Rural-Urban Migration and Structural Change: A Reinterpretation*

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November 20, 2023

Job Market Paper

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Abstract

Structural change and rural to urban migration are often seen as a single reallocation process. However, using panel data on Indonesian workers spanning two decades, I present evidence that challenges this standard view. First, I document that workers switch from agriculture to non-agriculture within rural areas, and that most rural-urban migrants are not farmers. Second, I show that aggregate reallocation out of agriculture is primarily driven by the entry of younger cohorts into the labor market, rather than by workers who leave agriculture. Third, I provide evidence that rural-urban migration has intergenerational effects, as the offspring of migrants are less likely to work in agriculture, attain higher levels of education, and earn more. To uncover the forces and frictions giving rise to these patterns of employment reallocation and their aggregate implications, I build an overlapping generations model with two sectors and two locations. In the model, switching sector or location is costly, and access to education differs by location. First, different from the standard view, I find that rural-urban migration has little impact on structural change. While the rural non-agricultural sector is able to absorb most of the workers leaving agriculture, this is detrimental for aggregate growth, as non-agriculture does not develop where it is more productive. Next, I uncover that sectoral switching costs, rather than differences in education, are the main driver of the cohort-level differences in sectoral employment shares. Finally, I show that intergenerational incentives for rural-urban migration are an important driver of urbanization and hence can have a large impact on economic growth.

*I am very greatful to Josep Pijoan-Mas for his support and guidance at all stages of this project. I would also like to thank Michael Waugh for continued advice and encouragement. I thank comments and suggestions by Nezih Guner, Mónica Martínez-Bravo, Michael Peters, Diego Puga, Ákos Valentinyi, and Fabrizio Zilibotti, and seminar and conference participants at CEMFI, the XXVI Vigo Workshop on Dynamic Macroeconomics, and Yale Macro Lunch. Email: tomas.budi@cemfi.edu.es.

1 Introduction

Structural change out of agriculture and urbanization are two defining features of economic development (Kuznets, 1971). Often, they are regarded as the same reallocation process: workers leave the farm in rural areas and migrate to cities for a non-agricultural job. Under this common view, frictions preventing migration have a large impact on economic development, as they limit structural change. However, we lack direct evidence on whether transitions from agriculture to non-agriculture do entail a move from rural to urban areas. This limits our understanding of the relevant frictions slowing down economic development and, more generally, of the driving forces of structural change.

In this paper, I revisit the relationship between rural-urban migration and structural change, with the goal of better understanding which are the relevant frictions hindering macroeconomic development. My analysis draws on a panel survey of Indonesian households spanning two decades, during which the country experienced a large reallocation of employment out of agriculture and from rural to urban areas.

First, I document that, contrary to common wisdom, most worker-level reallocation out of agriculture happens within rural areas. Switches from the rural agricultural sector to urban non-agriculture are very limited. Indeed, rural-urban migrants generally work in non-agriculture before moving to cities. These reallocations out of agriculture and out of rural areas are both associated with significant income gains for workers, which is suggestive of the presence of frictions preventing moves across sectors *and* across locations. Second, I show that aggregate reallocation out of agriculture is primarily driven by younger cohorts of workers entering the labor market in non-agriculture, rather than by workers who switch from agriculture to non-agriculture. This limited reallocation out of agriculture over an individual's working-life hints at the differential incidence that frictions may have for workers at different ages as an important limiting factor for structural change. It also points to the role of initial conditions as determinants of the sector of work. Third, I provide evidence on the intergenerational effects of rural-urban migration. To that end, I compare the offspring of rural workers who migrate to urban areas with the offspring of rural workers who remain in rural areas. I show that migrants' offspring are less likely to work in agriculture and have higher educational attainment, both unconditionally and conditional on parent's sector, educational attainment and unobservable characteristics (as proxied by individual fixed effects). They also have higher earnings, which suggests that intergenerational returns can be an important force behind rural-urban migration.

Given their prominent role in structural change, understanding the drivers of cohort effects is of central importance for macroeconomic development. On the one hand, frictions to switch sector may prevent older workers from leaving agriculture as non-agricultural demand increases over time (Hobijn et al., 2018). On the other hand, cohort effects may reflect differences in human capital across cohorts driven by increases in educational attainment over time (Porzio et al., 2022).

I offer a new and complementary explanation based on the spatial bias of these two mechanisms. Rural-urban migration increases the share of individuals in future cohorts that will be raised in urban areas. As I show, being raised in urban areas is associated with a lower agricultural share and higher educational attainment. Hence, rural-urban migration may be a driver of the cohort effects in structural change.

To quantify the importance of each of these forces and frictions for the patterns of employment reallocation and their aggregate consequences, I build an overlapping generations model with two locations, two sectors, and differential local access to education. In the model, workers bear a cost when they switch sector or location. Moreover, in line with the empirical evidence on the intergenerational effects of rural-urban migration, workers take into account that the location they choose determines where their offspring will get educated and begin their working-life. This affects their sector of work due to differences in the demand for human capital across sectors, and differences in sectoral demands and access to education across locations. Cohort effects in structural change may arise as a result of sectoral switching costs —which are not paid by young agents upon entering the labor market—, differences in human capital across cohorts —which arise endogenously as a result of educational investments by agents—, or rural-urban migrations —which place future cohorts where non-agricultural demand and access to education are higher—.

I calibrate the model to match the patterns of employment reallocation across locations and sectors documented for Indonesia between 1983 and 2013. Using the micro-data, I construct bilateral switching flows across location-sector pairs that allow me to discipline switching costs and relative productivities across locations and sectors. Then, changes over time in these reallocation patterns and growth in sectoral value added per worker identify the evolution of sectoral productivities in each location. I calibrate the parameters that control how educational investments translate into human capital in each location to match the evolution of the local stock of high-education workers. Importantly, my calibration rests on an estimate of the income elasticity of sectoral demand obtained from micro-data on households' consumption expenditure.

The calibrated model recovers a general increase in productivity over the sample period, faster in agriculture than in non-agriculture. This pattern of productivity growth generates structural change due to income and price effects, as the inferred elasticity of substitution across goods is smaller than one. Moreover, as the urban location has a comparative advantage in non-agriculture, it also generates urbanization. To match the data, the model needs a higher costs of switching from rural to urban areas and from agriculture to non-agriculture than viceversa, which sustains the income differences across locations and sectors in equilibrium. Finally, the calibration reveals that access to education is higher in urban than in rural areas.

To explore the impact of rural-urban migration on structural change, I study a counterfactual economy in which migration is not possible. In this economy, the fall in the agricultural share over time is remarkably similar to that of the benchmark economy (28 *vs* 30 percentage points). This is the result of the rural non-agricultural sector being able to absorb most of the workers released by agricultural productivity growth in rural areas. Structural change towards rural non-agriculture is, nonetheless, detrimental for aggregate value added per worker, which by 2013 is 4% lower than in the benchmark economy. Absent migration, the non-agricultural sector does not develop where it is more productive. In this way, rural-urban migration arises not as an essential force for structural change, but as an important force for economic growth, as it allows the economy to relocate workers to the location with a comparative advantage in non-agriculture.

Next, I analyze several counterfactual economies to understand the drivers of cohort effects in structural change. I find that sectoral switching costs account for most of the differences in employment patterns across cohorts. When older workers are free to move across sectors, they leave agriculture at a similar rate than younger workers, despite being less educated. In part, this result is due to the fact that the demand for skills in non-agriculture compared to agriculture is not very different. Hence, differences in educational attainment across cohorts are not a major determinant of their different agricultural employment shares. Similarly, rural-urban migration plays a limited role for the cohort effects, as the differences in non-agricultural demand across locations are significantly reduced in an economy in which migration is not possible. This finding calls for an increased effort to identify which specific frictions are captured in reduced form by the sectoral switching costs present in the model.[1]

Finally, I assess the importance of intergenerational incentives for rural-urban migration. In an economy in which agents do not internalize the effects of their decisions on their offspring, the increase urbanization is much smaller than in the benchmark economy (13 *vs* 20 percentage points), the agricultural share is higher (3 percentage points higher by 2013) and the economy grows much less (23% by 2013). Differences in access to education across locations are important for this result. As parents fail to internalize that their offspring will have more access to education in urban areas, they migrate less, which translates into a lower increase in educational attainment. This limits the growth of the non-agricultural sector and reduces aggregate output. While this result is an upper bound (as in the benchmark economy agents are fully altruistic), it speaks to the importance of considering intergenerational motives for rural-urban migration in the design of policies that aim to foster economic development.

Related literature. My work relates to the literature that has jointly studied urbanization and structural change or, more generally, the spatial dimension of structural change. This includes papers that aim to explain the distribution of economic activity in space (Michaels et al., 2012; Nagy, 2020; Coeurdacier et al., 2023), to understand regional growth and regional convergence (Caselli and Coleman, 2001; Eckert and Peters, 2022), or to quantify the importance of migrations for structural change and growth (Tombe and Zhu, 2019; Budí-Ors and Pijoan-Mas, 2022). This set of papers does not draw on panel data of workers, which limits our understanding of the interaction

[1] Sectoral switching costs may well represent frictions in land markets (Adamopoulos et al., 2022) or labor market frictions such as labor market power or informality (Donovan and Schoellman, 2023).

between these reallocation processes, as movers are not directly observed. By providing evidence on the patterns of worker-level reallocation across sectors and locations, I am able to separately assess the role of sectoral and spatial frictions, which I show to be an important distinction in order to understand the relationship between rural-urban migration and structural change.

Two recent papers, Hobijn et al. (2018) and Porzio et al. (2022), provide systematic evidence on the role that new cohorts play in the process of structural transformation. Both papers find that an important part of the reallocation out of agriculture is driven by the entry of younger cohorts into the labor market, as I also document. I offer a new and complementary interpretation to this cohort effects by considering the role that migration has in shaping the spatial distribution of future labor supply. Moreover, the use of panel data, rather than repeated cross-sections, allows me to provide direct evidence on the characteristics of movers, to quantify the returns to reallocations in terms of earnings, and to link within-cohort reallocation with between-cohort reallocation out of agriculture (through generations). This intergenerational linkages in structural transformation are also highlighted by Cavalcanti et al. (2016), who study the emergence of urban slums and their implications for structural transformation.

Next, the emphasis on the role of movers across sectors and locations connects with the literature on the agricultural productivity gap (Hicks et al., 2020; Pulido and Świecki, 2021) and the rural-urban gap (Lagakos et al., 2020) using panel data. My work is different as I focus on the role movers play in the long-run process of structural transformation. Based on this, I also explore the outcomes of movers' offspring.

The notion that there are differential barriers to labor mobility across sectors and across space is common to Adamopoulos et al. (2022). Different from these authors, I use a dynamic model to explore how frictions affect the choices of location and sector of different cohorts along the development path. In that sense, the paper is also related to a literature that explores the role of barriers to structural change or to rural-urban migration (Ngai et al., 2019; Gai et al., 2021; Lagakos et al., 2023; Donovan and Schoellman, 2023).

Finally, this work is related to a growing number of papers studying the development experience of Indonesia. In particular, Duflo (2001) and specially Hsiao (2022) study the effects of a large school construction on several development outcomes (including urbanization), but do not link the increases in educational attainment it generates to the process of structural transformation. Similarly, Bryan and Morten (2019) do not focus on structural change in their study of the effects of internal migration for aggregate productivity in Indonesia.

2 Context and Data

My analysis focuses on the development experience of Indonesia. Since the 1980s, the country has undergone a substantial reallocation of employment out of agriculture and from rural to urban areas, the two aggregate trends of interest, see Appendix Figure C.1 panel (a). These reallocation processes have come together with sustained population and GDP per capita growth, see Appendix Figure C.1 panel (b). More importantly for my purpose, the availability of a panel data set recording individuals' employment and location for a long time span enables the study of how rural-urban migration relates to structural change at the individual level.

In particular, the data set used in the analysis is the Indonesian Family Life Survey (IFLS). The IFLS is a panel survey that was conducted for the first time in 1993 in 13 out the 27 Indonesian provinces, representative of 83% of the Indonesian population. The IFLS was designed as a long-term panel survey, and subsequent interviews were unfold in 1997, 2000, 2007 and 2014.[2] While the first wave interviewed 22,019 individuals, this number has grown to 58,337 individuals interviewed in 2014. The reason is that, in general, households arising from 1993-interviewed households are also contacted. Moreover, the IFLS has been very successful at tracking households and individuals across waves, with recontact rates above 90%, limiting the loss of observations due to attrition (Thomas et al., 2012). These two features make it an appropriate data source to explore the intergenerational dimension of workers' reallocation across locations and sectors, as I do. The survey also collects information, among other variables, on individual earnings and consumption, which I use to estimate the gains to sectoral and spatial reallocations, in a similar fashion to what Hicks et al. (2020), Lagakos et al. (2020) and Pulido and Święcki (2021) have done with this same dataset. Notably, I focus not only on the returns to these reallocations, but more broadly on how they contribute to the aggregate employment reallocation out of agriculture and out of rural areas over time. Indeed, for the analysis of long run trends, I also make use of information on individuals' employment and location five and ten years prior to 1993, which was asked to households participating in the first wave of the survey.

Before exploring in detail the reallocation of employment across locations and sectors, it is important to verify whether the IFLS sample displays the aggregate trends documented for the Indonesian economy in Figure C.1. To that end, I use information on workers sector of work and rural/urban status[3] to compute the share of employment in the agricultural sector and in urban areas during my sample period. As we can see in panel (a) of Figure 1, the fall in the agricultural share and the increase in urbanization in the IFLS sample are similar to those documented for the whole Indonesia in Figure C.1. The use of micro-data on workers allows to go beyond this classification based on only the location or only the sector of work of the individual. In particular, classifying workers by location-sector status (i.e. the combination of a location and a sector), we can see in panel (b) of Figure 1 that the fall in the agricultural share is mainly driven by the reduction in the share of workers in rural agriculture, while the rise in urbanization is mainly driven by the increase in the share of workers in urban non-agriculture. Understanding the forces that relate these two trends is the main goal of next Section.

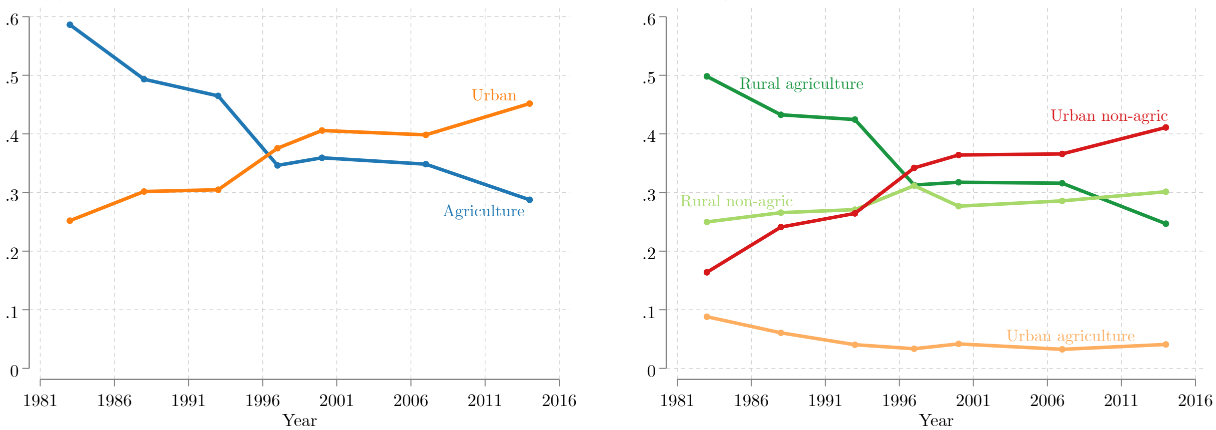
[2]See Witoelar and Sikoki (2016) for comprehensive details on the design and implementation of the IFLS.

[3]Section A in the Appendix gives a precise definition of the main variables used in the paper.

Figure 1: Employment Shares in the IFLS

(a) Employment Shares across Locations *and* Sectors

(b) Employment Shares across Location-sectors



Notes: aggregates computed from weighted individual observations of workers in the IFLS.

