Appendix 1 for comparisons with other countries.

[4]Calculated as $\frac{\text{Fraction Female} \times \text{Total Employment in RMG}}{\text{Female Population (15-64)} \times \text{FLFP Rate (15-64)}} \times 100$

fertility preference, marriage formation and education decisions of women. Doing this serves three purposes. First, it adds to the documentation of the role of RMG factories in fostering gender equality in Bangladesh. Second,

it adds to the literature discussing the mechanisms of manufacturing-led development path. This is particularly relevant given concerns about structural transformation bypassing the manufacturing sector in many of the currently developing countries as discussed in Rodrik (2015). Third, it adds to the literature examining the impact of exposure to trade on lives of workers (see for example, Autor, Dorn, and Hanson (2013), Autor, Dorn, and Hanson (2019) and Li (2018))

Heath and Mobarak (2015) investigated the impact of the RMG industry on FLFP, fertility and education outcomes in Bangladesh. In 2009, they surveyed 1395 households in 60 villages. 44 of these villages were within commuting zones (CZs) of RMG factories, while the remainder were not.[5] They reported that the bulk of the women employed in RMG factories were below 30 years old. Using a difference-in-difference estimator, they first documented that women in villages near RMG factory villages were about 15 percentage point (pp hereafter) more likely to have worked outside of home. Moreover, the effect was stronger among women exposed to RMG factories during critical exposure period (ages 10 - 23) by an additional 12 pp.

Using total years of exposure to capture the overall impact of RMG factories on marriage and child-bearing decision, Heath and Mobarak (2015) found that 6.4 years of RMG exposure (mean in their sample) reduced the probability of getting married and having first children by about 0.3 and 0.23 pp. Comparing it to the full sample probabilities, this represents a 28 percent and 29 percent decrease in probability of marriage and first birth for women. However, they found no effect on men. By using the same measure of exposure to RMG factory, (Heath and Mobarak 2015) also found increases in educational attainment for women and men by 0.22 and 0.26 years respectively. However, they did not find strong evidence suggesting increases in enrollment. The findings in Heath and Mobarak (2015) are consistent with Amin et al. (1998) and Kabeer and Mahmud (2004) who found an association between the RMG industry and increased FLFP, education and declining fertility in Bangladesh. However, in the context of Mexico, Atkin (2012) found that the availability of industrial sewing jobs induced older children to work instead of attending school.

The methodology of this paper takes inspiration from Autor, Dorn, and Hanson (2013), Autor, Dorn, and Hanson (2019) and Li (2018). Autor, Dorn, and Hanson (2013) and Autor, Dorn, and Hanson (2019) exploited differences in the spatial and gender patterns

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[5]Heath and Mobarak (2015) determined whether villages were in RMG factory CZs or not in consultation with officials from the Bangladesh Garments Manufacturers and Exporters Association.

of specialization in US manufacturing to estimate the impact of increased exposure to Chinese imports on US workers. Autor, Dorn, and Hanson (2019) found that one unit of import exposure, roughly equivalent to the average decade level exposure between 1990-2000, reduced manufacturing employment as a share of the population for both sexes by 1.06 pp. Sex-specific trade shocks reduced employment by 2.6 pp for both sexes. In addition, the authors also found a strong negative impact on male idleness, mortality rate, and absence. Lastly, they also find that shocks to male-dominated industries reduce family formation and fertility, whereas shocks to female-dominated industries tend to increase family formation and fertility. In the Chinese context, Li (2018) exploited variation in skill intensity of industries and spatial variation in industry specialization and found that high (low) skill export shock increased (decreased) high school and college enrollment in China between 1990 to 2005.

In addition to the direct impacts, it is possible that the opportunity to formal employment changes norms regarding women's work, education and reproductive decisions (Amin et al. 1998; Baudin 2010; Bhattacharya and Chakraborty 2012). About 90 percent of the women working in RMG factories are younger than 40 years old, gaining first experience of paid employment in the RMG sector (Matsuura and Teng 2020). Indeed, the findings of Munshi and Myaux (2006) that information about modern contraception and its usage spreads between, rather than across, religious groups, even though each group may be cohabiting in densely populated places, suggests a strong role of spread of changing norms within similar groups of people.

The objective of this research project is to estimate the impact of RMG factories on FLFP and fertility. I plan on extending the analysis to fertility preference, marriage formation and education decisions of women. However, here I present estimates of impact of RMG factories on FLFP and fertility only. I make use of the Demographic Health Survey (DHS) dataset. The DHS dataset contains information about sector of work of husband, and of wife, age at marriage, realized fertility, desired number of children, preference for male over female children, among other variables. This will allow me to shed light on the channel of cultural change surrounding gender-development in Bangladesh that precipitated from advent of the RMG industry. The DHS data was collected in 8 different years between 1999-2018. In addition, the factory dataset consists of data on nearly all of surviving export oriented RMG factories in Bangladesh. The use of these two dataset provides a much broader spatial and temporal variation in observations relative to Heath and Mobarak (2015).

The rest of the paper is organized as follows - Section 2 describes the data, Section 3 describes the empirical approach, Section 4 discusses the results and Section 5 concludes the paper.

2 Data

2.1 Factory Data

The primarily source of the factory data is the Mapped in Bangladesh (MiB) project of Centre for Entrepreneurship Development (CED), Brac University (CED-BracU) (CED-BracU 2021a) *(MiB dataset hereafter)*.[6] The MiB project gathered a list of factories compiled from multiple secondary sources, narrowed it down to RMG factories producing only for the export market (CED-BracU 2021b). Then they conducted field visits to ascertain existence of the factories and collect information on factory address, establishment date, factory specialization (i.e. whether the factory specializes in knit or woven manufacturing, or produces both), number of male and female workers, among others. I supplement the MiB dataset with data on Bangladesh Export Processing Zone (BEPZ) factories obtained by scraping the website of Bangladesh Garments Manufacturers and Exporters Association (BGMEA) Member List.

BGMEA website has data on the number of machines in a given factory, but not on total number of workers, and their gender composition consistently. I estimate these numbers by first matching BGMEA data from non-BPEZ areas with the MiB dataset, and then running regressions to model the number of total and female workers of BGMEA factories. *(See Appendix 2 for further details)* The factory locations from BGMEA data were geo-coded using Awesome Table and Google Maps. Summaries of the dataset used for analysis is presented below.

Table 1: Summary Statistics of RMG Factories

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Establishment Date	3,573	2008	8.4	1978	2003	2015	2021
Knit Factory	3,573	0.6	0.5	0	0	1	1
Total Workers	3,571	823.8	1,148.0	6.0	180.0	1,000.0	16,467.0
Female Workers	3,568	483.0	651.7	0.0	108.0	592.0	8,020.0

Table 1 and 2, and Figure 1 provides a brief overview of the factory data. The dataset contains data on 3,573 factories. Establishment date ranges from 1978 to 2021, with the bulk of the factories established within our DHS sample period 1999-2018. Most of the

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[6]Copyright Notice for Using MiB Data: "The Project titled Mapped in Bangladesh (MiB) is being implemented by Centre for Entrepreneurship Development (CED), Brac University (BracU) [hereinafter CED-BracU], and coordinated by Brac with lead funding by Laudes Foundation and co-funding by the Kingdom of the Netherlands (EKN), Bangladesh. The research findings, factory data, digital map, and any other related contents are the sole property(s) of CED-BracU and must not be reproduced and/or regenerated in any form without the expressed written consent of CED-BracU."
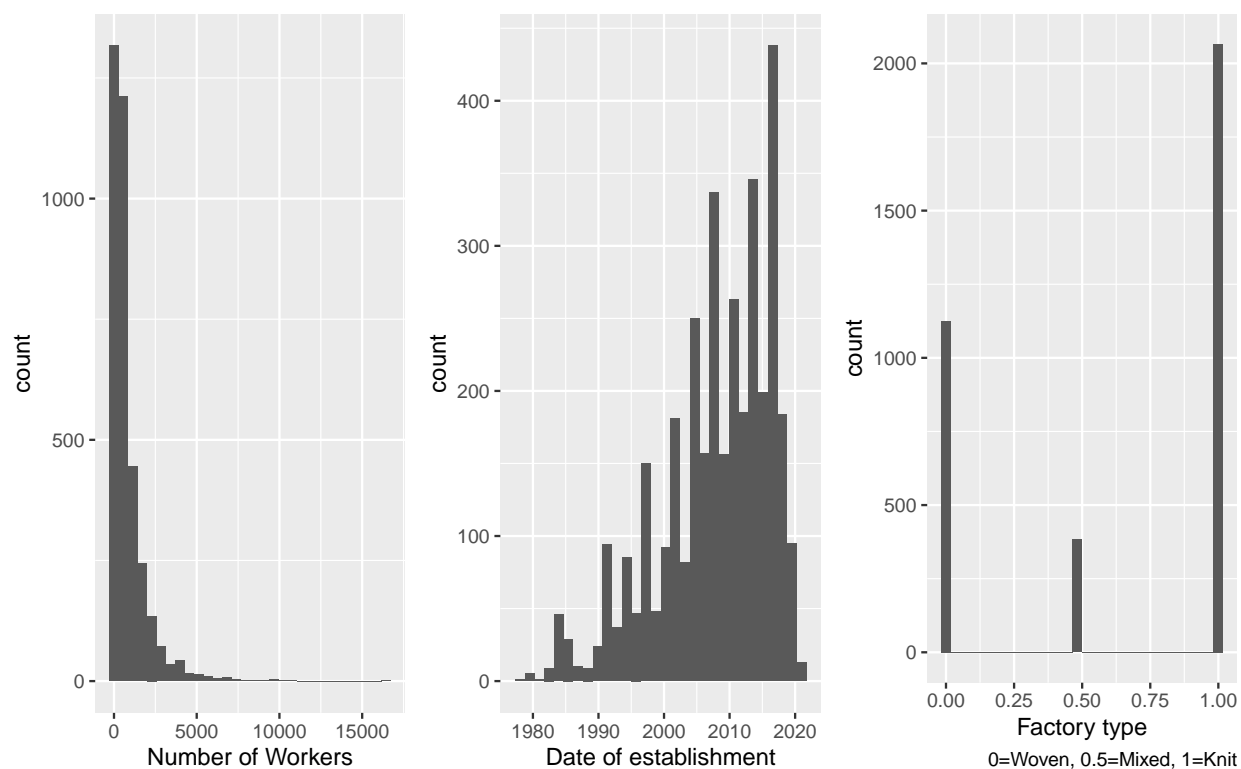
Figure 1: Factory Characteristics

factories have between 180-1000 workers. On an average, factories have about 823 workers and about 483 of them are females. About 60 percent of factories are knit factories. There appears to be clear differences between knit and woven factories. Knit factories tend to be smaller, are usually established later, located in the North Western part of the country and employ less female workers.

Table 2: Knit versus Woven Differences

	knit	Establishment Date	Total Workers	Female Share	Lat	Long
knit	1	0.21	-0.14	-0.39	0.06	-0.06
Establishment Date	0.21	1	-0.17	-0.08	0.14	-0.11
Total Workers	-0.14	-0.17	1	-0.05	0.08	-0.03
Female Share	-0.39	-0.08	-0.05	1	-0.30	0.29
Lat	0.06	0.14	0.08	-0.30	1	-0.95
Long	-0.06	-0.11	-0.03	0.29	-0.95	1

Exports data are taken from the calender year basis table of BGMEA export performance data (BGMEA 2021).

2.2 DHS data

To estimate the impact of RMG factories on the aforementioned gender equality outcomes, I obtain outcome and some of the control variables from the Demographic Health Survey (DHS) survey datasets (ICF 2000-2018). The surveys were conducted in Bangladesh in 6 waves[7] and 8 different years - 1999, 2000, 2004, 2007, 2011, 2014, 2017 and 2018. [8] *(See Appendix 3 for locations of the survey clusters)*. To maintain confidentiality, the cluster latitude and longitudes are displaced randomly so that urban clusters are displaced between 0-2 Kilometers (KMs) and rural clusters are displaced between 0-5 KMs 99 percent of the time and 0-10 KM 1 percent of the time (ICF 2021).

Survey clusters that fall into the factory-regions (see Section 3.2) are used in analysis. Out of concerns for random perturbation, I run probability weighted regressions when possible as robustness checks. I disregard clusters further away due to concerns that the gender development process may emanate from urban areas as documented in Guinnane (2011), Flückiger and Ludwig (2017), and Sánchez-Barricarte (2018) among others.

For my analysis, I use individual level data from the clusters in factory regions. In addition to data on outcome variables related to FLFP and fertility, I use individual level demographic data, cluster location and construct a measure of wealth index and electrification rates in each cluster, and population density from SEDAC.

There are 328 factory-exposed clusters in the sample. Data from Female Recode and Individual Recode was used. The Female Recode contains data on married female between the ages 13-49, and provides detailed data on FLFP and reproductive behavior. Individual Recode contains data on all individuals living in the same dwelling unit regardless of sex and marital status. Given data limitations, data from Individual Recode has only been used for analysis of impact of RMG exposure on education and marriage. For these purposes, data from sons, daughters and grandchildren who are usual residents of the dwelling unit are used.

3 Empirical Approach

3.1 Overview of the Identification Strategies

The Bangladeshi economy has been growing at an average rate of about 5.6 percent over 1990-2018. In addition to improvement in fertility, education and FLFP conditions of women discussed in the introduction; this period also saw a doubling of available work-

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[7]Earlier waves of surveys do not contain data on location of clusters, an essential element for my methodology.