3 Structural Change and Urbanization: Different but Related Processes

This section presents an empirical analysis of the reallocation of employment across sectors (agriculture and non-agriculture) and locations (rural and urban) in Indonesia between 1983 and 2014. First, I exploit the panel dimension of the data to document that workers move from agriculture to non-agriculture within rural areas, and that most rural-urban migrants are not farmers. Second, I show that the fall in the aggregate agricultural share is primarily driven by younger cohorts entering the labor market in non-agriculture, rather than by workers switching from agriculture to non-agriculture. Finally, I document that rural-urban migration has intergenerational effects, as the offspring of migrants, compared to the offspring of stayers, have a lower probability of working in agriculture, higher educational attainment, and higher earnings.

3.1 Worker-level reallocations

To understand the extent to which workers migrate from rural to urban areas when they leave agriculture, I restrict my analysis to individuals that are observed as workers for at least two periods. This is a sample of 21,862 individuals that are observed an average of four times, for a total of 84,538 observations. I first document the *quantity* of moves across the four location-sectors of Figure 1 panel (b), presenting most of my results in the form of transition matrices. Second, I estimate the worker-level returns to these moves, and discuss their interpretation in the context of the model I present later.

3.1.1 Transitions across location-sectors

The following matrix summarizes the transitions across location-sectors (rural agriculture, rural non-agriculture, urban agriculture, and urban non-agriculture) for my sample of workers. The rows and the columns of the matrix refer to the location-sector of work at t and $t+1$ respectively. The numbers in the matrix record the frequency of each transition conditional on an initial location-sector, and thus sum to 100 for each row. As the number of years between each cross-section in my dataset varies between 3 and 7, we can think of these numbers as representing the transition probabilities between location-sectors approximately every 5 years.

$$\begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 76.7 & 18.5 & 2.0 & 2.7 \\ 21.3 & 63.9 & 1.4 & 13.4 \\ \hline 9.2 & 3.9 & 47.7 & 39.3 \\ 0.9 & 4.2 & 4.4 & 90.5 \end{array}\right] \end{array} \tag{1}$$

Notes: This empirical transition matrix records the probability that a worker changes location-sector in a period of approximately 5 years. Rows and columns refer to the location-sector at t and $t+1$ respectively. R stands for rural, U for urban, A for agriculture, and N for non-agriculture. Hence, RA stands for rural agriculture, and so on. The numbers in each cell are computed by counting the total number of transitions between each pair of location-sectors and then normalizing over the total number of transitions with the same origin. The total number of transitions across all location-sector pairs observed in my sample is 56,865.

Several remarks about matrix (1) follow. Starting from the first row, we can see that most workers who leave agriculture in rural areas move to rural non-agriculture, instead of migrating to urban non-agriculture (18.5% *vs* 2.7%). Despite the fact that rural-agriculture shrinks in favor of urban non-agriculture at the aggregate level, transitions from agriculture to non-agriculture happen within rural areas at the individual level. Next, focusing on rural-urban migrants (the upper, right quadrant of the matrix), we can see that most of them work in the non-agricultural sector of rural areas before moving to cities, as reflected by a conditional probability of 13.4 + 1.4 = 14.8% of moving to urban areas next period for RN workers, compared to 2.0 + 2.7 = 4.7% for RA workers. This difference in conditional probabilities gets indeed translated into a difference in the quantity of workers arriving to urban areas from RN with respect to RA, as 71.1% of the total number of bilateral moves between rural and urban have as origin RN.[4]

Matrix (1) is an average of the transitions across location-sections between 1983 and 2014. However, it is possible that this pattern of transitions changes over time or across different groups of workers. I explore these possibilities in Appendix B. First, I show that this transition matrix is stable over time. Second, I note that the pattern of transitions is virtually the same if I restrict my sample to males between 25 and 59 years old. I also document that location-sector states are more persistent for older than for younger workers. Finally, I consider the possible bias induced

[4] In Appendix B, I present the counts that give rise to the probabilities in matrix (1), as well as bootstrap standard error for this probabilities.

by sample attrition or switches to non-employment. All robustness exercises point to the same direction: most worker-level reallocation out of agriculture happens within rural areas, and most workers who migrate from rural to urban areas are not farmers. This raises questions on the extent to which rural-urban migration is essential for structural change out of agriculture.

A potential reading of matrix (1) is that, starting from rural agriculture, a sizeable number of workers will switch first to non-agriculture in rural areas and then migrate to urban. This would convey the notion that the rural non-agricultural sector serves as a stepping-stone before workers can make it to the city. Focusing on all the workers that switch from rural agriculture to rural non-agriculture (and are observed at least three times), Figure B.3 shows that just 7.6% of them follow this history of locations. Alternatively, focusing on all the workers that end up in urban non-agriculture (and are observed at least three times), Figure B.3 shows that just 11.7% were in both rural agriculture and rural non-agriculture before. These numbers suggest that the quantitative relevance of rural non-agriculture as a stepping stone towards urban non-agriculture is limited.

3.1.2 Returns to transitions across location-sectors

After documenting the quantity of transitions across location-sectors, I now focus on the returns to these transitions. A number of recent papers (Lagakos et al., 2020; Hicks et al., 2020; Pulido and Świecki, 2021) has studied the gains in income associated to leaving the agricultural sector or to leaving rural areas with panel data. In a similar vein, I estimate the returns to transitions across location-sectors (rather than just locations, or just sectors), to be consistent with matrix (1). By using panel data, one can estimate these returns controlling for time-invariant unobservables, such as permanent ability, that may drive an important share of the observed income differences between agriculture and non-agriculture, and between rural and urban areas (Young, 2013). Worker's selection on income gains may be driven by other factors, such as sector-specific ability or location-specific amenities, which are not captured by individual fixed effects. Hence, the estimates I present below should not be interpreted as the causal effects of switching sector or location. Yet, if significant, they may be informative about the presence of factors preventing the equalization of incomes across sectors and locations.[5] Besides individual fixed effects, I control for other observables that may induce a correlation between the location-sector of work and income. The regression I run is

$$y_{it} = \alpha_i + \alpha_t + \beta \, \text{Location-sector}_{it} + X_{it}\Gamma + \varepsilon_{it}\,, \tag{2}$$

where y_{it} is a measure of income for an individual i at time t, α_i and α_t individual and time fixed effects, Location-sector$_{it}$ a categorical variable recording the location-sector status of the worker, and X_{it} a group of controls. The coefficient of interest is β, which measures the change in income y_{it} associated to a change in the location-sector of the worker (with respect to a reference one), and is

[5]See Lagakos et al. (2020) and Schoellman (2020) for a discussion on the interpretation of the returns to rural-urban migration estimated with panel data.

Table 1: Returns to Switching Location-sector

	log household earnings per adult (1)	(2)
Rural Non-agriculture	0.177^{***}	0.159^{***}
	(0.029)	(0.028)
Urban Agriculture	0.217^{***}	0.136^{***}
	(0.053)	(0.050)
Urban Non-agriculture	0.366^{***}	0.241^{***}
	(0.045)	(0.041)
District FE	No	Yes
N	63,857	63,819
R-squared	0.50	0.52

Note: individual controls include age, education and household size.
SEs clustered at the sampling unit level in parenthesis. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

identified by switchers. Table 1 reports the estimation results for income measured as log household earnings per adult, omitting the rural-agriculture category. In column (1), we can see that workers who leave *only* agriculture or *only* rural locations (while remaining in the same location or sector) experience significant income gains, 18 and 22 log points respectively. Remarkably, workers who leave *both* the agricultural sector and rural locations in order to work in urban non-agriculture experience much larger gains, 37 log points. To the extent that individual fixed effects can control for selection due to unobserved worker characteristics, this difference in estimates is in line with the presence of factors preventing the equalization of incomes across sectors *and* locations, such as frictions or differences in location-sector specific amenities. Consistent with the presence of spatial frictions, adding controls for the district of workers –such that identification comes from moves within district– reduces the estimates for rural-urban migration gains, while estimates for the gains from leaving agriculture remain relatively stable.[6]

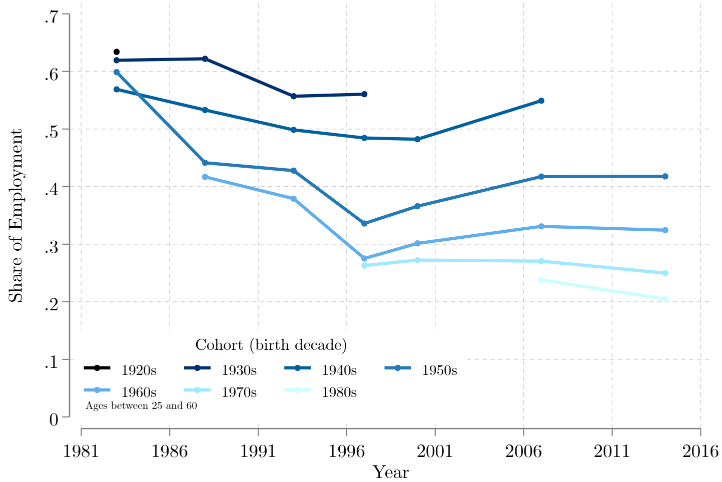
3.2 Aggregate reallocation out of agriculture: cohort effects

Aggregate reallocation of employment across locations and sectors is the result of the worker-level reallocations documented above but also of changes in the composition of the labor force over time. This is, as new cohorts join the labor market and others retire, the aggregate share of employment in agriculture may change, as sectoral employment shares may differ across cohorts.

In the case of Indonesia, the large persistence of location-sector states at the worker-level in matrix (1) already suggests that younger cohorts may be responsible for an important part of aggregate reallocation out of agriculture. Following Porzio et al. (2022), Figure 2 plots the

[6] Baysan et al. (2023) estimate that around 30% of the agricultural wage gap within rural villages in India is due to the harsher working conditions of rural non-agricultural jobs, with the rest being attributed to frictions to switch sector.

Figure 2: Cohort-level Agricultural Share



Notes: this figure plots the evolution of the agricultural share for individuals aged 25 to 60, classifying them into cohorts based on their by birth-decade.

evolution of the employment share in agriculture for different birth-decade cohorts. We can see that, in general, the lines for each cohort do not overlap, and that they are relatively flat. Moreover, at any given point in time, younger cohorts have a lower agricultural share than older cohorts. For most years, the difference between the agricultural share of the youngest and the oldest cohort is above 20 percentage points. This illustrates the importance of between-cohort (rather than within-cohort) reallocation for the aggregate reallocation out of agriculture.

To formalize this observation, I decompose the fall in the agricultural share into a within-cohort component (capturing changes in the agricultural share of each cohort) and a between-cohort component (capturing changes in the share of total employment represented by each cohort) using a standard within-between decomposition

$$\frac{L_{a\,t}}{L_t} - \frac{L_{a\,t-1}}{L_{t-1}} = \underbrace{\sum_c \left(\frac{L_{ac\,t}}{L_{c\,t}} - \frac{L_{ac\,t-1}}{L_{c\,t-1}}\right)\frac{L_{c\,t}}{L_t}}_{\text{within-cohort}} + \underbrace{\sum_c \left(\frac{L_{c\,t}}{L_t} - \frac{L_{c\,t-1}}{L_{t-1}}\right)\frac{L_{ac\,t-1}}{L_{c\,t-1}}}_{\text{between-cohort}}, \tag{3}$$

where $\frac{L_{a\,t}}{L_t}$ is the agricultural share of employment in year t, $\frac{L_{ac\,t}}{L_{c\,t}}$ the agricultural share of cohort c at t, and $\frac{L_{c\,t}}{L_t}$ the share of total employment represented by cohort c at t. This decomposition attributes 73% of the fall in the agricultural share in Indonesia between 1983 and 2014 to the between component, and 27% to the within component.[7] Alternatively, using Porzio et al. (2022) decomposition, I compute in Appendix D that 81% of structural change out of agriculture can be attributed to younger cohorts disproportionately working in non-agriculture.

[7] To compute each component of equation (3), I use the same sample as in Figure 2, but define cohorts by their birth-year (rather than their birth-decade).

3.3 Intergenerational effects of rural-urban migration

As emphasized by the previous fact, reallocation out of agriculture over an individual's working-life is limited. This points to the importance of initial conditions as determinants of the sector of work. An important initial condition may be the location where a worker is raised. In particular, in the presence of spatial frictions, working in non-agriculture from the beginning of working-life may be easier for workers raised in urban areas, where the demand for non-agriculture is higher. Moreover, if access to education is also higher in urban areas, urban-raised workers may be able to acquire more human capital than rural-raised workers. As the demand for human capital is higher in non-agriculture, this may also be an important determinant of their initial sector of work.

Rural-urban migration by young workers will affect the initial conditions of their offspring, who will be raised in urban areas. To explore the role of differences in the location where workers are raised, I make use of the information on workers' family linkages and compare the descendants of rural-urban migrants to the to descendants of rural stayers. Specifically, I follow a group of young rural workers,[8] of whom some migrate to urban and some do not. Then, I compare the offspring of migrants to the offspring of stayers in terms educational attainment, probability of working in agriculture, and earnings. Specifically, I run regressions like

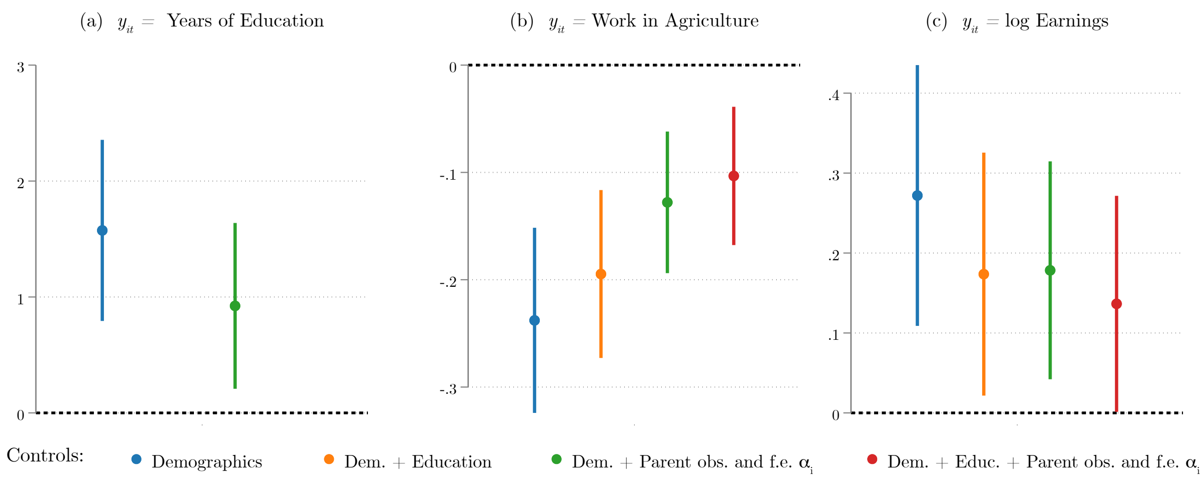
$$y_{it} = \alpha_t + \beta \text{ R-U Mig Offspring}_i + X_{it}\Gamma + \varepsilon_{it} \tag{4}$$

where y_{it} is the outcome of interest for the sample of descendants, R-U Mig Offspring$_i$ an indicator that takes value 1 for individuals whose parents migrated from rural to urban areas, and X_{it} a group of controls. Estimates of β for different outcomes and specifications are presented in Figure 3. First of all, we can see that unconditionally (other than in standard demographic controls), offspring of migrants have 1.58 more years of education, 24 percentage points lower probability of working in agriculture, and 27 log points higher earnings. Once we control for education, offspring of migrants still have a significantly lower agricultural share (19 percentage points) and higher earnings (17 log points). A reasonable concern in the interpretation of these results is that rural-urban migrants are selected on both observable and unobservable characteristics that may affect the outcomes of their offspring.[9] Therefore, I also present estimates for β in which I control for parents education, sector, and the individual fixed effect of an earnings regression like (2). The result that rural-urban migrants offspring have higher educational attainment, a lower agricultural share, and higher earnings remains. I interpret this as evidence of intergenerational returns to rural-urban migration.