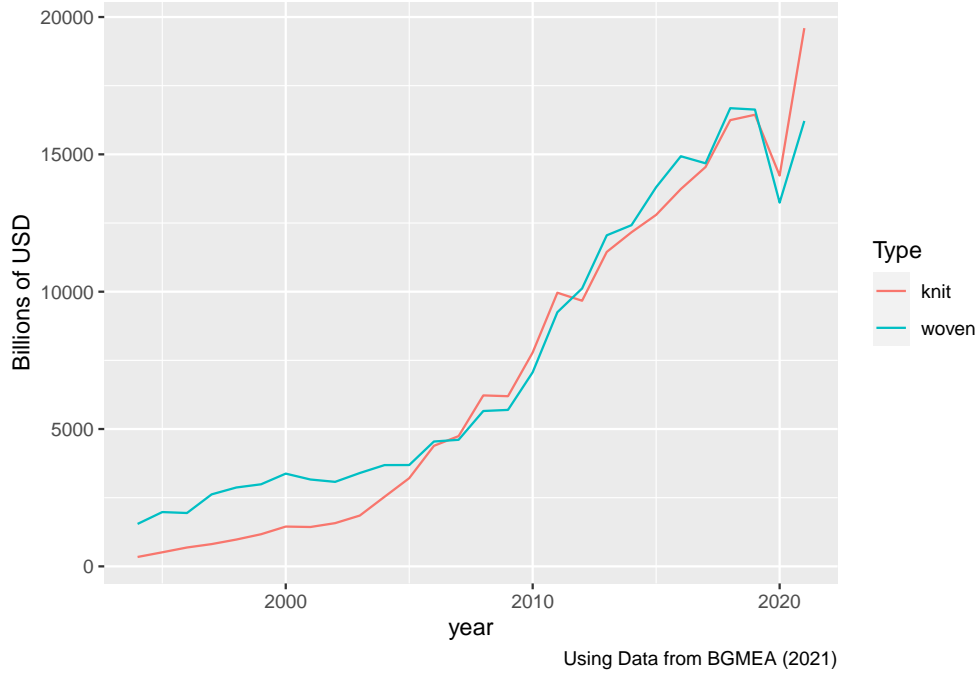[8]Clusters with missing location data were dropped from the sample.

Figure 2: Knit and Woven Exports Over the Years

force, rapid urbanization and improvements in infrastructure. For example, electrification rate increased from about 15 percent in 1991 to over 90 percent by 2018 (The World Bank 2021). Quality of infrastructure and utilities have been found to be the key drivers of RMG factory location choice, whereas access to educated workforce is not a concern for most factory owners (Kagy 2014). The primary concern for identification in this context of is that placement of factories are correlated with location-specific infrastructure conditions. This may independently change FLFP, fertility and education outcomes and may encourage selective in-migration.

To overcome these challenges, I construct Bartik-style measures of demand for labor coming from the RMG industry. Specifically, I estimate the impact of exposure to RMG factories on FLFP and fertility by exploiting the variation in exposure generated by differences in knit versus woven specialization across different factory-regions, and the temporal differences in knit and woven exports from Bangladesh (see Figure 2). This identification avoids comparing FLFP and fertility among people living in locations exposed to RMG factories with people living in locations that are not exposed to RMG factories. Therefore, some concerns regarding unobserved differences in locations that maybe correlated with the FLFP and fertility choices is ameliorated. However, this identification strategy assumes that there is no difference between places varying in degree of knit specialization. I account for time trends using birth year fixed effects, and year of survey fixed effects. I also use population density at the region level as a proxy control for the level of development

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and urbanization in the regions of interest. Further controls are regression specific and discussed below.

3.2 Generating factory regions

Boudreau, Heath, and McCormick (2020) found that the commute for female RMG workers is about 19-27 minutes. Matsuura and Teng (2020) reports that the average monthly transportation cost for RMG workers was about BDT 144 (less than 2 USD). The minimum bus fare of any single bus ride set by the Bangladeshi Road Transport Authority was BDT 7 (Akhter 2019). This is strongly suggestive of the fact that most workers walk to their employing factory.[9] Using estimates of female pedestrian speed in Bangladesh (Nazir 2014), I used a radius of 1.686 KM around a factory as locations where factory workers are likely to reside.[10] I used the data on factory locations to generate regions with factories producing RMG exports using the Territory Design toolbox of the software ArcGIS Pro 2.8. The territory design toolbox creates regions by spatially grouping point features (in this case, factories). Constraints, such as distance and impedance to walking, are used to define regions' boundaries, and assign factories to each of the regions.

Figure 3 illustrates the process of generating regions from locations of individual factories. It starts with spatial locations of factories (Panel A). Major rivers is used as an impedance constraint. As such, factories close to each other in distance (defined soon) but in opposite banks of major rivers are not binned in same region. This is because even though the two factories may be close in a linear distance sense, presence of rivers may make the actual commuting distance prohibitively larger. The major river shapefile is obtained from OpenStreetMap (2017). Distance constraints in the grouping and boundary generation process includes the following - first, a minimum distance between centers of regions was set to 4.215 KMs. The estimated maximum commute distance is 1.686 KM. At an extreme, someone living 1.686 KM from two regions with centers 3.372 KM away could work in either region. This is resolved by adding a 20 percent buffer in distance between centers. Second, the tolerance to determine adjacency of factories was set at 1.686 KM.[11]

The algorithm first groups factories into different regions based on the distance constraints. Panel B shows the grouping of factories into different regions in South Eastern Bangladesh. Afterwards, regions boundaries are created based on the constrained that workers are likely to live within 1.686 KMs from a factory. Panel C shows an example of the regions generated in the South Eastern Bangladesh. The process generated 119 re-

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[9]Cost of commuting five days a week for four weeks at the minimum fare = BDT $7 \times 2 \times 5 \times 4 =$ BDT 280

[10]Distance = Speed $\times$ Time = 62.44 m/min $\times$ 27 min = 1.686 KMs.

[11]For reproducibility, the additional parameters needed are - search tolerance of (5 KM, default value), automatic extent fill, random number generator seed of 15, quality parameter of 200 percent; and determination of optimal number of regions by the computer program.

Panel A. Factory Locations

Panel B. Grouping Factories

Panel C. Creation of Borders
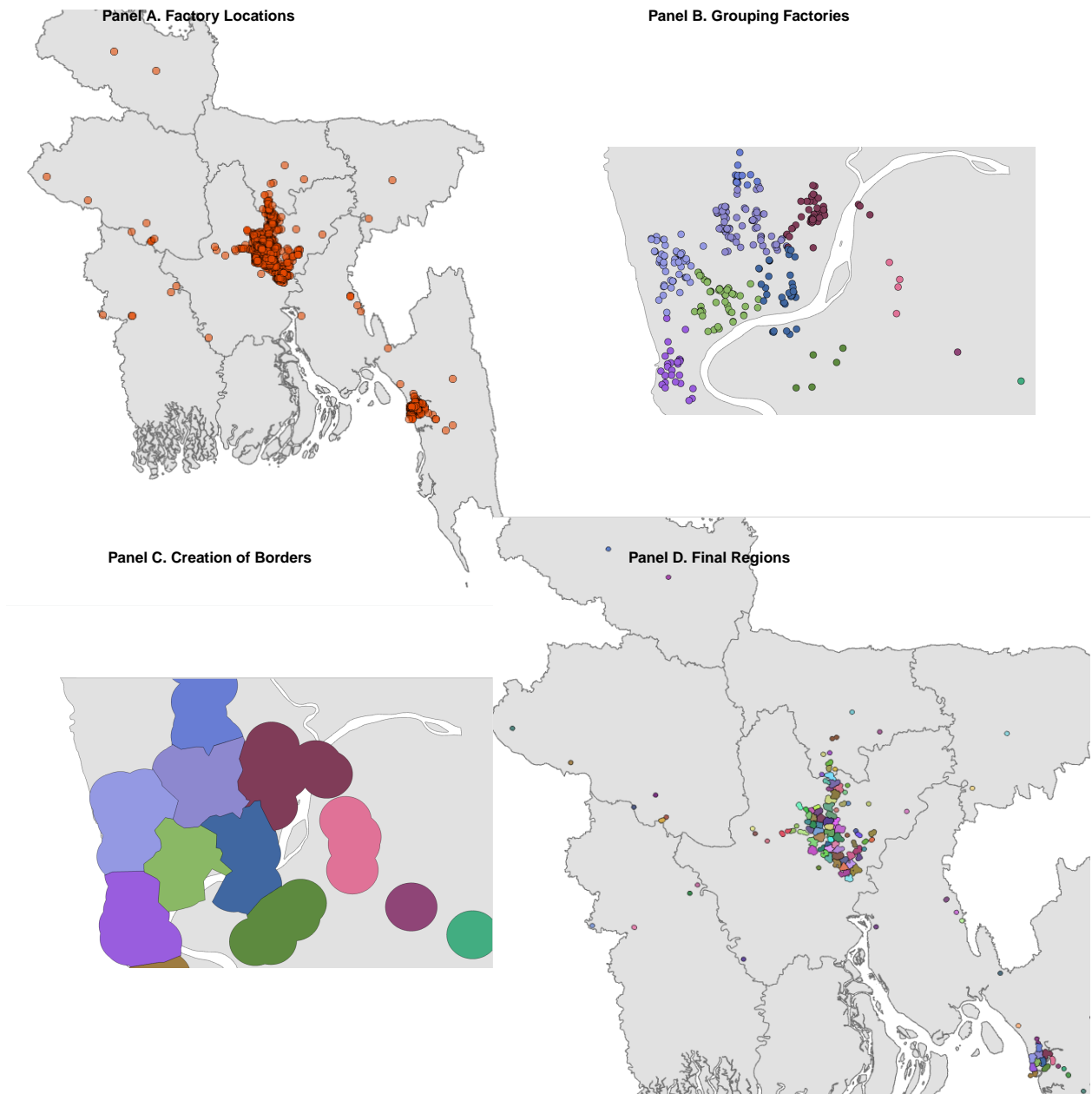
Panel D. Final Regions

Figure 3: Creating Factory Regions

gions. Panel D shows all of the generated regions. The regions were then overlapped with population density raster files of Bangladesh for 1990, 1995, 2000, 2005, 2010, 2015, 2020 from (Center for International Earth Science Information Network - CIESIN - Columbia University and Centro Internacional de Agricultura Tropical (CIAT) 2005; Center for International Earth Science Information Network - CIESIN - Columbia University 2018). These provides estimates of population density at approximately 5 KM grids. The projections are matched to the United Nation's World Population Prospects. Brief overview of the regions are below.
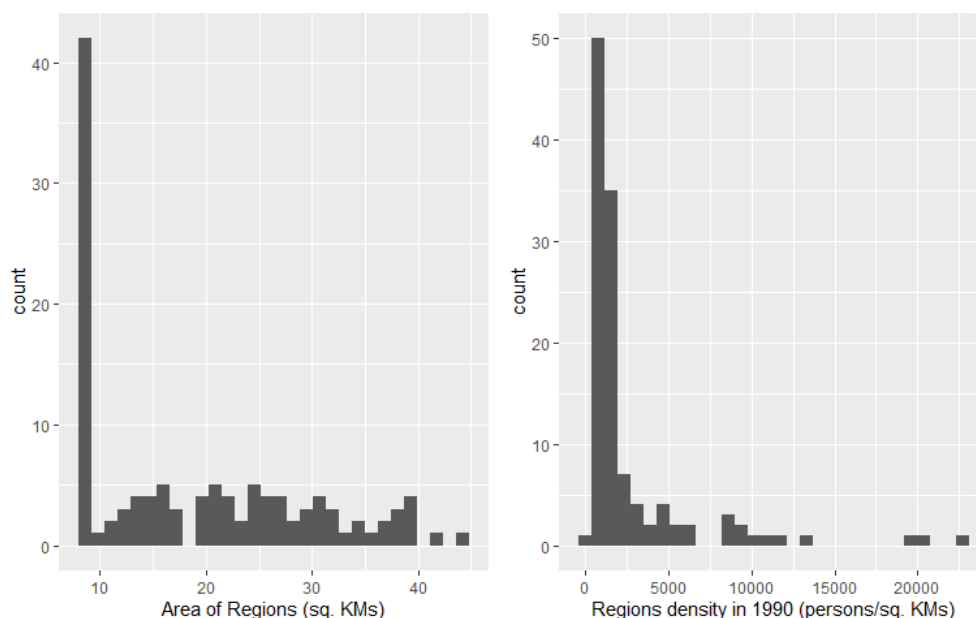

Figure 4: Region Characteristics

Judging by the distribution of area (left panel), about 40 of the regions created seem to be the result of single, or agglomeration of a small number of factories. The remainder of the regions seems to display varying area. On the other hand, there is also a large variation in the estimated population density of the regions in 1990 (right panel). This may be taken to indicate a varying degree of initial levels of urbanization in the different regions.