[8] I keep individuals that are observed as workers at least two times and that the first time they are observed: (a) work in rural areas, (b) are less than thirty years old, and (c) are not classified as children of the household head. This restricts my sample to 3,346 individuals and 13,126 individual-year observations.

[9] For instance, it is reasonable to think that parents educational attainment or sector of work have an effect on those of their children. Similarly, children unobserved ability may be inherited from their parents.

Figure 3: Intergenerational Effects of Rural-Urban Migration



Notes: this figure plots the regression coefficient of R-U Mig Offspring$_i$ in (4) for different controls X_{it} and outcomes y_{it}. Dots represent the point estimate of β and whiskers the 95% confidence interval based on standard errors clustered at the sampling unit. Blue is for regressions that only control for demographics (age, gender) and time, orange for regressions that also control for educational attainment –hence, orange does not show up in panel (a), where the outcome is educational attainment–, green for regressions that control for demographics, time, parent observables (sector and location of work) and the individual fixed effects in a regression like (2), and red for regressions including all the previous controls. The number of observations in the regressions of panel (a) is 4,485, of panel (b) 4,433, and of panel (c) 3,357.

3.4 Interpreting the cohort effects in structural change

Given their prominent role in structural transformation, the interpretation of cohort effects is of central importance to better understand the driving forces of economic development, as well as the relevant frictions slowing it down. Previous work has provided different explanations for cohort effects. On the one hand, Hobijn et al. (2018) emphasize the presence of retraining costs in order to switch sectors, which prevent older workers to leave agriculture as non-agricultural demand increases over time. On the other hand, Porzio et al. (2022) argue that cohort effects mostly reflect differences in human capital across cohorts, driven by increases in educational attainment over time, which may come both from falling costs or higher incentives to acquire education as economies grow. I argue that cohort effects can also reflect rural-urban migration of previous generations. As I showed before, being raised in urban areas is associated with a lower agricultural share upon joining the labor market, due to both spatial frictions and higher educational attainment. Hence, rural-urban migration of a given cohort, by increasing the share of members of future cohorts raised in urban areas, can also generate cohort effects in structural change. The importance of each of these mechanisms for cohort effects and other aggregate outcomes is a quantitative question that I address in the rest of the paper.

4 Model

This section develops a quantitative model to study the forces relating rural-urban migration to structural change highlighted by the empirical analysis. In line with Section 3.1, workers may switch sector, location, or both, and switching is costly. In line with Section 3.2, aggregate structural change may be the result of within-cohort and between-cohort reallocation out of agriculture. In line with Section 3.3, rural-urban migration of one generation may have effects on the future agricultural share due to differences in local access to education and spatial frictions. The model combines elements from dynamic quantitative spatial models, such as forward-looking location decisions as in Caliendo et al. (2019), and elements from general equilibrium models of structural change, such as non-homothetic preferences and asymmetric sectoral productivity growth as in Herrendorf et al. (2013).

Environment. Consider an economy with two locations $\ell = r, u$ (rural and urban), and two sectors $j = a, n$ (agriculture and non-agriculture) that are present in both locations. The economy is populated by overlapping generations of agents who live for six 10-year periods. The first two periods of their life, agents are children and do not work. Then, at age 21, agents enter the labor market, where they work until they retire and die at age 60. At any point in time, generations are indexed by their age group $g = 1, \ldots, 6$. Agents consume and work in the location where they live, and can switch sector and/or location as they age after paying a switching cost. On the production side, there is a final good in each sector j that is a composite of varieties indexed by x in the continuum $[0, 1]$. Sectoral varieties can be produced in any of the two regions by competitive producers combining high- and low-skill local labor. Productivity is region-, sector-, and variety-specific, and varieties are tradable between locations subject to transport costs.

4.1 Workers

Timing and Demographics. Agents are born as children in the location of their parents, with whom they stay their first two periods of life, until they become 20 years old. At age $g = 2$ (from 11 to 20 years of age), agents acquire education in their parents' location. The moment they turn 21 years old ($g = 3$), agents become high-skill workers with probability $p^H_{\ell t}(i)$. This probability is a function of an investment i made by their parents in the previous period, with location-specific returns. At the same time, they choose where to live and in which sector to work, and they give birth to a child. The choice of where to live and work considers the utility associated to location-sector ℓj and the expected access from location-sector ℓj to any other location-sector $\ell' j'$ next period, as switching across ℓj is costly. The moment they turn 31 years old ($g = 4$), agents have the opportunity to switch sector and location again. As they are altruistic, their decision of where to spend their adult period takes into account that their children get educated and will start youth in the location they choose.[10] As agents become age $g = 5$ (41 years old), they decide again where to work, while their children become age $g = 3$ (21 years old) and leave the household to start their working-life. Finally, agents turn 51 years old ($g = 6$) and choose for the last time where to live and work before they die.

Preferences. Working agents (i.e. everyone but children) value the consumption of both agricultural and non-agricultural goods. Following Boppart (2014), individuals have PIGL (Price-Independent Generalized Linear) preferences represented by the indirect utility function

$$\mathcal{V}(y^s_{\ell j}, P_{\ell a}, P_{\ell n}) = \frac{1}{\eta}\left(\frac{y^s_{\ell j}}{P^{\phi}_{\ell a} P^{1-\phi}_{\ell n}}\right)^{\eta} - \frac{\nu}{\iota}\left(\frac{P_{\ell a}}{P_{\ell n}}\right)^{\iota}, \tag{5}$$

where $y^s_{\ell j}$ are the earnings of a worker of skill s in location-sector ℓj and $P_{\ell j}$ the price of final good j in location ℓ. This class of preferences features non-unitary income and substitution elasticities, so changes in income $y^s_{\ell j}$ and in relative prices $\frac{P_{\ell a}}{P_{\ell n}}$ change the share of expenditure allocated to each good. In particular, using Roy's identity, the share of expenditure allocated to agricultural goods by consumers of skill s working in sector j of location ℓ is given by

$$\varphi^s_{\ell a} = \phi + \nu\left(\frac{P_{\ell a}}{P_{\ell n}}\right)^{\iota}\left(\frac{y^s_{\ell j}}{P^{\phi}_{\ell a} P^{1-\phi}_{\ell n}}\right)^{-\eta}. \tag{6}$$

This expression shows that η and ι control how changes in real income and in relative prices translate into changes in relative sectoral expenditure, respectively. The importance of both forces depends on parameter ν. Finally, ϕ determines the asymptotic share of expenditure on agriculture as real income tends to infinity.

Reallocations across locations and sectors. Individuals can move across location-sector pairs as they age. Switching is costly, as moving from ℓj to $\ell' j'$ entails switching costs $\mu_{\ell j\, \ell' j'}$. Switching decisions are forward-looking, as individuals internalize that next period they will have the opportunity to change location or sector again. Moreover, adult agents ($g = 4$) take into account that their offspring is affected by their location and educational investment decisions, which gives rise to additional dynamics.

It is useful to begin by describing the value functions that characterize the dynamic location-sector choice problem of individuals in age group $g \neq 4$, this is, individuals in a period of life in which they do not invest in the education of their offspring. Denote by $V^{g\, s}_{\ell j\, t}$ the value of being in location-sector ℓj for an agent of skill s and age group $g \neq 4$ at time t. This value is given by the

[10] Throughout the exposition of the model, I sometimes refer to individuals in age group $g = 4$ (with 31-40 years of age) as adults, and to individuals in age group $g = 3$ (with 21-30 years of age) as youngs.

flow indirect utility associated to ℓj at t and the option value of starting next period in ℓj,

$$V_{\ell j\, t}^{g\, s} = \mathcal{V}(w_{\ell j\, t}^{s}, P_{\ell a\, t}, P_{\ell n\, t}) + \beta\, \psi_{\ell j\, t+1}^{g+1\, s}\,, \tag{7}$$

where β is the rate at which individuals discount the future. Importantly, the option value associated to location-sector ℓj, $\psi_{\ell j\, t+1}^{g+1\, s}$, varies by age. In particular, for individuals aged $g = 6$, $\psi_{\ell j\, t+1}^{g+1\, s} = 0$, as period t is their last period alive and there are no savings to bequest. For individuals aged $g = 3$ or $g = 5$,

$$\psi_{\ell j\, t+1}^{g+1\, s} = \mathbb{E}\left[\max_{\ell' j'}\left\{V_{\ell' j'\, t+1}^{g+1\, s} - \mu_{\ell j\, \ell' j'} + \epsilon_{\ell' j' t+1}\right\}\right]\,, \tag{8}$$

where $V_{\ell' j'\, t+1}^{g+1\, s}$ is the value of being in location-sector $\ell' j'$ next period, $\mu_{\ell j\, \ell' j'}$ the cost of switching from ℓj to $\ell' j'$, and $\epsilon_{\ell' j' t+1}$ an idiosyncratic preference shock for $\ell' j'$ experienced by the individual, over which the expectation $\mathbb{E}$ is taken. Assuming that $\{\epsilon_{\ell' j'\, t}\}$ is i.i.d. across $\ell' j'$ and over time, and drawn from a Gumbel distribution with scale parameter κ, this expectation has a closed-form expression, and we can write the value of ℓj for a skill s individual of age $g = 3$ or $g = 5$ as

$$V_{\ell j\, t}^{g\, s} = \mathcal{V}(w_{\ell j\, t}^{s}, P_{\ell a\, t}, P_{\ell n\, t}) + \beta\, \kappa\, \log \sum_{\ell'} \sum_{j'} \exp\left(V_{\ell' j'\, t+1}^{g+1\, s} - \mu_{\ell j\, \ell' j'}\right)^{1/\kappa}\,. \tag{9}$$

Next, consider the value functions of individuals in age group $g = 4$. For this group of agents, the value of a location-sector ℓj resides not only on the flow utility and option value that ℓj provides for them, but also on the opportunities it provides for their offspring. Specifically, $V_{\ell j\, t}^{4\, s}$ reflects that parents make an investment in the education of their children. This investment i affects the probability $p^H = p_{\ell t}^H(i)$ that their children become high-skill agents. The mapping of investment i to p^H is controlled by the function $p_{\ell t}^H(i) = 1 - \exp\{-\lambda_{0\ell\, t}\, i^{\lambda_{1\ell\, t}}\}$, with location-specific parameters $\lambda_{0\ell\, t}$ and $\lambda_{1\ell\, t}$, which aim to capture the differences in access to education between rural and urban areas, and how these may have changed over time. Broadly speaking, $\lambda_{0\ell\, t} \geq 0$ controls the average probability of becoming high-skill in location ℓ, while $\lambda_{1\ell\, t} \in [0, 1]$ affects the differences in p^H across different agents within location ℓ. Adults' choice of location-sector also factors in that their offspring will start youth in the location they choose, which is relevant in the presence of spatial frictions. Then, the value of location-sector ℓj for an adult agent of skill s at time t is given by

$$\begin{aligned} V_{\ell j\, t}^{g\, s} = \max_{i} \Bigg\{ & \mathcal{V}(w_{\ell j\, t}^{s} - i, P_{\ell a\, t}, P_{\ell n\, t}) \;+\; \beta\, \psi_{\ell j\, t+1}^{g+1\, s} \\ & + \beta\Big(p_{\ell t}^H(i)\, \psi_{\ell\, t+1}^{y\, H} \;+\; \big(1 - p_{\ell t}^H(i)\big)\; \psi_{\ell\, t+1}^{y\, L}\Big)\Bigg\} \\ & \text{s.t.}\quad p_{\ell t}^H(i) = 1 - \exp\{-\lambda_{0\ell\, t}\, i^{\lambda_{1\ell\, t}}\} \end{aligned} \tag{10}$$

where $\psi_{\ell j\, t+1}^{g+1\, s}$ is the individual continuation value of the adult agent, given by (8), and $\psi_{\ell\, t+1}^{y\, s}$ is the continuation value of her offspring, defined as $\psi^{s\,y}_{\ell\,t+1} \equiv \mathbb{E}\left[\max_{\ell' j'}\left\{V^{3\,s}_{\ell' j'\,t+1} - \mu_{\ell\,\ell'} + \epsilon_{\ell' j'\,t+1}\right\}\right]$.[11,12] The solution to the investment problem for an adult of skill s in location-sector ℓj at time t satisfies the FOC

$$\frac{\partial \mathcal{V}(w^s_{\ell j\,t} - i, P_{\ell a\,t}, P_{\ell n\,t})}{\partial i} = \beta\,\frac{\partial p^H_{\ell\,t}(i)}{\partial i}\,\left(\psi^{y\,H}_{\ell\,t+1} - \psi^{y\,L}_{\ell\,t+1}\right) \quad \forall \ell j,\, s,\, t, \tag{11}$$

which simply equalizes the marginal cost of investing in child's education (in terms of individual indirect utility), to the expected returns of this investment, as captured by the difference in the expected continuation values of high- and low-skill young agents.

Once we have expressed how the value functions associated to each location-sector vary by age, we can set up the discrete-choice problem that agents face when choosing where to live and work. The location-sector chosen by an agent of skill s that just became age g in location-sector ℓj at time t solves

$$\max_{\ell' j'}\left\{V^{g\,s}_{\ell' j'\,t} - \mu_{\ell j\,\ell' j'} + \epsilon_{\ell' j'\,t}\right\} \quad \forall \ell j,\, s,\, g,\, t. \tag{12}$$

Using again the properties of the Gumbel distribution of the shocks $\{\epsilon_{\ell' j'\,t}\}$, the solution to this problem implies that the share of skill s age g individuals that move from location-sector ℓj to location-sector $\ell' j'$ as they turn age $g+1$ is

$$\rho^{g+1\,s}_{\ell j\,\ell' j'\,t} = \frac{\exp\left(V^{g+1\,s}_{\ell' j'\,t} - \mu_{\ell j\,\ell' j'}\right)^{1/\kappa}}{\sum_m \sum_k \exp\left(V^{g+1\,s}_{mk\,t} - \mu_{\ell j\,mk}\right)^{1/\kappa}}\,. \tag{13}$$

The problem for agents that just became young is analogous to (12), with the only difference that they only pay switching costs if they move to a different location, as they are not working in any sector yet. Therefore, the share of agents that just became young and move from location ℓ to location-sector $\ell' j'$ is given by

$$\rho^{y\,s}_{\ell\,\ell' j'\,t} = \frac{\exp\left(V^{y\,s}_{\ell' j'\,t} - \mu_{\ell\,\ell'}\right)^{1/\kappa}}{\sum_m \sum_k \exp\left(V^{y\,s}_{mk\,t} - \mu_{\ell\,m}\right)^{1/\kappa}}\,, \tag{14}$$

where y corresponds to age group $g = 3$.

Labor supply. Once we have characterized the solution to the location-sector choice problem for each age group, we can compute the skill-s labor supply in each location-sector $\ell' j'$. This is given

[11] In an abuse of notation, I use letter y to emphasize that adult agents care about the value of their offspring as *young*, yet note that $\psi^{y\,s}_{\ell\,t+1} = \psi^{s\,3}_{\ell\,t+1}$.

[12] It is important to note that young agents only pay switching costs if they decide to change location upon entering the labor market, as they are not working in a sector yet. This is reflected in their switching costs μ, which only carry subindex $\ell\ell'$, and not jj'.

by the total mass of agents of skill s in each age group g that choose to work in $\ell' j'$ at time t

$$L^{s\mathcal{S}}_{\ell' j'\, t} = \underbrace{\sum_{\ell} \rho^{y\, s}_{\ell\, \ell' j'\, t} L^{c\, s}_{\ell j\, t-1}}_{\substack{\text{skill-}s\text{ children who become} \\ \text{young and choose } \ell' j'}} + \underbrace{\sum_{g \neq y} \sum_{\ell} \sum_{j} \rho^{g\, s}_{\ell j\, \ell' j'\, t} L^{g-1\, s}_{\ell j\, t-1}}_{\substack{\text{rest of skill-}s\text{ agents that} \\ \text{turn age } g \text{ and choose } \ell' j'}} \tag{15}$$

where $L^{c\,s}_{\ell j\, t-1}$ and $L^{g-1\, s}_{\ell j\, t-1}$ are, respectively, the stock of skill-s children and of agents of age group $g-1$ in location-sector ℓj at time $t-1$.