3.3 Female Labor Force Participation

The results presented in this paper is plausible only if the DHS sample contains women who are exposed to export-oriented RMG factories. I do not have data on whether an interviewed woman was working in an RMG factory. Hence, I first document whether export exposure increases female participation in occupation groups such as handicraft producers, factory workers, tailoring, and small business owners. The choices are motivated by findings that alumnus of a RMG job training project tended to be employed in

these occupation classes (The World Bank 2019). Then, I document the impact of export exposure on i) traditional occupation categories (agricultural, household and domestic paid work), ii) low-skilled non-traditional sectors (services and manual labor), and iii) high-skilled non-traditional sectors (sales, professional / technical, clerical). I investigate whether greater exposure to RMG export increases propensity of married women to work outside of their home by estimating Probability Models of the following form:

$$Y_{i,r,t} = \beta_z Z_{i,r,t} + \beta X_{r,t} + \delta_t + \text{Birth Year}_{i,r,t} + \epsilon_{i,r,t} \tag{1}$$

where $Y_{i,r,t}$ is an indicator variable capturing whether an interviewed woman i is working in some selected occupation in a region r at time t. Changes in RMG factory exposure is measured as follows:

$$X_{r,t} = ExportShock_{r,t}$$
$$where\ ExportShock_{r,t} = \frac{\alpha_{r,t}^{knit} * \Delta KnitExport_{t-T} + (1 - \alpha_{r,t}^{knit}) * \Delta WovenExport_{t-T}}{Population_{r,t}}$$
$$and\ \alpha_{r,t}^{knit} = \frac{Workers_{r,knit,t}}{Workers_{BD,t}}$$

$\alpha_{r,t}^{knit}$ measures the share of knit exports of Bangladesh attributable to region r in time t. When $T = 1$, $\Delta Knit_{t-1}$ and $\Delta Woven_{t-1}$ measures the change in knit and woven exports from Bangladesh over the last year period from time t. In the first case, the measure $X_{r,t}$ then measures the total exports originating from a region's factories in the year before the date of survey. Thus, $X_{r,t}$ then measures the contemporaneous export exposure of a region r in time t. To estimate the medium term effect, I also estimate the regressions with $T = 3$. $\Delta Knit_{t-3}$ and $\Delta Woven_{t-3}$ are the changes in knit and woven export over a three year period. In addition, to ameliorate potential simultaneity bias, I instrument $\alpha_{r,t}^{knit}$ with $\alpha_{r,5}^{knit}$.

In eq (1) $Z_{i,r,t}$ are the control variables. Cluster level controls include rural dummy and electrification rate; and individual level controls including education level, age, square of age, religion, pregnancy status at the time of survey, and number of children at home. I also control from husband's education and industry of employment to account for possible marriage market sorting behavior. δ_t are time fixed effects, and Birth Year$_{i,r,t}$ are birth cohort fixed effects. $X_{r,t}$ measures the changes in exposure to RMG factory at the cluster level.I also use population density of the region as a proxy control for the level of

development and urbanization in the regions of interest. Heath and Mobarak (2015) and Matsuura and Teng (2020) find that younger women are more likely to be employed in RMG factories. This leads to the expectation that export shocks would induce younger women to enter the work force at higher rates. Thus, I restrict my data to include only women 35 years and younger.

Factory location is possibly an outcome of an optimization process of the RMG entrepreneurs based on unobservables that could be correlated with the outcome variables. By exploiting the knit versus woven variation, I control for the unobserved location characteristics that maybe correlated with both the existence of a factory nearby and the outcome variables. Thus, β estimates the impact of differences in export exposure within factory-exposed regions, ameliorating some of the concerns about unobserved location characteristics by avoiding comparison between clusters near a factory, and further from a factory.

Autor, Dorn, and Hanson (2019) use a similar measure of import exposure to study the impact of Chinese imports in US labor markets. In their specification, CZ level labor market shock is calculated as a weighted average change in Chinese import penetration, where the weights are each industry's share in initial employment in a CZ. They measure each industry's import penetration as the growth of Chinese import. My measure differs from theirs primarily because a shorter time frame in my case means that levels, instead of growth rates, better capture the influence on female labor market. Additionally, their regressand is CZ level outcome variables. Since I do not have reliable measures of region level outcome variables, I use individual level outcome variables as my regressand.

3.4 Fertility Behavior

Next, I estimate the impact of exposure to RMG factory on fertility behavior of women. This is done by estimating an equation of the following form:

$$Y_{i,r,t} = \beta_z Z_{i,r,t} + \beta X_{r,t} + \delta_t + \gamma \text{Birth Year}_{i,t,y} + \epsilon_{i,r,t} \tag{2}$$

where $Y_{i,r,t}$ is pregnancy indicator, or the total births till survey date of an interviewed woman i is working in some selected occupation in a region r at time t. In addition to the controls in FLFP regression, I also control for the age of marriage in the fertility regressions.

4 Results

4.1 Female labor force participation

The regression results estimating the impact of exposure to RMG factories on FLFP are shown in table 3 and 4. Table 3 documents the association between contemporaneous changes in export exposures and FLFP. The signs on control variables are mostly as expected. Education level has negligible effect on participation in non-high skilled work, but a statistically significant effect on participation in high skilled work. Age seems to have a strong association with participation in RMG adjacent work, and matches with findings of Boudreau, Heath, and McCormick (2020). Unsurprisingly, pregnancy and existence of young children at home reduces FLFP of all type other than for the high skill who maybe able to afford help in Bangladesh. Other variables are not associated with FLFP in persistent ways.

On the other hand, contemporaneous export exposure seem to be strongly associated with FLFP in RMG adjacent occupational groups, and in low skilled non-traditional work groups. In addition, there is some evidence that greater export exposure decreases FLFP in traditional occupation groups (agricultural and domestic) whereas it has no effect on highly skilled women.

A similar story emerges when the medium term impact of export exposure is estimated (Table 4). Specification related to regression results attempt to control for simultaneity. Moreover, choices of women may take longer than one year to come to culminate into an actual decision to move across occupation types. It can be seen that changes in export exposure does not impact participation in very high skill work (as expected). However, it does seem to increase participation in RMG adjacent work, non-traditional low skill work and decrease participation in traditional work.

Using results from table 4, one thousand dollars worth of export shock per person in a region is associated with about 17-18 percentage point (pp) and about 12 - 13 pp increase in FLFP in RMG adjacent occupations and in non-traditional, low skilled occupations (which contains RMG adjacent occupations). A decline of 1 - 1.4 pp of FLFPin traditional sectors is also seen. At average value of export exposure (0.25 thousand dollars per person), this translates to about 4 pp and 3 pp increase in RMG adjacent and non-traditional, low skilled occupation respectively. Using 2010 population, this translates to about 264,623 additional women working in non-traditional sectors, and about 88,207 less women working in traditional sectors. Anderson and Eswaran (2009) finds the beneficial impact of women working outside of home for their autonomy. As such, this shift is likely to enhance empower of women as well.