4.2 Production and trade

The (non-tradable) sector j final good consumed by region ℓ workers comes from the CES aggregation of (tradable) intermediate varieties $q_{r\ell}(x)$ available in that location. Within each sector j of location ℓ, varieties are produced with a technology that combines high- and low-skill labor

$$y_{\ell j}(x) = A_{\ell j\, t}(x) \left(\omega_j^{H\, 1/\sigma} L^H_{\ell j}(x)^{\frac{\sigma-1}{\sigma}} + \omega_j^{L\, 1/\sigma} L^L_{\ell j}(x)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{16}$$

where σ is the elasticity of substitution between high- and low-skilled labor, ω^s_j is a parameter controlling the skill-s intensity of each sector, and $A_{\ell j\, t}(x)$ denotes the productivity of region ℓ in the production of variety x of sector j in period t. Following Eaton and Kortum (2002), productivity $A_{\ell j\ t}(x)$ is a random variable drawn from an independent location- and sector-specific Fréchet distribution with c.d.f. $F_{\ell j}(A) = \exp\{-T_{\ell j\, t} A^{-\theta_j}\}$. The shape parameter θ_j is sector-specific and common across locations, and governs the (inverse of) dispersion of productivity in the production of sector j varieties. The scale parameter $T_{\ell j\, t}$ is location- and sector-specific and controls the average level of regional efficiency in the production of sector j varieties in period t. Regional trade is subject to iceberg transport costs. In particular, $\tau_{\ell \ell' j} \geq 1$ units of sector j varieties must be shipped from location ℓ to location ℓ' such that one unit arrives to ℓ'. As goods markets are perfectly competitive, cost minimization by firms implies that the price of variety x in sector j that is offered by region ℓ producers to region ℓ' consumers is $p_{\ell\ell' j}(x) = \frac{c_{\ell j\, t}}{A_{\ell j\, t}(x)} \tau_{\ell \ell' j}$ where

$$c_{\ell j\, t} \equiv \left(\omega^H_j w^{H\, 1-\sigma}_{\ell j\, t} + \omega^L_j w^{L\, 1-\sigma}_{\ell j\, t} \right)^{\frac{1}{1-\sigma}}$$

is the unit cost of an input bundle. Consumers in location ℓ' only purchase variety x from the location that can provide at the lowest price, which means that $p_{\ell' j\, t}(x) = \min_{\ell \in \{r,u\}} p_{\ell \ell' j\, t}(x)$. Using the the properties of the Fréchet distribution (see Eaton and Kortum, 2002), this implies that the price $P_{\ell j}$ of the sector j composite good (the price index of sector j varieties) in region ℓ at time t is given by

$$P_{\ell j\, t} = \gamma_j \left[\sum_{\ell'} \left(c_{\ell' j\, t} \tau_{\ell' \ell j} \right)^{-\theta_j} T_{\ell' j\, t} \right]^{-1/\theta_j} \tag{17}$$

where $\gamma_j = \Gamma\left(\frac{\theta_j+1-\eta}{\theta_j}\right)^{1/(1-\eta)}$, and $\Gamma(.)$ is the gamma function. It can be shown that the share of region ℓ' sector j expenditure that is spent in region ℓ varieties is given by

$$\pi_{\ell\ell' j\, t} = \frac{\left(c_{\ell j\, t}\tau_{\ell\ell' j}\right)^{-\theta_j} T_{\ell j\, t}}{\sum_n \left(c_{nj\, t}\tau_{n\ell' j}\right)^{-\theta_j} T_{nj\, t}}\,. \tag{18}$$

Hence, region ℓ''s expenditure in sector j varieties produced by region ℓ at time t is higher if region ℓ has a low unit costs of production $c_{\ell j\, t}$, low trade costs $\tau_{\ell\ell' j}$ or higher productivity $T_{\ell j\, t}$.

4.3 Equilibrium

First, I state the market clearing conditions that must hold in equilibrium for every location-sector ℓj and every period t. Then, I provide formal definitions of a static equilibrium, a sequential competitive equilibrium, and a Steady State equilibrium of the economy.

4.3.1 Market clearing

Every period, goods markets clearing in each location-sector implies

$$P_{\ell j\, t}Y_{\ell j\, t} = \sum_{\ell'} \pi_{\ell\ell' j\, t}X_{\ell' j\, t} \quad \forall\, \ell j,\, t \tag{19}$$

where $P_{\ell j\, t}Y_{\ell j\, t}$ is the total value of production in location-sector ℓj, and $\sum_{\ell'} \pi_{\ell\ell' j\, t}X_{\ell' j\, t}$ is the total expenditure in varieties produced in ℓj. Note that $X_{\ell' j\, t}$ is the aggregate expenditure of region ℓ' consumers in sector j at time t, which can be expressed as

$$X_{\ell' j\, t} = \int \varphi^s_{\ell' j\, t} w^s_{\ell' j\, t} dw^s_{\ell' j} = \phi \bar{w}_{\ell'\, t} L_{\ell'\, t} + \nu\left(\frac{1}{P^{\phi}_{\ell a\, t}P^{1-\phi}_{\ell n\, t}}\right)^{-\eta} \sum_g \sum_{s=H,L} \sum_j \left(w^s_{\ell' j\, t}\right)^{1-\eta} L^{g\, s}_{\ell' j\, t}$$

for $j =$ agriculture and similarly for non-agriculture, and where $\bar{w}_{\ell\, t}L_{\ell'\, t}$ are total labor payments in region ℓ at time t.

Similarly, labor market clearing for each skill in each location-sector implies

$$L^{s\mathcal{S}}_{\ell j\, t} = L^{s\mathcal{D}}_{\ell j\, t} \forall\, s\, \ell j,\, t \tag{20}$$

where labor supply $L^{s\mathcal{S}}_{\ell j\, t}$ is given by equation (15) and labor demand $L^{s\mathcal{D}}_{\ell j\, t}$ is implied by the goods market clearing condition in equation (19), as perfect competition and constant returns mean that total sales $P_{\ell j\, t}Y_{\ell j\, t}$ in location-sector ℓj equal total labor payments $\sum_{s=H,L} w^s_{\ell j\, t}L^s_{\ell j\, t}$, which in turn implies

$$L^{s\mathcal{D}}_{\ell jt} = \frac{1}{w^s_{\ell jt}}\xi^s_{\ell jt}\sum_{\ell'} \pi_{\ell\ell' jt}X_{\ell' jt}$$

where $\xi^s_{\ell jt}$ is the share of skill s in total labor payments[13]

$$\xi^s_{\ell jt} = \frac{w^s_{\ell j\,t} L^s_{\ell j\,t}}{w^H_{\ell j\,t} L^H_{\ell j\,t} + w^L_{\ell j\,t} L^L_{\ell j\,t}} = \frac{\omega^s_j w^{s\,1-\sigma}_{\ell j\,t}}{\omega^H_j w^{H\,1-\sigma}_{\ell j\,t} + \omega^L_j w^{L\,1-\sigma}_{\ell j\,t}}\,.$$

4.3.2 Definitions

For the purpose of formally defining the equilibrium, I call $\Theta_t \equiv \left\{\lambda_{0\ell\,t}, \lambda_{1\ell\,t}, \mu_{\ell j\,\ell' j'}, \tau_{\ell\ell' j}, T_{\ell jt}\right\}$ the set of constant and time-varying fundamentals that characterize the economy at time t.

Definition 1. Given fundamentals Θ_t and a distribution of workers of each age-skill group across location-sectors $\left\{L^{g\,s}_{\ell j\,t}\right\}^{s=H,L;g=y,d,m,o}_{\ell=r,u;j=a,n}$, a *static equilibrium* consists of wages for each skill in each location-sector $\left\{w^s_{\ell j\,t}\right\}_{\ell j,s}$ such that goods markets clear in each location-sector (so equation (19) holds), and labor markets clear for each skill in each location-sector (so equation (20) holds).

Note that, in a static equilibrium, for given allocation of workers across location-sectors (so for given labor supply), wages are pinned down by the downward sloping labor demand, which depends on goods prices $P_{\ell j\,t}$ and trade flows $\pi_{\ell j\,\ell' j'\,t}$ across location-sectors, which can be both expressed as a function of wages and fundamentals.

Definition 2. Given an initial distribution of workers of each age-skill group across location-sectors $\left\{L^{g\,s}_{\ell j\,0}\right\}^{s=H,L;g=y,d,m,o}_{\ell=r,u;j=a,n}$ and a sequence of fundamentals $\{\Theta_t\}_t$, a *sequential competitive equilibrium* consists of sequences of wages and employment allocations for each skill in each location-sector $\left\{w^s_{\ell jt}, L^s_{\ell jt}\right\}_{\ell j,s,t}$; a sequence of educational investments $\left\{i^s_{\ell j\,t}\right\}_{\ell j,s,t}$ made by adult agents ($g = 4$) of each skill in each location-sector; and sequences of value functions for each age-skill group in each location-sector $\left\{V^{g\,s}_{\ell jt}\right\}_{\ell j,g,s,t}$ such that, for all time periods, workers solve their dynamic location-sector choice problem (so equations (7), (10), and (11) hold), and the static equilibrium conditions are satisfied.

Note that, in a sequential competitive equilibrium, labor supply is the result of the dynamic location-sector choice problem solved by workers, which depends on the full sequence of (possibly time-changing) fundamentals $\{\Theta_t\}_t$.

Definition 3. A *Steady State equilibrium* is a sequential competitive equilibrium in which fundamentals $\{\Theta_t\}_t$, wages and employment allocations for each skill in each location-sector $\left\{w^s_{\ell jt}, L^s_{\ell jt}\right\}_{\ell j,s,t}$; educational investments $\left\{i^s_{\ell j\,t}\right\}_{\ell j,s,t}$ made by adult agents of each skill in each location-sector; and

[13] Note that while we can differentiate labor supply from young and old generations, we cannot do the same for labor demand, as young and old of a given skill are perfect substitutes in production.

value functions for each age-skill group in each location-sector $\left\{V_{\ell jt}^{g\,s}\right\}_{\ell j,g,s,t}$ are constant.

4.4 Discussion

In a Steady State equilibrium, $\Theta_t = \bar{\Theta}$ and does not change, the economy does not grow and employment allocations are constant over time. Net employment flows across location-sectors are zero, and hence there is no structural change nor urbanization. In the transitional dynamics towards a Steady State, Θ_t can change and hence there can be growth and employment reallocation across locations and sectors.[14] In particular, the model can generate structural change due to symmetric and asymmetric productivity growth across sectors due to the standard income and price effects. Moreover, if the urban location has a comparative advantage in the production of non-agriculture goods, these changes in sectoral productivities may as well generate urbanization. Finally, structural change may accelerate if becoming a high-skill agent becomes easier over time as productivity grows, provided that non-agricultural is more skill intensive than agriculture, a mechanism first highlighted by Caselli and Coleman (2001).

In the transition to a Steady State equilibrium, the model can also generate cohort effects in structural change out of agriculture. A variety of mechanisms are at play. First, note that young workers do not pay sectoral switching costs upon entering the labor market, and that these costs can trap some older workers in agriculture after the value of working in non-agriculture increases. Second, younger cohorts may have higher human capital than older cohorts, which is more in demand in non-agriculture. The model can endogenously generate the increase in human capital over time if the value of being a high-skill agent or the probability of becoming a high-skill agent (for a given level of investment) increase over time. Finally, rural-urban migration may also generate cohort effects by increasing the stock of agents raised in urban areas, where access to education and the demand for non-agriculture are higher. The quantitative importance of each mechanism is assessed in the following Sections.

5 Calibration

This section devises a strategy to calibrate the parameters of the model presented in the previous section. Before that, I discuss some adjustments that allow me to square the timing of the model with the frequency of the data, as well as to have a mapping of several objects in the data to objects in the model.

[14] To solve for the equilibrium allocations during this transition, one needs to assume that at some point $t = T$, the economy reaches a Steady State equilibrium in which $\Theta_t = \bar{\Theta}$ for $t \geq T$. Then, one can use the Steady State value function $V_{\ell jT}^{g\,s}$ to solve for the full transition given that at $t = T - 1$ we know that $V_{\ell jt+1}^{g\,s} = V_{\ell jT}^{g\,s}$.

5.1 Timing and Measurement Adjustments

Timing adjustments. I have data approximately every five years since 1983, see Section 2, while a model period is ten years. Due to this discrepancy between the length of a model period and the frequency of the data, I have to give up on targeting some years of data in the calibration of the model. In particular, for the calibration, I take the observed employment allocation of each age-skill group across location-sectors in 1983 as initial condition, and aim to match data in 1993, 2003, and 2013, for which I construct moments accordingly.

Measurement adjustments. The first adjustment necessary to map the data to model-objects regards the age of agents. Recall that, in the model, agents live for six 10-year periods. Hence, in the micro-data, I classify individuals in age groups based on ten-year age thresholds. At any given point in time, I consider agents up to age 20 as children, agents between ages 21 and 30 as young, agents between ages 31 and 40 as adults, and so on. Next, to compute the transition probabilities across location-sectors $\rho^{g\,s}_{\ell j\,\ell' j'}$ for each age-skill group $g\,s$, I use the location-sector information of individuals that are observed in subsequent years, this is, both in 1983 and 1993, both in 1993 and 2003, or both in 2003 and 2013. The last adjustment concerns the skill group of agents. Given the education system in Indonesia[15] and the average years of education in the data —around 7—, it is reasonable to consider any individual with more than 8 years of completed education as high-skill.

5.2 Calibration strategy

To present the calibration of model parameters, I classify them in three groups. First, I discuss the strategy to calibrate the parameters governing consumer demand. Second, I focus on the parameters directly affecting workers' choice of location-sector (so the labor supply). And third, I turn to the calibration of those related to the production-side of the model economy. In all three groups of parameters, there are some that I calibrate externally, either directly from the data or borrowing them from the literature, and some that I calibrate internally to match a set of moments in the data. Importantly, for the internal calibration I assume that the economy is experiencing a transition towards a Steady State equilibrium that is reached several periods after 2013 —the last date at which I observe data—, and from an initial condition given by the observed allocation of workers across location-sectors in 1983, which is not necessarily an equilibrium. I describe the details of this procedure towards the end of the Section.

[15] Primary education in Indonesia lasts for 6 years. Secondary education is divided in two levels: junior secondary (grades 7-9) and senior secondary (grades 10-12). Before 1994, Indonesians were only required to complete primary school. From 1994 to 2015, compulsory education was raised to 9 years (primary plus junior highschool). From 2015, completion of 12 years of education is compulsory.

5.2.1 Consumption demand parameters

Parameter ϕ (the agricultural expenditure share as real income tends to infinity) and parameter η (the income elasticity of sectoral demands) can be directly estimated from the micro-data on household consumption expenditures. In particular, following Fan et al. (2021), I can transform equation (6) to obtain an expression in which the agricultural expenditure share minus parameter ϕ are a log-linear function of income and relative prices:

$$\log\left(\varphi^s_{\ell j\, t} - \phi\right) = \underbrace{\iota \log \nu}_{\alpha_0} - \eta \log w^s_{\ell j\, t} + \underbrace{\iota \log\left(\frac{P_{\ell a\, t}}{P_{\ell n\, t}}\right) + \eta \log\left(P^{\phi}_{\ell a\, t} P^{1-\phi}_{\ell n\, t}\right)}_{\alpha_{\ell t}}.$$

Then, η can be estimated by linear regression for different values of ϕ using household-level data on the share of expenditure on food to proxy for $\varphi^s_{\ell j}$ and on total expenditure to proxy for $w^s_{\ell j}$, adding location-time fixed effects $\alpha_{\ell t}$ to control for differences in prices across locations and over time. The identification of η comes from the cross-sectional covariation of food shares and total expenditure, while ϕ corresponds to the food share for high-income households. Results for different values of ϕ are presented in table E.1. First, we can see that η ranges between 0.302 and 0.420, depending on the value chosen for ϕ. This is a remarkably similar range of values to what Fan et al. (2021) find for Indian households (between 0.319 and 0.378). Second, also in line with these authors, I find that the share of variation in expenditure shares explained by the variation in income slightly falls as I increase ϕ. This does not come as a surprise, as the expenditure share on food is close to log-linear in household expenditure, see Figure E.1. Therefore, I keep $\eta = 0.302$ and set $\phi = 0$.

I calibrate the remaining demand parameters ι (which controls the elasticity of substitution across sectoral goods) and ν (which controls the strength of non-unitary income and price elasticities) internally to match the joint evolution of aggregate sectoral productivity and aggregate sectoral employment in Indonesia between 1983 and 2013, where I retrieve aggregate sectoral productivity from the Economic Transformation Database (ETD) of the GGDC.

5.2.2 Labor supply parameters

Switching costs and switching elasticity. In line with the evidence of section 3.1 showing that workers who leave agriculture experience larger income gains if they also leave rural locations, I assume that switching sector and switching location entail different costs. In particular, I impose that the cost of switching location-sector ℓj for $\ell' j'$ has the parametric form $\mu_{\ell j\, \ell' j'} = \mu^{\text{loc}}_{\ell\, \ell'} + \mu^{\text{sec}}_{jj'}$. This means that there is a differentiated cost for workers who change only location ($\mu^{\text{loc}}_{\ell\, \ell'}$), only sector ($\mu^{\text{sec}}_{jj'}$), or both ($\mu^{\text{loc}}_{\ell\, \ell'} + \mu^{\text{sec}}_{jj'}$). Moreover, as I want the model to be flexible enough to match the main patterns of reallocation across locations-sectors, I allow $\mu^{\text{loc}}_{\ell\, \ell'\, t}$ and $\mu^{\text{sec}}_{jj'\, t}$ to vary by bilateral pairs. I calibrate switching costs internally. Hence, the main moments in the data that will discipline the values of switching costs are the bilateral flows across location-sectors over time $\rho_{\ell j\, \ell' j'\, t}$. Note that these bilateral flows are the average of age-skill group bilateral flows $\rho^{g\,s}_{\ell j\,\ell' j'\,t}$, which are the objects delivered by the model. Then, the labor supply of each age-skill group (and thus the agricultural share of each cohort) is a non-targeted moment that the model may deliver due to the different incentives and constraints faced by agents at different ages.

Regarding the estimation of the switching elasticity κ, one can use the switching probabilities $\rho^{g\,s}_{\ell j\,\ell' j'\,t}$ combined with Bellman equations to derive an expressing relating flows across location-sectors for a given age-skill group to indirect utility differences and future migration flows across location-sectors. For the group of workers aged g at time t, we have

$$\log\left(\frac{\rho^{g\,s}_{\ell j\,\ell' j'\,t}}{\rho^{g\,s}_{\ell j\,\ell j\,t}}\right) = \frac{1}{\kappa}\left(\mathcal{V}(w^s_{\ell' j'\,t}, P_{\ell' a\,t}, P_{\ell' n\,t}) - \mathcal{V}(w^s_{\ell j\,t}, P_{\ell a\,t}, P_{\ell n\,t})\right) + \beta\log\left(\frac{\rho^{g+1\,s}_{\ell j\,\ell' j'\,t+1}}{\rho^{g+1\,s}_{\ell' j\,\ell' j\,t+1}}\right) + \tilde{C} \quad (21)$$

where $\tilde{C}$ is a constant. Intuitively, flows between location-sector pairs depend on the differences in the indirect utility they provide and on the option value they offer, which is captured by the migration flows next period. As I do not observe local prices $P_{\ell j\,t}$ nor I do know all the parameters of the indirect utility function, equation (21) cannot be directly used to estimate κ. Alternatively, I propose the following auxiliary model, which in essence captures the same idea as equation (21), but is amenable to direct estimation in the data

$$\log\left(\frac{\rho^{gs}_{\ell j\,\ell' j'\,t}}{\rho^{gs}_{\ell j\,\ell j\,t}}\right) = \alpha_g + \alpha_t + \alpha_s + \gamma\log\left(\frac{w^s_{\ell' j'\,t}}{w^s_{\ell j\,t}}\right) + u_t\,, \quad (22)$$

where α_g, α_t, and α_s are age, time and skill fixed effects, and u_t an estimation error term. I estimate γ in equation (22) in the data by PPML regression.[16] Then, in the internal calibration of the model, I run the same regression and target the value of γ estimated in the data, thus following a standard indirect inference procedure (Smith, 2016).

Education probability function. In the model, the function $p^H_{\ell t}(i) = 1 - \exp\{-\lambda_{0\ell\,t}\, i^{\lambda_{1\ell\,t}}\}$ determines the share of children that become skill-s youngs in a given location at $t+1$, before they choose where to live and work. It also controls how, within location, differences in investment across agents translate into differences in the skill composition of their offspring. Therefore, to calibrate $\lambda_{0\ell\,t}$ and $\lambda_{1\ell\,t}$, I target both the share of high-skill young workers in each location and the difference between high- and low-skill parents in the probability that their children are high-skill within location. In particular, I target these quantities in 2003 and 2013, which in the model correspond to investments made by parents in 1993 and 2003. Hence, I allow $\lambda_{0\ell\,t}$ and $\lambda_{1\ell\,t}$ to take a different value in 1993 and 2003, but assume that they remain constant (and equal to their 2003 values) afterwards.[17]

[16] Unlike OLS, the PPML estimator of gravity equations like (22) accommodates zeros in the outcome variable and is immune to heteroskedasticity in the error term, see Silva and Tenreyro (2006).

[17] This assumption responds to the fact that, in order to assign values for $\lambda_{0\ell\,t}$ and $\lambda_{1\ell\,t}$ in 2013, I would need to observe the share of high-skill young workers in 2023, which is not the case, as my last data period is 2013.

Time discounting. I set the parameter discounting future periods β to 0.65, corresponding to a period length of 10 years and an interest rate of approximately 4.5 percent.

5.2.3 Production parameters

Productivities, trade costs and trade elasticity. Location-sector productivity $T_{\ell j\,t}$ is allowed to change during the transition to the Steady State. This means that, for each of the three periods in which I am matching data (1993, 2003 and 2013), I need to internally calibrate $2 \times 2 = 4$ parameters. In terms of identification, the distribution of employment across location-sectors pins down relative productivities, while growth in sectoral value added per worker pins down changes in sectoral productivities over time. Bilateral trade costs $\tau_{\ell\ell' j}$ are specific to each pair of locations $\ell\ell'$ and each sector j. Absent data on trade flows, the differences between sectoral employment and expenditure shares at the local level are informative about their magnitude.[18] For simplicity, trade frictions are kept constant over time, yet they are allowed to be asymmetric for each bilateral pair $\ell\ell'$. Finally, I set the trade elasticity θ_j to 4 in both sectors, a standard value in the literature.

CES skill intensities and elasticity of substitution between skills. The production of intermediate varieties combines high- and low-skill labor with elasticity of substitution σ and intensities ω_j^s that differ by sector j. I set $\sigma = 2.5$, a central value in the literature (Acemoglu and Autor, 2011). Given σ, I use the ratio of firm's FOC for labor of each skill in each location-sector sector

$$\frac{L^H_{\ell j\,t}}{L^L_{\ell j\,t}} = \frac{\omega_j^H}{1-\omega_j^H}\left(\frac{w^H_{\ell j\,t}}{w^L_{\ell j\,t}}\right)^{-\sigma} \quad \forall \ell j,\, t \tag{23}$$

to retrieve a value for ω_j^H, where I impose that $\omega_j^L = 1-\omega_j^H$. In particular, I use data on $L^H_{\ell j\,t}/L^L_{\ell j\,t}$ and $w^H_{\ell j\,t}/w^L_{\ell j\,t}$ and take the average of (23) across locations and over time for each sector. This procedure delivers $\omega_a^H = 0.39$ and $\omega_n^H = 0.77$, which means that, for the same wages, high-skill labor is use more intensively in non-agriculture than in agriculture. Then, to be consistent with this imputation, I target the average $L^H_{\ell j\,t}/L^L_{\ell j\,t}$ across locations and time for each sector, such that on average (23) is satisfied.

5.2.4 Internal calibration by SMM

SMM Algorithm. Taking as initial condition the employment allocations of each age-skill group across location-sectors ℓj in 1983 $\left\{L^{g\,s}_{\ell j\,1983}\right\}^{s=H,L;g=y,d,m,o}_{\ell=r,u;j=a,n}$, and the calibrated values for η, ϕ, β, θ_j, σ, and ω_j^s, the algorithm searches for values of

[18] If, for instance, the urban location has a high expenditure share relative to its employment share in agriculture, the model will predict that it is a net importer of agricultural goods, which will be rationalized by a low cost of sending agricultural goods from rural to urban areas, see for instance Gervais and Jensen (2019).

(a) preference parameters ι and ν,

(b) bilateral switching costs across locations $\mu^{\text{loc}}_{\ell\,\ell'\,t}$ (2 parameters) and sectors $\mu^{\text{sec}}_{j\,j'\,t}$ (2 parameters),

(c) switching elasticity κ,

(d) location-specific education probability function parameters $\lambda_{0\ell\,t}$ and $\lambda_{1\ell\,t}$ ($2{\times}2 = 4$ parameters both in 1993 and in 2003),

(e) location-sector productivity parameters $T_{\ell j\,t}$ ($2 \times 2 = 4$ parameters per time period),

(f) bilateral trade costs in each sector $\tau_{\ell\ell' j}$ ($2 \times 2 = 4$ parameters),

to minimize the distance between a set of model moments and their data counterparts in 1993, 2003, and 2013 during a transition to a Steady State equilibrium.

The set targeted moments in the data consists of switching flows across locations and sectors $\rho_{\ell j\,\ell' j'\,t}$ in 1993, 2003, and 2013 ($(4-1) \times 4 = 12$ moments per time period), the share of high-skill young agents and the difference in the share of children that are high-skill between high- and low-skill parents for each location ($2 \times 2 = 4$ moments in both 2003 and 2013), the average wage gap across locations and across sectors (2 moments), the average high-skill share of employment in each sector (2 moments), and growth in value added per worker in each sector in Indonesia in the periods 1993-2003, and 2003-2013 ($2 \times 2 = 4$ moments). These are a total of 30 parameters (as I normalize $T_{ra\,1993} = 1$) to match 52 moments. Importantly, I assume that all parameters except productivities $T_{\ell j\,t}$ remain unchanged after 2013. For productivities, I allow them to grow for five more periods after 2013, which means that I allow them to grow until the year 2063 ($2013 + 5 \times 10$). In particular, I compute the growth in sectoral value-added per worker in Indonesia between 2003 and 2013 using the ETD, and apply this growth rate to the values of $T^{1/\theta}_{\ell j\,t}$ for the next two periods (so in 2023 and 2033). Then, I assume that productivity grows at 2% per year in both sectors for three extra periods (so in 2043, 2053 and 2063). After that, productivity settles and the economy reaches a Steady State (which may take a few more periods, as reallocation across locations and sectors is costly).

A couple of aspects of the internal calibration are worth highlighting. First, by targeting the data on switching flows across locations-sectors ℓj for a given initial distribution of employment, I am implicitly targeting employment in each location-sector next period $L_{\ell j\,t}$, which is equal to the product of initial employment stocks and switching flows across ℓj, see equation (15). Second, the fact that I am matching data during the transition to a Steady State that I am free to choose deserves further discussion. In my model, labor reallocation across sector and locations and growth are only possible during the transition to a Steady State, which is the reason why I target the data of 1993, 2003 and 2013 (a period in which Indonesia experienced growth and employment reallocation) during a transition. A natural question is what to do with the values of parameters after 2013, my last year of data. The only time-changing parameters in the model are those controlling the high-skill probability function $p^H_{\ell\,t}(i)$ and productivities. As explained above, the parameters of $p^H_{\ell\,t}(i)$

are assumed to remain constant since 2003.[19] Regarding productivity $T_{\ell jt}$, it seems reasonable to assume that Indonesia is growing (and will grow) at a similar rate than it did in the recent past. Hence, I assume that for the next twenty years (two model periods) Indonesia grows at the same rate as in the last ten years observed. However, as the country gets richer, we may expect that it converges to the growth rate of richer countries. This is why I assume that, twenty years after 2013, Indonesia starts growing at a 2% yearly rate. Finally, note that the economy converges to a Steady State (recall, a situation with no growth) at least five periods after 2013, so far enough to barely affect the model moments computed for 2013.

5.3 Calibration results

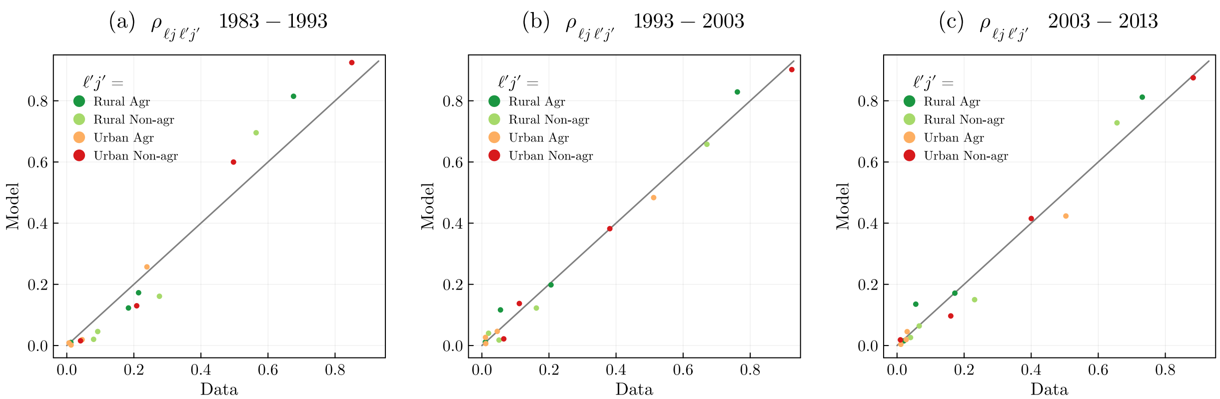
This section presents the results of the model calibration outlined above. In the main text, I present the fit of the model to the targeted moments and the estimated values for the main parameters of interest. I present the remaining calibrated parameters and model fit in Appendix E.2, which also reports the values for the parameters calibrated directly from the data or borrowed from the literature. In general, the model provides a good fit to all the targeted moments.

Starting with the flows across location-sectors in every period, we can see in Figure 4 that the model does a good job at matching the patterns of gross employment reallocation, particularly in 2003 and 2013. This is then reflected in the fact that it reproduces very well the evolution of employment shares across location-sectors observed in the data, see Figure 5. The calibrated values for $T^{1/\theta}_{\ell j t}$, $\mu^{\text{loc}}_{\ell\ell'}$, and $\mu^{\text{sec}}_{jj'}$ behind these moments are presented in Figure 6, while the calibrated values bilateral trade costs $\tau_{\ell\ell' j}$ are reported in Appendix E.2. The calibrated model recovers a general increase in productivities, faster in agriculture than in non-agriculture, which matches well the increase in sectoral value added per worker in the data, see Table E.3. This pattern of productivity growth leads to income growth and changes in relative prices between 1993 and 2013 that generate structural change out of agriculture and, given that the urban location has a comparative advantage in non-agriculture (note in that urban non-agriculture is more productive than rural non-agriculture), also urbanization. To match these reallocation patterns across sectors and locations, the model asks for higher costs of moving to non-agriculture and to urban than to agriculture and to rural, see panel (b) of Figure 6. This is reasonable, as non-agriculture and urban carry a wage premium that the model is able to match well, see Table E.3. Finally, the SMM calibration recovers a higher value of bilateral trade costs in non-agriculture than in agriculture, consistent with the notion that non-agriculture contains non-tradable services.