Table 3: RMG exports and Contemporaneous FLFP

	Dependent variable:							
	FLFP(RMG Adjacent)		FLFP Traditional		FLFP (Non-trad, Low skill)		FLFP (Non-trad, High skill)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
export_exposure1	0.305***	0.290***	−0.018**	−0.013	0.161***	0.126***	0.010	0.014
	(0.044)	(0.046)	(0.009)	(0.009)	(0.031)	(0.029)	(0.008)	(0.010)
educ	−0.003	−0.003	−0.001	−0.001	−0.00005	0.002	0.004**	0.003*
	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
age	0.038**	0.038**	0.007	0.006	0.023	0.016	0.002	0.003
	(0.016)	(0.018)	(0.005)	(0.005)	(0.016)	(0.018)	(0.009)	(0.009)
I(age^2)	−0.001***	−0.001***	−0.0001	−0.0001	−0.0004*	−0.0003	0.0001	0.00003
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
childathome	−0.095***	−0.095***	0.002	0.002	−0.077***	−0.079***	−0.004	−0.006
	(0.007)	(0.008)	(0.003)	(0.003)	(0.006)	(0.007)	(0.003)	(0.003)
preg_survey	−0.089***	−0.104***	−0.018***	−0.019***	−0.077***	−0.093***	−0.011	−0.012
	(0.020)	(0.023)	(0.005)	(0.004)	(0.018)	(0.020)	(0.008)	(0.009)
religion	0.041**	0.045*	0.005	0.011*	0.042**	0.036	−0.033**	−0.022
	(0.021)	(0.023)	(0.008)	(0.007)	(0.018)	(0.022)	(0.014)	(0.015)
husb_educ	−0.016***	−0.013***	−0.003*	−0.003*	−0.012***	−0.011***	0.008***	0.008***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
husb_worklocalgroup	−0.025***	−0.028***	−0.022***	−0.021***	−0.013**	−0.011	0.021***	0.020***
	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)
rural	−0.030	−0.019	0.033***	0.025**	0.035	0.061**	−0.006	−0.012
	(0.025)	(0.029)	(0.013)	(0.012)	(0.025)	(0.028)	(0.009)	(0.008)
density	−0.00000***	−0.00000***	0.00000	0.00000	−0.00000***	−0.00000***	0.00000**	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
electrification_rate	0.081	0.125**	−0.080**	−0.063*	0.110**	0.145**	−0.036	−0.023
	(0.062)	(0.062)	(0.038)	(0.034)	(0.048)	(0.058)	(0.022)	(0.026)
Observations	4,414	4,414	4,414	4,414	4,414	4,414	4,414	4,414
Adjusted R^2	0.150	0.166	0.034	0.029	0.169	0.180	0.057	0.050

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 4: RMG exports and FLFP

	Dependent variable:							
	FLFP(RMG Adjacent)		FLFP Traditional		FLFP (Non-trad, Low skill)		FLFP (Non-trad, High skill)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
export_exposure3	0.180***	0.179***	−0.014***	−0.011**	0.135***	0.123***	0.004	0.006
	(0.017)	(0.018)	(0.004)	(0.005)	(0.015)	(0.016)	(0.005)	(0.006)
educ	−0.004	−0.004	−0.001	−0.001	−0.001	0.001	0.004**	0.003
	(0.004)	(0.004)	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
age	0.036**	0.036**	0.007	0.006	0.021	0.014	0.002	0.003
	(0.015)	(0.017)	(0.005)	(0.005)	(0.016)	(0.018)	(0.009)	(0.009)
I(age^2)	−0.001***	−0.001***	−0.0001	−0.0001	−0.0003	−0.0003	0.0001	0.00003
	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
childathome	−0.090***	−0.090***	0.002	0.001	−0.072***	−0.074***	−0.004	−0.005
	(0.007)	(0.008)	(0.003)	(0.003)	(0.006)	(0.007)	(0.003)	(0.003)
preg_survey	−0.086***	−0.102***	−0.019***	−0.019***	−0.075***	−0.092***	−0.011	−0.011
	(0.020)	(0.023)	(0.005)	(0.004)	(0.018)	(0.020)	(0.008)	(0.009)
religion	0.035*	0.037	0.006	0.012*	0.036**	0.027	−0.033**	−0.022
	(0.020)	(0.023)	(0.008)	(0.007)	(0.017)	(0.022)	(0.014)	(0.015)
husb_educ	−0.015***	−0.012***	−0.003*	−0.003*	−0.012***	−0.010***	0.008***	0.008***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
husb_worklocalgroup	−0.027***	−0.031***	−0.022***	−0.020***	−0.015**	−0.013*	0.021***	0.020***
	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)
rural	−0.052**	−0.052*	0.035***	0.027**	0.016	0.032	−0.006	−0.013
	(0.024)	(0.028)	(0.013)	(0.012)	(0.024)	(0.028)	(0.009)	(0.009)
density	−0.00000***	−0.00000***	0.00000	0.00000	−0.00000***	−0.00000***	0.00000**	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
electrification_rate	0.015	0.054	−0.075**	−0.058*	0.050	0.084	−0.036	−0.025
	(0.061)	(0.061)	(0.038)	(0.034)	(0.048)	(0.058)	(0.022)	(0.026)
Observations	4,414	4,414	4,414	4,414	4,414	4,414	4,414	4,414
Adjusted R^2	0.169	0.185	0.035	0.029	0.187	0.196	0.057	0.050
Residual Std. Error (df = 4357)	0.370	0.307	0.150	0.125	0.330	0.277	0.171	0.137

Note: *p<0.1; **p<0.05; ***p<0.0

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4.2 Reproductive Behavior

Table 5 documents the relationship between fertility and exposure to exports from RMG industry. It appears, that neither pregnancy at the time of survey, nor, fertility is influenced by the regional exposure to exports. Interestingly, the fertility models have a relatively high R-squared values. This suggests that most of the changes in fertility behavior is captured in time trends, i.e., determined by factors outside of our model.

5   Conclusion

This paper investigates the impact of exposure to RMG factories on FLFP, and fertility. Exploiting changes in export exposure, I find strong evidence that exposure to RMG has increased FLFP in RMG adjacent as well as non-traditional low skilled work. It also decreases traditional employment of women. However, I do not find any evidence of changes in fertility behavior due to RMG exposure. This is surprising since Heath and Mobarak (2015) finds that RMG exposure of about 6 years reduces hazard of first birth in sample year by about 30 percent. However, length of exposure could be correlated with age and development process - leading to overestimation of fertility response to RMG exposure. I do find a strong association between FLFP and and having child at home, as seen elsewhere (Bloom et al. 2009). Taking the results at face value, this seems to indicate fertility transition in Bangladesh is somewhat independent of RMG exposure. Indeed, it is possible that it is the lower fertility that has allowed women to engage in the labor force.

One aspect that remains to be explored is the role of changes in norms surrounding women due to peer effects. As long as people from RMG exposed clusters and control clusters interact directly and indirectly, norms regarding FLFP, marriage, reproduction and education that evolves as a result of exposure to RMG factories could transmit to control clusters. Under such social mechanisms, similar to those explored in Fernández (2013) and Fogli and Veldkamp (2011) in context of US FLFP, the impact of long run exposure is underestimated in this paper. An exploration of the importance of such mechanisms in Bangladesh is left for future work. Further exploration of education and other reproductive behavior will also be part of an update to this research.