Next, consider the moments on the skill distribution of young agents in each location, which in the model are controlled by function $p^H_{\ell t}(i)$. I report the estimates for $\lambda_{0\ell t}$ and $\lambda_{1\ell t}$ for each location in 1993 and 2003 as well as the model fit in Table 2. The model reproduces well the targeted moments for the share of high-skill young agents in each location, falling short of producing

[19] To allow function $p^H_{\ell t}(i)$ to change after 2003, one would need to take a stand on how the supply of educational facilities evolves in both rural and urban areas from 2013 onwards.

Figure 4: Switching flows across location-sectors



Notes: this figure plots the switching flows across location-sectors in the calibrated model and in the data, for each period. Colors correspond to the location-sector of destination.

enough high-skill youngs in rural areas in 2013, and very well the moments for the differences in the probability of having a high-skill child between high- and low-skill parents within location. The function $p^H_{\ell t}(i)$ associated to the calibrated values for $\lambda_{0\ell t}$ and $\lambda_{1\ell t}$ is presented in Figure 7, where the dots over each line corresponds to the investment choices made by agents in the model. Consistent with the notion that access to higher education is larger in urban than in rural areas, the model recovers a $p^H_{\ell t}(i)$ function that, specially for high levels of investment, assigns a higher probability of becoming high-skill to children educated in urban areas than to children educated in rural areas. Moreover, for both locations, the model infers a higher probability of becoming high-skill for (almost) any level of investment in 2013 than in 2003. This implies that the costs of acquiring education fall over time.

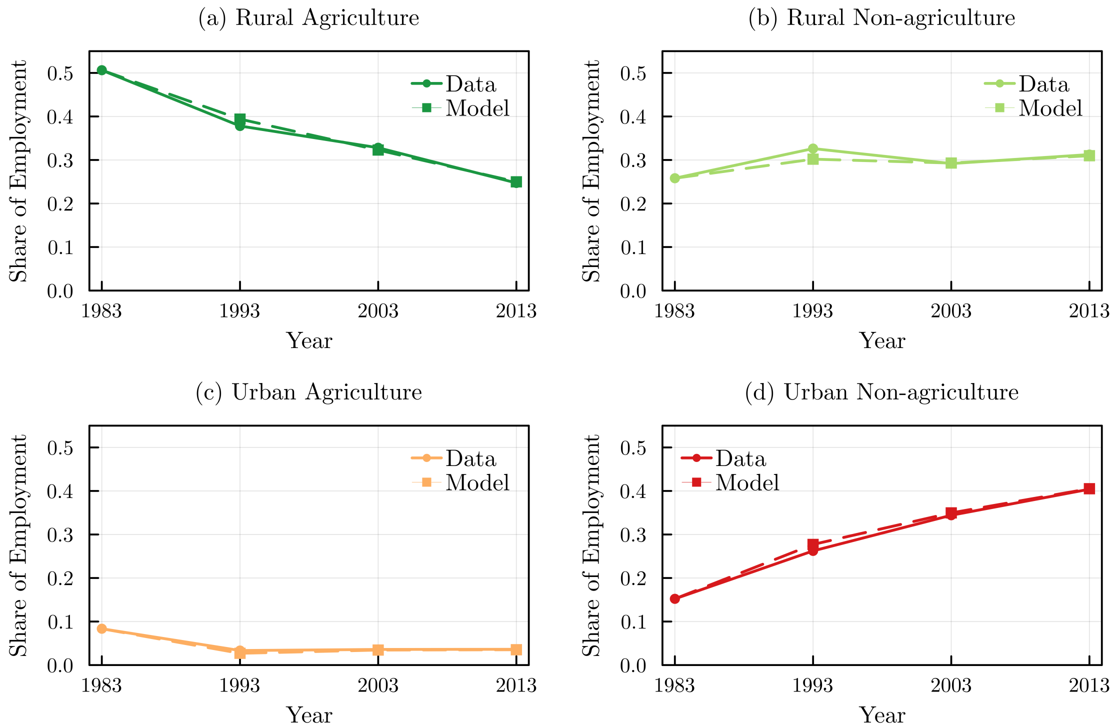
Non-targeted moments. Recall that the calibration exercise does not target employment allocations in each location-sector for each age group. Hence, cohort effects in structural change are the result of how incentives and constraints built-in in the model vary by age. The fit to this non-targeted moments is presented in Figure 8. Remarkably, the model is able to reproduce the

Table 2: Calibrated parameters probability of becoming high-skill function

Education probability function parameters									
Par	Description	Value		Target		Model	Data	Model	Data
		Rural	Urban		Year	Rural		Urban	
$\lambda_{0\ell\,1993}$	Scale of $p^H_\ell(i)$	0.77	0.83	Sh of high-skill	2003	0.36	0.37	0.63	0.61
$\lambda_{0\ell\,2003}$		0.80	2.04	young agents in ℓ	2013	0.38	0.52	0.71	0.68
$\lambda_{1\ell\,1993}$	Curvature of $p^H_\ell(i)$	0.37	1.25	Diff. in $p^H_\ell(i)$ children of	2003	0.11	0.11	0.22	0.22
$\lambda_{1\ell\,2003}$		0.27	0.77	high- and low-skill parents	2013	0.05	0.05	0.10	0.09

Notes: this table shows the calibrated values for the parameters of the function that determines the probability of becoming high-skill agent for each location in 1993 and 2003, as well as the model fit to the targeted moments.

Figure 5: Evolution of employment shares across location-sectors



Notes: this figure plots the evolution of employment shares across location-sectors in the calibrated model (dashed lines with squared markers) and in the data (solid lines with circled markers).

cohort effect in structural change observed in the data.

6 Quantitative results

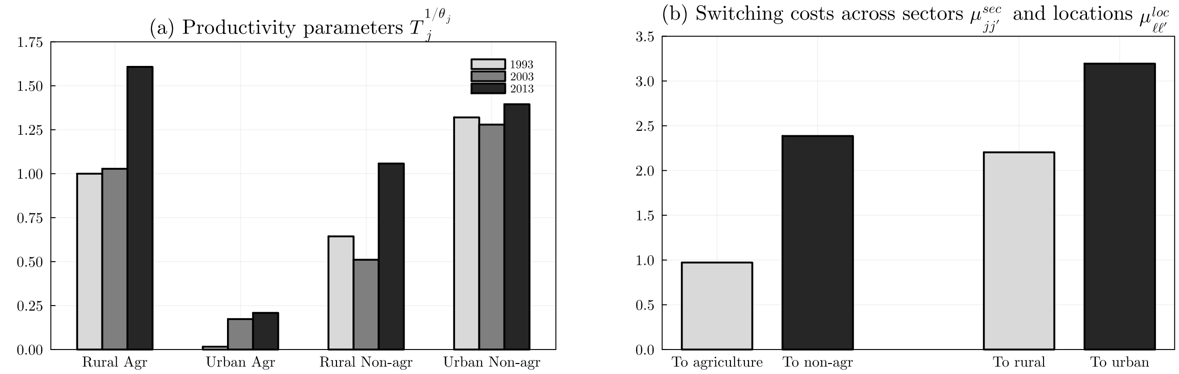
This section presents the results of number of counterfactual exercises. First, I explore the impact of rural-urban migration on structural change by studying an economy in which migration is not possible. Second, I explore several economies to understand the drivers of cohort effects in structural change out of agriculture. Finally, I assess the importance of intergenerational incentives for rural-urban migration on several aggregate outcomes.

6.1 Rural-urban migration and structural change

To understand the effect of rural-urban migration on structural change, I analyze an economy in which migration is not possible.[20] In this economy, the only ways to reallocate labor out of agriculture are switches of workers to the local non-agricultural sector and the entry of young local generations into non-agriculture. The results in terms of the evolution of the agricultural share

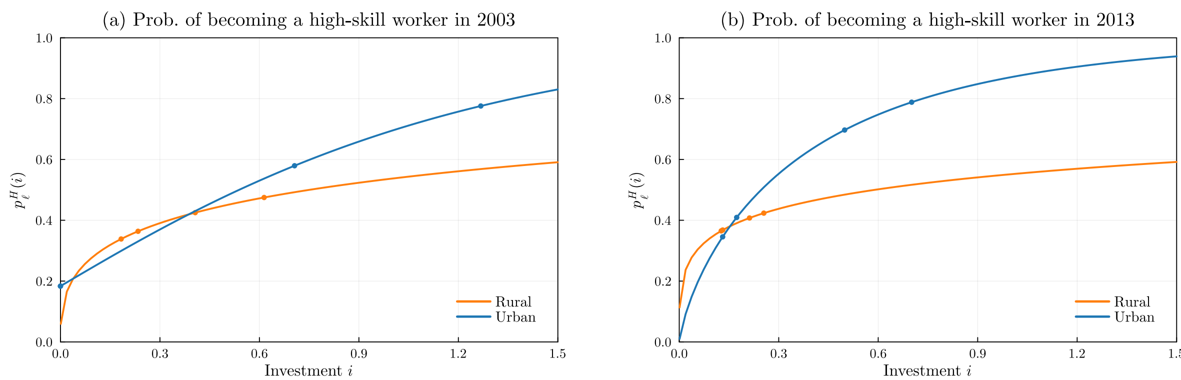
[20]In particular, I set the bilateral switching costs across locations $\mu^{\text{loc}}_{\ell\ell'}$ to infinity.

Figure 6: Evolution of location-sector productivities



Notes: in panel (a), the evolution of location-sector productivities $T_{\ell j\, t}^{1/\theta_j}$ in the calibrated model. In panel (b), the values of switching costs across locations $\mu^{\text{loc}}_{\ell\,\ell'}$ and across sectors $\mu^{\text{sec}}_{j\,j'}$.

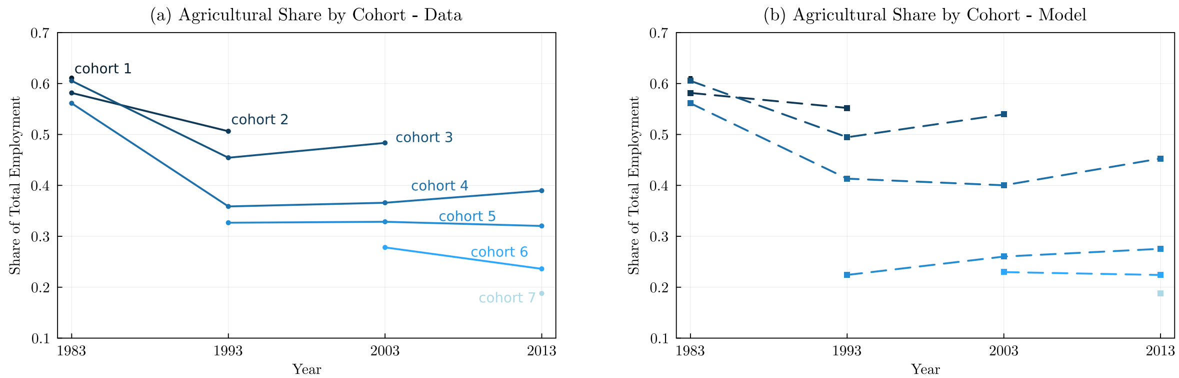
Figure 7: Probability of becoming high-skill young



Notes: this figure plots the probability of becoming a high-skill young worker as a function of the level of investment in education for each location in 2003 and 2013. The dots over each line correspond to the investment choices made by agents in the model.

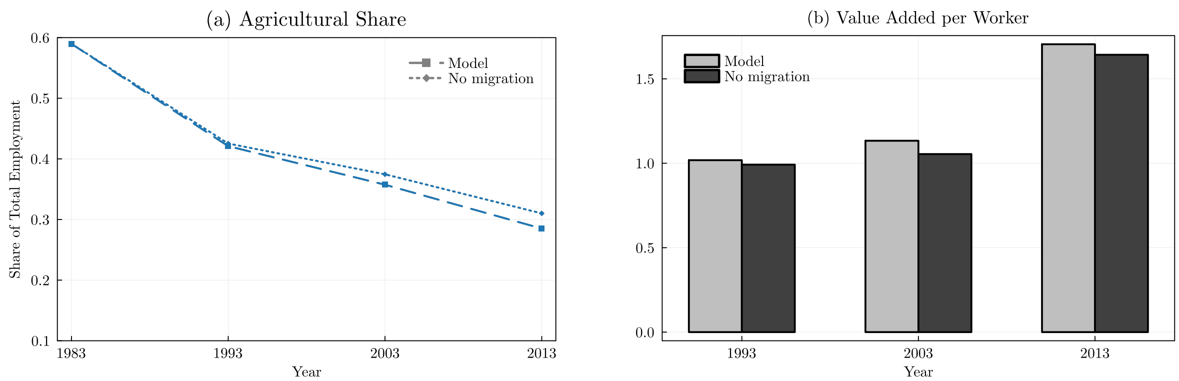
are presented in Figure 9 panel (a). Remarkably, the fall in the agricultural share between 1983 and 2013 in the no migration economy is just 2 percentage points smaller than in the benchmark economy. This happens as a result of the growth in the rural non-agricultural sector, which is able to absorb most of the workers released by the rural agricultural sector due to its faster productivity growth. In particular, in the no migration economy new cohorts of rural workers join non-agriculture in a very similar proportion than in the benchmark economy. However, as they cannot migrate, they join non-agriculture in rural areas. Trade is relevant for this result. As income grows and the relative price of agriculture falls (driven by asymmetric increases in sectoral productivity), the demand for non-agricultural goods increases. In the benchmark economy, this increase in demand is satisfied by the growth of the urban non-agricultural sector. In the no migration economy, urban non-agriculture cannot grow as much. Hence, the increase in demand has to be satisfied by the growth of the rural non-agricultural sector which, compared to the benchmark, exports more goods to urban areas and, more importantly, caters a larger local demand.

FIGURE 8: Cohort-level agricultural share



Notes: this figure plots the cohort-level agricultural share in the data (panel a) and in the calibrated model (panel b).

FIGURE 9: Agricultural share of employment and value added per worker - model *vs* no migration



Notes: this figure plots the evolution of the agricultural share of employment (panel a) and value added per worker (panel b) in the benchmark economy (solid lines and light grey bars) and in the economy in which migration is not possible (dashed lines and dark grey bars).

While the growth in rural non-agriculture is able to compensate for the lack of growth in urban non-agriculture in terms of employment, this is not the case in terms of value added per worker, which is consistently lower in the counterfactual than in the benchmark economy, see Figure 9 panel (b). The reason is that the non-agricultural sector in rural areas is less productive than the non-agricultural sector in urban areas, see panel (a) of Figure 6. This goes in line with the differences in the sectoral composition of non-agriculture in rural and urban areas observed in the data, see Figure B.2 in the Appendix. The lack of migration does not prevent the economy from reallocating workers out of agriculture, but it does prevent the economy from reallocating workers to the location with a comparative advantage in non-agriculture, which is detrimental for aggregate productivity. In this way, rural-urban migration emerges not as an essential force for structural transformation, but as an important force for economic growth.

6.2 Understanding cohort effects in structural change

The calibrated model is able to reproduce the differences in the agricultural share of different cohorts, see Figure 8. This differences may be driven by different forces present in the model. First, younger cohorts do not pay sectoral switching costs, which may prevent older cohorts —incumbent workers— to leave agriculture after changes in the relative value of working in non-agriculture, a mechanism highlighted by Hobijn et al. (2018). Second, younger cohorts may have higher human capital than older cohorts, which is more in demand in the non-agricultural sector, a mechanism highlighted by Porzio et al. (2022). Finally, younger cohorts may be disproportionately born and raised in urban areas compared to older cohorts, where the demand for non-agriculture is higher and the access to education is better. This Section explores several counterfactual economies that help us understand the relevance of these mechanisms. Table 3 presents the results of these exercises in terms of the change in the agricultural share, providing various statistics that summarize the part of this change accounted for by between-cohort reallocation.