Table 5: RMG exports and Reproductive Behavior

| | *Dependent variable:* | | | | | | | |
| | Pregnancy During Survey | | | | Fertility | | | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
export_exposure1	−0.006	0.002			−0.158	−0.147		
export_exposure3			−0.005	−0.002			−0.085	−0.089
educ	0.001	0.001	0.001	0.001	−0.023	−0.029	−0.023	−0.028
age_mar	0.006	0.006	0.006	0.006	−0.138	−0.137	−0.138	−0.137
age	−0.016	−0.017	−0.016	−0.017	0.351	0.355	0.352	0.356
I(age^2)	0.0002	0.0001	0.0002	0.0001	−0.003	−0.003	−0.003	−0.003
childathome	−0.036	−0.034	−0.036	−0.034	0.411	0.410	0.409	0.408
religion	0.008	0.006	0.008	0.007	0.177	0.189	0.180	0.193
husb_educ	−0.003	−0.001	−0.003	−0.001	−0.021	−0.017	−0.021	−0.017
husb_worklocalgroup	−0.003	−0.003	−0.003	−0.003	−0.083	−0.098	−0.082	−0.097
rural	0.022	0.021	0.023	0.022	0.092	0.079	0.099	0.093
density	0.00000	0.00000	0.00000	0.00000	−0.00000	−0.00000	−0.00000	−0.00000
electrification_rate	−0.062	−0.061	−0.060	−0.059	−0.609	−0.595	−0.581	−0.563
Observations	6,087	6,087	6,087	6,087	6,087	6,087	6,087	6,087
Adjusted R^2	0.058	0.057	0.058	0.057	0.596	0.600	0.596	0.601

Note: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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Appendix 1: Evolution of women's work and fertility in Bangladesh
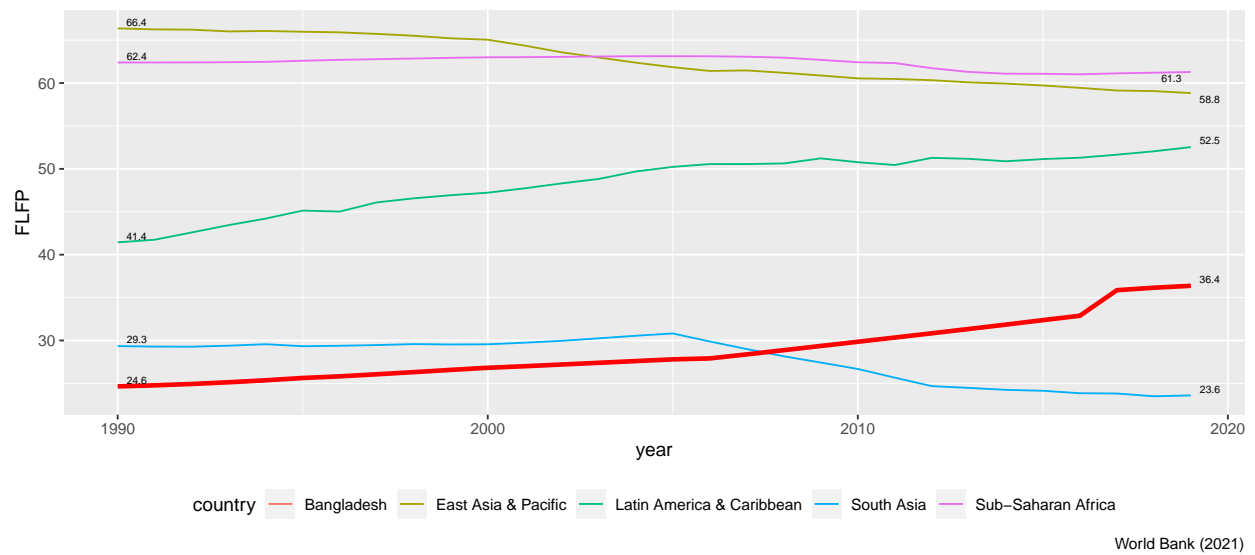

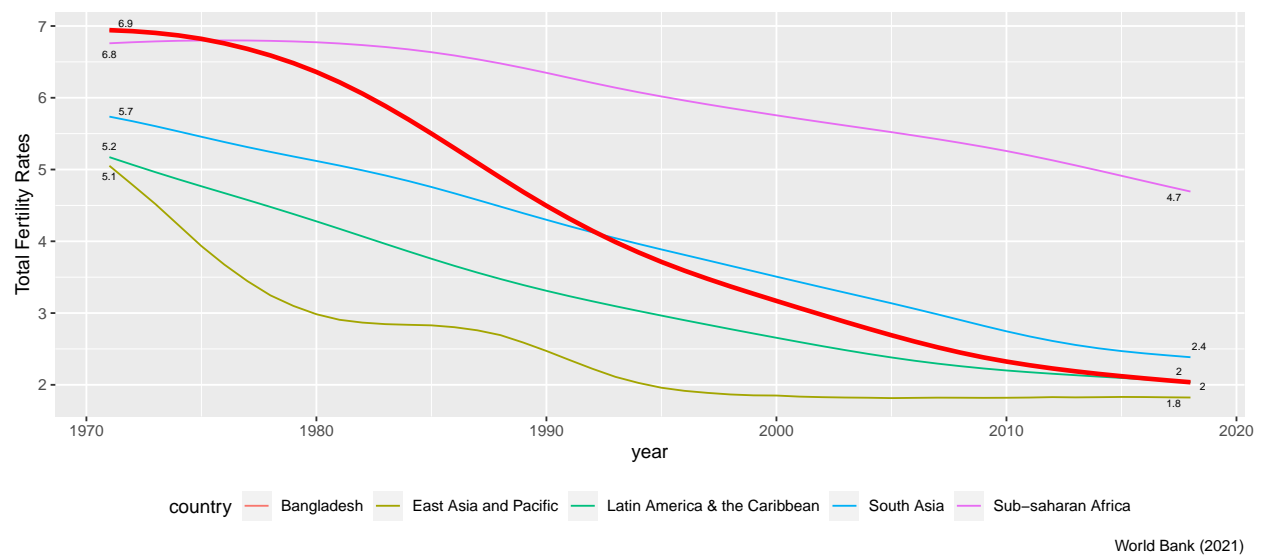Figure 5: Female Labor Force Participation in Bangladesh

Figure 6: Fertility in Bangladesh

Appendix 2: Estimating missing BEPZ data

The MiB dataset consists of 3409 factories. But they were unable to collect data from RMG factories located in Bangladesh Export Processing Zones (BEPZs) CED-BracU (2021b). A secondary dataset of factories that includes BEPZ factories is obtained by scraping the website of Bangladesh Garment Manufacturer's and Exporters Association (BGMEA). I found 164 factories located in BEPZs as of March 30, 2021. BGMEA website has consistent data on number of machines but not on number of workers and their gender composition, a critical component of this analysis. One option is to ignore the BEPZ data. However, BEPZs represent concentration of large factories - often in otherwise underdeveloped regions of Bangladesh compared to location of most factories in key cities of Dhaka and Chittagong. Indeed, the average number of machines in BEPZ factories was 999.897 as opposed to 369.004 in non-EPZ factories as per the dataset obtained by scraping BGMEA website. Hence, I decided to estimate the number of workers and their gender composition in BEPZ factories.

Among others, the MiB dataset contains data on date of establishment, number of total, male and female workers, membership to various trade associations, location (latitude, longitude and address), and factory type (knit versus woven specialization). The BGMEA dataset contains date of establishment, data on number of machines (but not number and gender composition of workers), location (latitude, longitude and address), and factory type (knit versus woven specialization). The details of the estimation process is below.

1. Factories in BEPZ locations were identified based on address information. 8 of the factories does not have information on number of machines. They are assigned the mean BEPZ number of machines.
2. 2,199 Factories in the MiB dataset with BGMEA membership is identified using membership information.
3. BGMEA factories in MiB dataset are matched using their names, yielding 1648 matches. BGMEA website contains information of all BGMEA members. As such, it can be suspected that the drop is due to spelling differences in name.
4. Regression of the following form is used to model the total number of workers in BGMEA factories in MiB dataset.

$$\text{Total Workers}_v = \alpha_0 + \alpha_1 * \text{longitude}_v + \alpha_2 * \text{latitude}_v + \alpha_3 * \text{date of establishment}_v +$$

$$+\alpha_4 * \text{factory type dummy}_v + \alpha_5 * \text{machine}_v + \epsilon_v$$

This model is used to estimate the total workers in BEPZ factories.

6. Regression of the following form is used to model the fraction of female workers in BGMEA factories in MiB dataset.

$$\text{Total Workers}_v = \alpha_0 + \alpha_1 * \text{longitude}_v + \alpha_2 * \text{latitude}_v + \alpha_3 * \text{date of establishment}_v +$$

$$\alpha_4 * \text{factory type dummy}_v + \alpha_5 * \text{machine}_v + \epsilon_v$$

This model is used to estimate the share of female workers, and combined with estimates of total workers to estimate the total number of female workers in BEPZ factories.

Table 6: Modelling total workers and female shares in BEPZ

|	*Dependent variable:*	
	workers_total	fshare
	(1)	(2)
longitude	377.551**	−0.020
	(169.559)	(0.021)
latitude	587.306***	−0.108***
	(162.068)	(0.020)
date_est	−6.256*	0.001**
	(3.378)	(0.0004)
knit	−32.089	−0.140***
	(59.119)	(0.007)
machine	1.138***	−0.00004***
	(0.048)	(0.00001)
Constant	−34,969.190*	3.363
	(19,497.580)	(2.357)
Observations	1,646	1,645
R^2	0.276	0.302
Adjusted R^2	0.273	0.300
Residual Std. Error	1,103.950 (df = 1640)	0.132 (df = 1639)
F Statistic	124.855*** (df = 5; 1640)	142.122*** (df = 5; 1639)
Note:		**p<0.1; **p<0.05; ***p<0.01*

Appendix 3: DHS surveys in Bangladesh
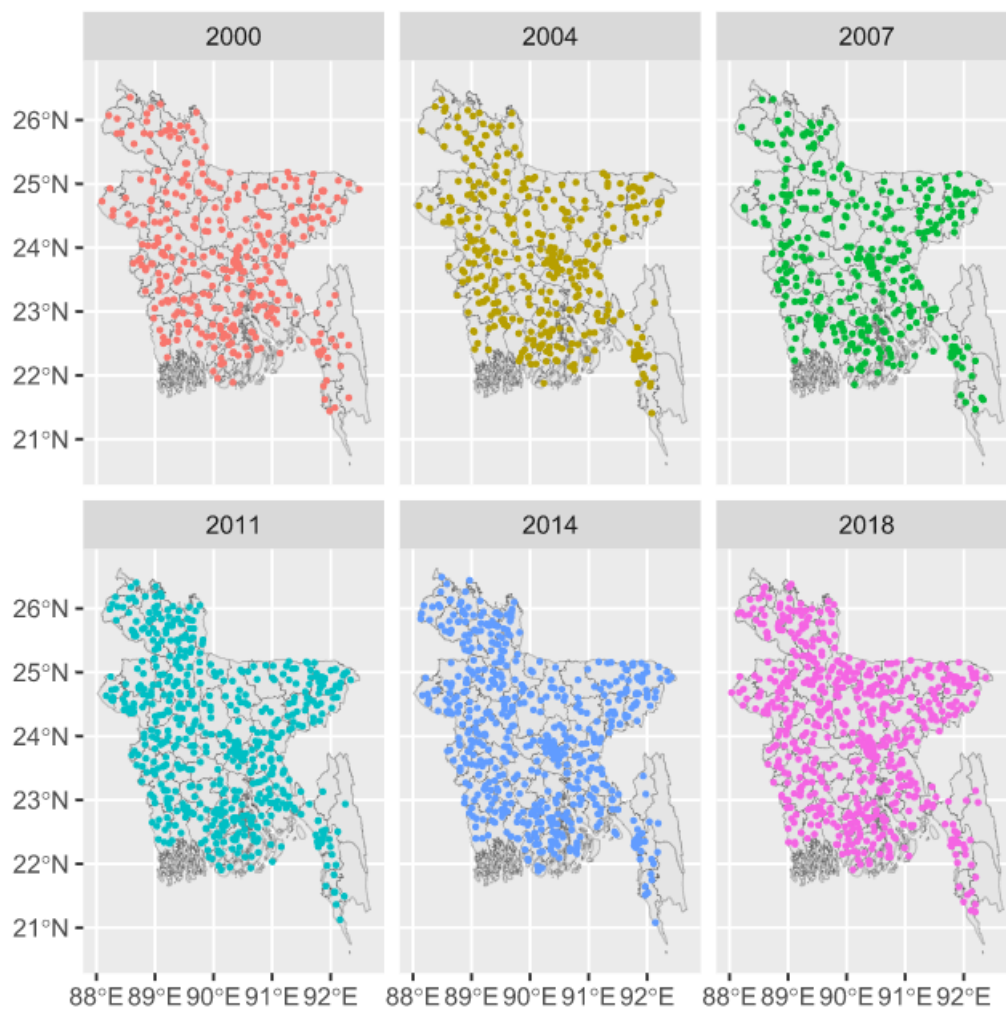
Figure 7: DHS Survey Regions in Different Survey Waves