First, focusing on Column (2), we can see that, absent switching costs across sectors, the between-cohort component of a within-between decomposition of the fall in the agricultural share accounts for only 5% of total reallocation, compared to 68% in the benchmark economy. When there is free mobility across sectors, all cohorts react almost symmetrically to changes in the value of working in non-agriculture, despite their differences in human capital. This is also reflected in the difference in the agricultural share between the youngest and oldest cohort, which on average is only 5 p.p., compared to 29 p.p. in the benchmark economy. The emergence of sectoral switching costs as a first order determinant of the cohort effects points to the importance of identifying the specific friction that these costs represent.

Second, I explore an economy in which both sectors are equally high-skill intensive, such that differences across cohorts in the share of agents that are high-skill are not a relevant determinant of their different sectoral employment shares. In particular, I set $\omega_a^H = \omega_n^H = 0.5$ in the CES production function, such that the demand for high-skill labor is not biased to non-agriculture. Compared to the benchmark economy, the between-cohort share of the total fall in the agricultural share is smaller (55% *vs* 68%), but still large, see Column (3). The differences in the demand for skills across sectors is hence not a first order determinant of the cohort-level differences in sectoral employment shares. In a similar spirit, I explore the role of falling costs of acquiring education, which drive part of the increase in educational attainment across cohorts over time. Specifically, I study an economy in which $\lambda_{0\ell t}$ and $\lambda_{1\ell t}$ are kept constant at their 1993 values. In this experiment, summarized in Column (4), the between-cohort share of aggregate reallocation is almost unaffected and the change in the aggregate agricultural share is the same as in the benchmark economy, in line with the previous counterfactual exercise. While costs of acquiring education fall, this has a limited effect on the increase over time in the share of agents becoming high-skill, and hence on other aggregate outcomes.

Table 3: Drivers of cohort effects in structural change

	Drivers of cohort effects				
	Benchmark (1)	No sec costs (2)	$\omega_a^H = \omega_n^H$ (3)	Const $p_\ell^H(i)$ (4)	No migration (5)
Δ Agricultural sh (1983-2013)	-0.30	-0.26	-0.31	-0.30	-0.28
Between cohort %	68	5	55	67	68
Avg diff agr sh old-young	0.29	0.05	0.24	0.28	0.26

Notes: this table presents the results of several counterfactual economies in terms of the change in the agricultural share and the part of that change accounted for by between-cohort reallocation. In Column (1), I report the results of the benchmark economy. In Column (2), of an economy in which sectoral switching costs are set to zero. In Column (3), of an economy in which both sectors are equally high-skill intensive. In Column (4), of an economy that keeps constant $\lambda_{0\ell\, t}$ and $\lambda_{0\ell\, t}$ at their 1993 values. In Column (5), I report the results of the economy in which migration is not possible.

Finally, in Column (5), I report the results regarding cohort effects of the economy in which migration is not possible. In this counterfactual, the between cohort component of the fall in the agricultural share remains as in the benchmark, and the average difference in the agriculture share of the youngest and oldest agents falls by 3 p.p.. As discussed in the previous Section, the growth in the rural non-agricultural sector is mainly fuelled by younger cohorts who cannot migrate to urban areas. This creates differences in the agricultural share between young and old (incumbent) workers that are almost as large as in the benchmark economy, and thus limits the role of rural-urban migration for the cohort effects in structural change.

6.3 The role of intergenerational returns to rural-urban migration

In the data, I showed that offspring of rural-urban migrants (compared to offspring of stayers) have a lower probability of working in agriculture, higher educational attainment, and higher earnings (see Section 3.3). In the model, this intergenerational returns to rural-urban migration are internalized by agents when making their location decisions, see equation (10). In particular, agents may migrate *because of* their offspring due to the higher access to education provided by urban areas or due to their higher future non-agricultural demand (which, in the presence of spatial frictions, is easier to access from urban areas). This Section explores the role of these two intergenerational incentives for migration, as well as an economy in which parents are not altruistic and hence do not internalize the impact of their decisions on their offspring. The results of these counterfactual economies are presented in Table 4.

First, we can see in Column (2) that, in an economy in which access to education is equalized across locations,[21] the increase in urbanization is 4 p.p. lower than in the benchmark economy. Due to the increase in the share of young agents becoming high-skill workers, this economy has also a lower agricultural share and higher value-added per capita by 2013. Next, consider an economy in which young agents can freely choose their location-sector of work upon entering the labor market,

[21] In particular, I equalize the function $p^H_{\ell\, t}(i)$ in rural areas to the one of urban areas, for every period.

Table 4: Intergenerational incentives for rural-urban migration

INTERGENERATIONAL MOTIVES FOR RURAL-URBAN MIGRATION				
	Benchmark (1)	Same $p_\ell^H(i)\,\forall\ell$ (2)	Free mob young (3)	No altru (4)
Δ VA per worker (1993-2013)	0.52	0.55	0.53	0.26
VA per worker 2013	1.00	1.04	1.01	0.77
Δ Agricultural sh (1983-2013)	-0.30	-0.30	-0.32	-0.27
Agricultural sh youngs	0.21	0.20	0.19	0.26
Δ Urban sh (1983-2013)	0.20	0.15	0.28	0.13
Urban sh youngs	0.45	0.40	0.60	0.37

Notes: this table presents the results of several counterfactual economies in terms of the change in value added per worker, agricultural share and urban share of employment. In Column (1), I report the results of the benchmark economy. In Column (2), of an economy in which access to education is equalized across locations. In Column (3), of an economy in which young agents can freely choose their location-sector of work upon entering the labor market. In Column (4), of an economy in which parents are not altruistic and hence do not internalize the impact of their decisions on their offspring.

regardless of where they acquired education.[22] In this economy, parents do not have an incentive to migrate in order to facilitate their children to work in non-agricultural in the future. While this keeps some agents in rural areas, the fact that youngs can freely migrate dominates this effect and the urban share of employment increases by 8 p.p. more by 2013 than in the benchmark economy. Free mobility by young agents also lowers the agricultural share, which falls by 2 p.p. more. Finally, consider an economy in which parents are not altruistic and hence do not internalize the impact of their decisions on their offspring. Interestingly, in this economy the increase in the share of employment in the urban location is 7 p.p. lower than in the benchmark. Moreover, the agricultural share decreases by 3 p.p. less, and the economy grows by 26 log points less, half as much as in the calibrated economy. This is a relevant result that speaks to the importance of intergenerational incentives for rural-urban migration and economic growth.

7 Conclusion

In this paper, I have revisited the relationship between structural change out of agriculture and urbanization, two fundamental processes in the economic development of countries. Drawing on a panel dataset of Indonesian workers, I have shown that, at the worker-level, reallocation out of agriculture tends to happen within rural areas. Yet, at the aggregate level, reallocation out of agriculture is mainly driven by younger cohorts working in non-agriculture upon joining the labor market. This points to the importance of initial conditions and age-related frictions in the process of structural change. In particular, I have explored the role of location as initial condition, and shown that workers raised in urban areas have a larger probability of working in non-agriculture than workers raised in rural, part of it as a result of being more educated.

To understand the driving forces of these employment reallocation patterns, I have developed a quantitative overlapping generations model with two locations, two sectors, and differential local

[22]In particular, I set $\mu_{\ell j\,\ell' j'} = 0\,\forall \ell j$ for young agents.

access to education in which switching location or sector is costly. Using the model, I have shown that the lack of rural-urban migration does not prevent the economy from reallocating workers out of agriculture, but it does prevent the economy from reallocating workers to the location with a comparative advantage in non-agriculture, which is detrimental for aggregate productivity. Moreover, I have uncovered a large role of sectoral switching costs for cohort effects in structural change. This paper is silent on the specific friction that these costs represent, which is a relevant question left for future research.

Finally, I have shown that intergenerational incentives for rural-urban migration are an important driver of urbanization and hence can have a large impact of economic development. This result points at the importance of considering intergenerational linkages in the design of development policies.

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Appendix A: Data Appendix

This section defines the main variables used in the body of the paper, discussing the different adjustments I apply to the raw information collected by the survey.

Employment. I classify as employed workers all individuals that meet any of the following criteria: (i) their primary activity during the past week was working or helping to earn income; (ii) had worked for pay for at least 1 hour during the past week ; (iii) had a job or business, but were temporarily not working during the past week; (iv) had worked at a family-owned (farm or non-farm) business during the past week. This relatively broad definition of employment is meant to capture the heterogenous forms of employment that are prevalent in a developing country setting like Indonesia.

Sector of work. I use the information on the sector of work of individuals at the 1-digit level provided by the IFLS, which follows the International Standard Industrial Classification (ISIC) of economic activities. I classify as agricultural workers those individuals working in the sector "Agriculture, forestry and fishing" and as non-agricultural workers those working in the remaining sectors. The classification made by the IFLS team is based on the reply to the question "What does you company do/make?". Importantly, I assign the sector of work based on the industry of the main job of the individual. In my sample, 17% of all workers hold two jobs and 6% of workers are employed simultaneously in agriculture and non-agriculture. Among all agricultural workers, 8% also work in non-agriculture. Among all non-agricultural workers, 4% also work in agriculture.

Rural/Urban status. I use the information on the rural/urban status provided by the IFLS, which is based on the classification as rural or urban of the place where individuals live determined by the Indonesian Central Bureau of Statics (BPS). The BPS uses a functional definition based on several indicators, such as population density or the availability of infrastructure, in order to classify a place as rural or urban. The IFLS documentation does not provide further details on the criteria used by the BPS, yet it does provide information on the total population. Table A.1 gives number for the median and average population in rural and urban communities surveyed in the IFLS. We can see that urban communities tend to be 3-4 times more populous than the rural communities. Moreover, the numbers for urban communities refer to the population of the district that is surveyed within a city, see Witoelar and Sikoki (2016). Hence, the actual population of urban areas in which the households of my analysis live is larger.

Earnings. I compute annual earnings for each individual pooling wage income, net business income and transfers. To compute income at the household-level, my preferred measure to estimate the returns to transitions reported in Section 3.1, I aggregate annual earnings for all household

Table A.1: Population of rural and urban communities in the IFLS

	1997		2000		2007		2014	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Median	3,313	9,125	3,459	9,916	3,763	9,613	4,022	9,667
Mean	4,258	16,514	4,311	13,951	4,739	15,569	5,540	16,767

Notes: this table presents the median and average population of rural and urban communities surveyed in the IFLS. The data on population is not available in 1993.

members and divide this quantity by the number of individuals in the household. I deflate all earnings by the Indonesian CPI for the corresponding year.

Appendix B: Empirical Appendix

This section presents additional evidence on the patterns of employment reallocation across locations and sectors in Indonesia between 1983 and 2014.

B.1 Worker-level reallocations across locations and sectors

The transition probabilities in matrix (1) are computed by aggregating all observed transitions between location-sectors for the period 1983-2014. The counts that give rise to those probabilities are the following:

$$
\begin{array}{c|c}
 & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\
\begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} &
\left[\begin{array}{cc|cc}
14,343 & 3,453 & 381 & 514 \\
3,171 & 9,523 & 214 & 1,991 \\
\hline
278 & 117 & 1,448 & 1,194 \\
184 & 848 & 898 & 18,308
\end{array}\right]
\end{array}
\tag{B.1}
$$

The standard error associated to each probability in matrix (1) (computed by bootstrapping the initial sample 500 times) are presented in Matrix (B.2) below. As we can see, the standard errors are small, which is not surprising given the relatively large number of transition.

$$
\begin{array}{c|c}
 & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\
\begin{array}{c} RA \\ \\ RN \\ \\ \hline UA \\ \\ UN \\ \\ \end{array} &
\left[\begin{array}{cc|cc}
76.7 & 18.5 & 2.0 & 2.8 \\
(3.9) & (2.0) & (0.6) & (0.7) \\
21.3 & 63.9 & 1.4 & 13.4 \\
(2.1) & (3.6) & (0.6) & (1.7) \\
\hline
9.1 & 3.9 & 47.7 & 39.3 \\
(1.4) & (0.9) & (3.3) & (3.0) \\
0.9 & 4.2 & 4.4 & 90.5 \\
(0.4) & (0.9) & (0.9) & (4.1)
\end{array}\right]
\end{array}
\tag{B.2}
$$

Given that the number of years between each pair of waves of the survey changes over the sample period –ranging between 3 and 7 years–, matrix (1) might not be the most accurate description of worker-level transitions across location-sectors every 5 years. As an alternative, I compute a transition matrix for every pair of subsequent waves (1983-1988, 1988-1993, 1993-1997, etc.), and then take a weighted average of those transition matrices, with the weight given by the number of years between waves. In this case, each element of the matrix is the weighted average of the transition probabilities between any pair of subsequent waves. Importantly, the transition probabilities across location-sectors patterns are almost identical to those displayed in matrix (1).

$$\begin{array}{c|cc|cc|}
 & RA & RN & UA & UN \\
\hline
RA & 76.1 & 18.9 & 2.2 & 2.8 \\
RN & 22.6 & 61.9 & 1.6 & 13.9 \\
\hline
UA & 9.6 & 4.1 & 47.5 & 38.7 \\
UN & 1.0 & 4.3 & 5.2 & 89.5
\end{array} \tag{B.3}$$

Both matrix (1) and matrix (B.3) are averages over time of the five-year transition probabilities of the period 1983-2014. However, the structure of worker-level transitions may have changed over time, particularly in a period of large aggregate employment reallocation out of agriculture and towards urban areas. To see if this is the case, I split my sample in two subperiods (up to 1997 and from 1997) and compute transition probabilities for each of them. I report these transition matrices in (B.4) below. As we can see, the main patterns of how workers switch across sectors and locations are pretty stable over my sample period. Remarkably, the fact that most workers who leave the agricultural sector in rural areas switch to rural non-agriculture instead of migrating holds true for both subperiods. Moreover, we observe that the non-agricultural sector in both rural and urban areas becomes more persistent over time (the entry in the diagonal increases from 60.5% to 65.6% for RN and from 87.8% to 91.8% for UN), which is in line with the increasing importance of the non-agricultural sector for total employment.

(a) Up to 1997 (b) From 1997

$$\begin{array}{c|cc|cc|}
 & RA & RN & UA & UN \\
\hline
RA & 76.2 & 19.1 & 2.3 & 2.3 \\
RN & 24.8 & 60.5 & 1.7 & 12.9 \\
\hline
UA & 13.8 & 5.2 & 37.2 & 43.8 \\
UN & 1.0 & 5.5 & 5.8 & 87.8
\end{array}
\qquad
\begin{array}{c|cc|cc|}
 & RA & RN & UA & UN \\
\hline
RA & 77.1 & 18.0 & 1.9 & 3.0 \\
RN & 19.6 & 65.6 & 1.3 & 13.6 \\
\hline
UA & 4.8 & 2.6 & 57.6 & 35.0 \\
UN & 0.8 & 3.5 & 3.8 & 91.8
\end{array} \tag{B.4}$$

The previous transition matrices are computed using the full sample of individuals that are observed working for at least two periods, which includes workers of all ages above 15, and both males and females. If I restrict my sample to prime-age men (between 25 and 59) years old, I obtain very similar transition probabilities to those shown in matrix (1), see matrix (B.5).

$$\begin{array}{c|cc|cc|}
 & RA & RN & UA & UN \\
\hline
RA & 77.3 & 18.3 & 2.1 & 2.2 \\
RN & 22.3 & 62.6 & 1.6 & 13.5 \\
\hline
UA & 9.9 & 3.0 & 47.8 & 39.3 \\
UN & 0.9 & 4.0 & 4.9 & 90.2
\end{array} \tag{B.5}$$

Next, it is worth exploring how the transition probabilities across location-sector states vary by age and educational attainment, given their importance for location-sector allocations, which gets reflected in their role as state variables in the model. First, to explore heterogeneity by age, I split my sample into the three age-groups to which I later map my model to: *young* workers (between 15 and 29 years old), *adult* workers (between 30 and 44 years old), and *old* workers (older than 44). I present these matrices in (B.6). Looking at the diagonal elements in each matrix, we see that all location-sectors except RN are more persistent for workers as they age. Notably, the agricultural sector is much more persistent for older than for younger workers in both rural and urban locations, in line with the evidence presented in Figure 2. Second, to explore heterogeneity by education, I split my sample into *low-skill* workers (up to 6 years of formal education) and *high-skill* workers (more than 6 years of formal education), also consistently with the groups I map my model to. I present these matrices in (B.7), where we can see that the agricultural (non-agricultural) sector in both rural and urban is a more persistent state for *low-skill* (*high-skill*) workers.

$$\begin{array}{ccc}
\text{(a) } \textit{Young} \text{ workers} & \text{(b) } \textit{Adult} \text{ workers} & \text{(c) } \textit{Old} \text{ workers} \\
\begin{array}{cc} & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 66.0 & 25.8 & 1.6 & 6.6 \\ 18.8 & 64.6 & 1.0 & 15.6 \\ \hline 11.6 & 7.8 & 35.1 & 45.4 \\ 1.6 & 7.8 & 3.9 & 86.7 \end{array}\right] \end{array} &
\begin{array}{cc} & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 75.7 & 20.3 & 2.0 & 2.0 \\ 18.6 & 68.5 & 1.0 & 11.9 \\ \hline 8.8 & 2.9 & 46.2 & 42.1 \\ 0.6 & 3.7 & 3.7 & 92.0 \end{array}\right] \end{array} &
\begin{array}{cc} & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 83.0 & 13.4 & 2.1 & 1.5 \\ 30.1 & 57.6 & 2.4 & 9.9 \\ \hline 7.6 & 2.5 & 58.7 & 31.1 \\ 0.8 & 1.8 & 7.0 & 90.4 \end{array}\right] \end{array}
\end{array} \tag{B.6}$$

$$\begin{array}{cc}
\text{(a) } \textit{Low-skill} \text{ workers} & \text{(b) } \textit{High-skill} \text{ workers} \\
\begin{array}{cc} & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 79.2 & 17.0 & 1.8 & 2.0 \\ 27.7 & 61.9 & 1.5 & 8.9 \\ \hline 9.0 & 3.5 & 55.4 & 32.1 \\ 1.1 & 3.6 & 7.5 & 87.8 \end{array}\right] \end{array} &
\begin{array}{cc} & \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ \hline UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 67.6 & 23.9 & 2.8 & 5.7 \\ 12.7 & 66.6 & 1.4 & 19.3 \\ \hline 9.4 & 4.6 & 34.0 & 52.1 \\ 0.8 & 4.5 & 2.8 & 91.9 \end{array}\right] \end{array}
\end{array} \tag{B.7}$$

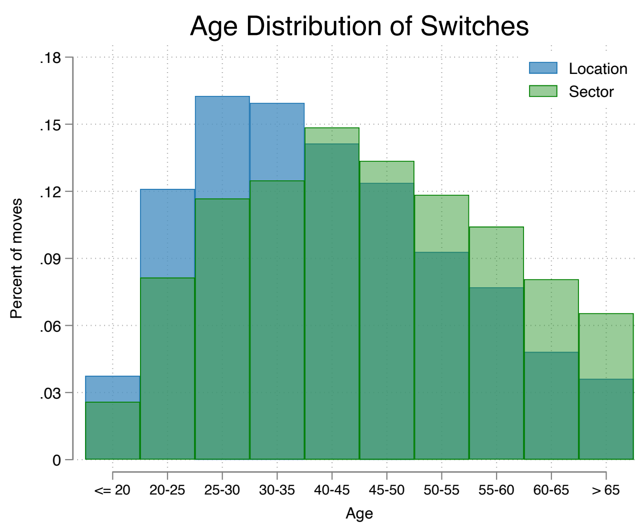
Finally, I explore the possible bias induced by transitions to non-employment or sample attrition. Note that, if a worker leaves a sector because of non-employment or not being interviewed in that wave, but comes back to the employment sample the period after, it will not show up in the transition matrices presented so far, as her employment spells are not consecutive. Moreover, if this type of events are correlated with the location-sector of work, they may bias the transition probabilities. I present a matrix with non-employment and moving out of the sample as additional states in (B.8).[23] The probability of making a transition to non-employment or to leave the sample

[23] I consider all periods of non-employment or attrition between the first and the last cross-section in which I observe an individual working, as well as the first period after the individual is last observed working. Hence, an individual that works in 1993, does not work in 1997, works again in 2000, but is not observed working again, will be in the sample that is used to construct matrix (B.8) in the years 1993, 1997, 2000 and 2007, but not in 2014. To avoid transitions to non-employment associated to retirement or movements out of the labor force, matrix (B.8) focuses on

next period is similar across location-sectors, see the fifth and sixth columns of (B.8), with slightly higher values for urban non-agriculture.

$$
\begin{array}{c|cc|cc|cc|}
 & RA & RN & UA & UN & ne & out \\
\hline
RA & 69.2 & 16.8 & 1.6 & 1.7 & 7.1 & 3.6 \\
RN & 18.5 & 59.6 & 1.0 & 10.8 & 6.1 & 4.0 \\
\hline
UA & 8.7 & 3.3 & 42.2 & 35.4 & 7.7 & 2.8 \\
UN & 0.6 & 3.2 & 3.5 & 78.5 & 9.4 & 4.7 \\
\hline
ne & 25.8 & 18.2 & 4.7 & 36.2 & 14.4 & 0.7 \\
out & 22.9 & 25.1 & 3.2 & 37.4 & 3.6 & 7.7
\end{array}
\tag{B.8}
$$

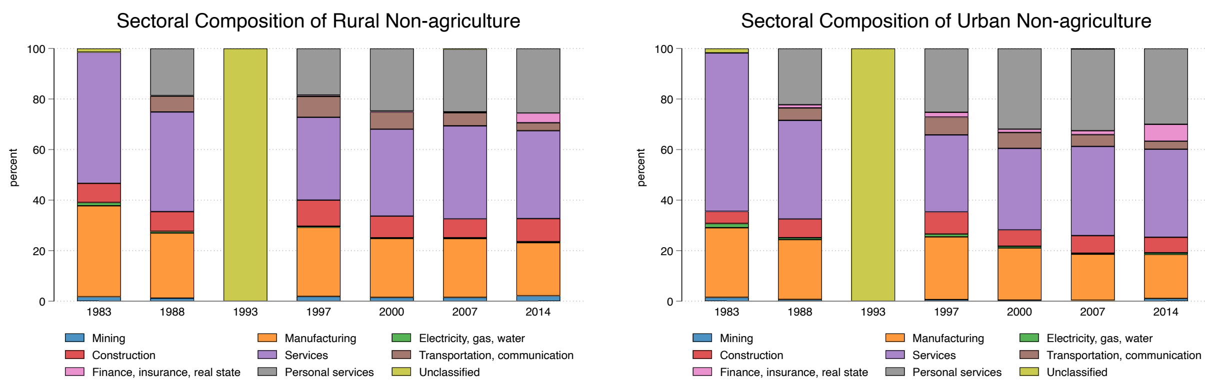
FIGURE B.1



Notes: age distribution of changes from agriculture to non-agriculture (green bars), and from rural to urban (blue bars). The age of the event is approximated as the average between worker's age the last period she is observed in agriculture (rural) and worker's age the first period she is observed in non-agriculture (urban).

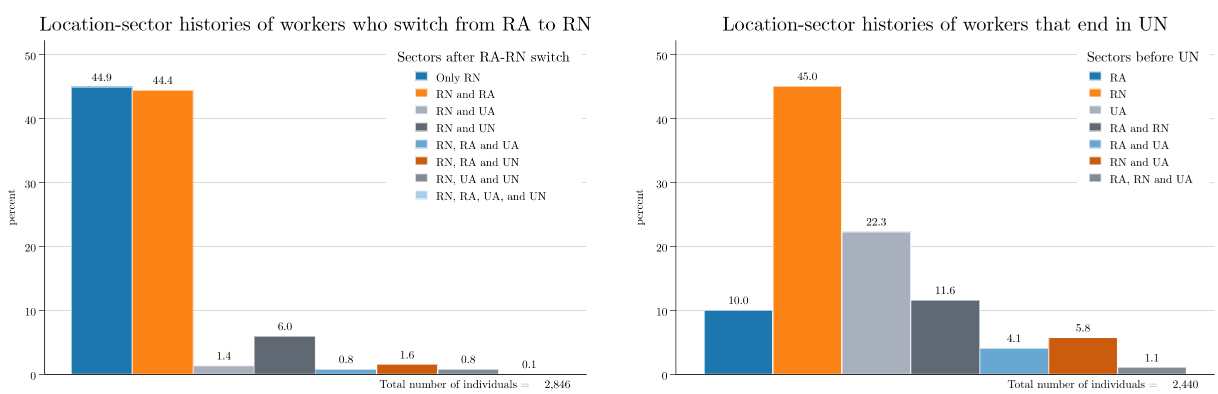
men age 25-59.

Figure B.2: Sectoral Composition of Rural Non-agriculture and Urban Non-agriculture



Notes: distribution of employment across sector within rural non-agriculture (panel a) and within urban non-agriculture (panel b). This within-sector partition is not available for 1993, and the "Personal services" category is included in into "Services" in 1983.

Figure B.3: Assessing the role of RN as an stepping stone for UN

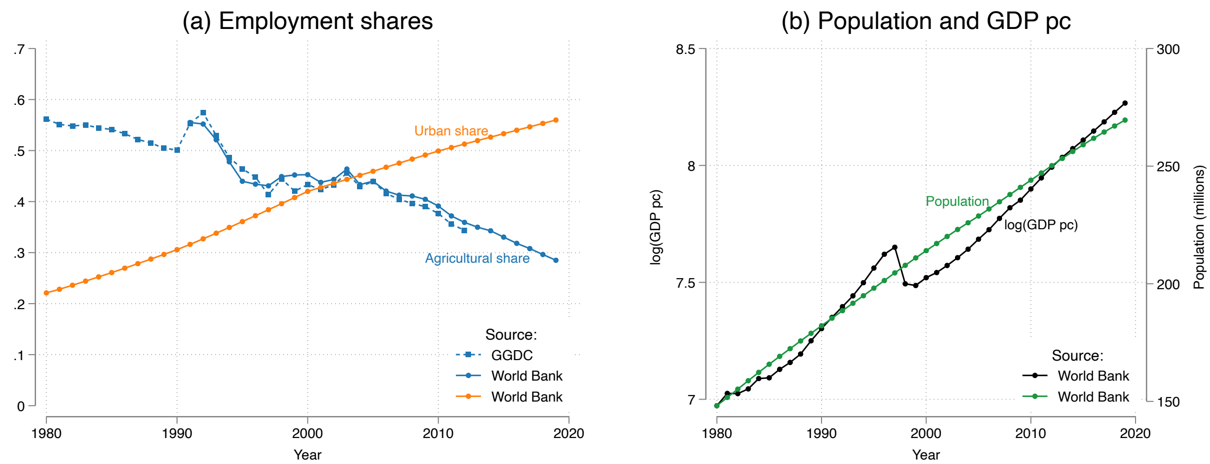


Notes: in panel (a), distribution of location-sector histories of workers that are ever observed switching from rural agriculture (RA) to rural non-agriculture (RN) —and are observed at least three times—. In panel (b), distribution of location-sector histories of workers that start working in location-sectors different than urban non-agriculture (UN) but end up working in UN —and are observed at least three times—.

Appendix C: Extra figures and tables

C.1 Aggregates [back]

FIGURE C.1: Main aggregates



Appendix D: Cohort effects in structural change out of agriculture

Following Porzio et al. (2022), we can decompose the fall in the agricultural share into year effects, which capture forces affecting the sectoral allocation of employment for individuals in all cohorts, and cohort effects, which capture cohort-specific factors affecting this allocation. Formally,

$$\underbrace{\log l_{A,t,c}}_{\text{AGR SHARE OF COHORT } c \text{ AT TIME } t} = \underbrace{\mathbb{Y}_t}_{\text{YEAR EFFECTS}} + \underbrace{\mathbb{C}_c}_{\text{COHORT EFFECTS}} + \varepsilon_{t,c}\,. \tag{D.1}$$

Then, we can compute which share of the annual rate of aggregate reallocation $\log g_{L_A,t} = \frac{1}{k_t} \log \frac{L_{A,t+k_t}}{L_{A,t}}$ is due to cohort *vs* year effects

$$\underbrace{\log g_{L_A,t}}_{\text{RATE OF LABOR REALLOCATION}} = \underbrace{\log \psi_t}_{\text{YEAR COMPONENT}} + \underbrace{\log \chi_t}_{\text{COHORT COMPONENT}}\,, \tag{D.2}$$

where $\log \psi_t = \frac{1}{k_t} (\mathbb{Y}_{t+k_t} - \mathbb{Y}_t)$ and $\log \chi_t \equiv \log g_{L_A,t} - \log \psi_t$. I run equation (D.1) using either all observations or excluding migrants, for several samples (employed and nonemployed individuals, employed and nonemployed males, employed individuals, employed males). Table D.1 reports the share of the average annual rate of reallocation accounted for by year effects in each case. Numbers in the first row show that, in general, year effects account only for 10-25% of aggregate reallocation.[24]

Table D.1: Year Effects and Rural-Urban Migration

Sample:	All		All males		Employed		Emp males	
	$\log g_{L_A}$	$\log \chi$	$\log g_{L_A}$	$\log \chi$	$\log g_{L_A}$	$\log \chi$	$\log g_{L_A}$	$\log \chi$
All observations	-2.04	91.1	-2.21	80.60	-2.49	72.05	-2.34	81.88

Notes: this table shows the average annual rate of reallocation out of agriculture $\log g_{L_A}$ and the share of it accounted for by cohort effects $\log \chi$ for different samples and groups. Samples: "All" refers to both employed and non-employed individuals between 25 and 64 years old; "All males" refers to employed and non-employed males aged 25-64; "Employed" and "Employed males" refer to all employed individuals and all employed males aged 25-64 respectively.

D.1 Cohort effects and initial urban share

Rural-urban migration can be a driver of the cohort effects behind structural change because the offspring of migrants join the labor force in urban areas, where non-agricultural labor demand is higher. One possibility to explore this hypothesis is to relate the size of the estimated cohort effects to the share of people in each cohort that enter the labor market in urban areas, controlling for cohort's level of schooling. Given that rural-urban migration may happen before joining (or in order to join) the labor force, we can use alternative measures to compute the *initial* urban share

[24] Porzio et al. (2022) find that the year effects account for 82% of the average rate of reallocation in Indonesia, similar to what I find when I use their sample restrictions, see Column "All Males" of Table D.1.

Table D.2: Cohort Effects, Education and Rural-Urban Migration

Sample:	All Males		
	Outcome Var: Cohort Effects $\mathbb{C}_c$		
	(1)	(2)	(3)
Cohort Education	-0.060***		-0.040***
	(0.009)		(0.011)
Cohort Urban Sh. Age 12		-0.991***	-0.718***
		(0.150)	(0.182)
N	265	265	265
R-squared	0.907	0.908	0.914

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of each cohort such as its urban share at birth or at age 12. Closely following Porzio et al. (2022) again, I run

$$\mathbb{C}_c = \beta_1 s_c + \beta_2 urb_c + \delta_1 (c - \bar{c}) + \delta_2 (c - \bar{c})^2 + \varepsilon_c, \tag{D.3}$$

where $\mathbb{C}_c$ is the cohort effect estimated in (D.1), s_c and urb_c denote cohort c average years of education and urban share respectively, and $\bar{c}$ indexes the first cohort observed. Hence $(c - \bar{c})$ leverages that cohorts are observed several times to control for time trends. Results are shown in Table D.2 for the sample including all men (i.e. both employed and non-employed) for the sake of comparability with Porzio et al. (2022). As we can see, cohort effects are negatively associated to cohort schooling (column 1), but also to its urban share at age 12 (column 2). More importantly, column (3) shows that when including cohort urban share at age 12, the effect of cohort schooling on the estimated cohort effects is smaller. For a given cohort, joining the labor force in an urban environment is associated to a lower agricultural share beyond cohort's educational attainment. As rural-urban migration increases the share of future workers who join the labor force in urban areas, it has an effect on the cohort effects driving structural change.

Appendix E: Quantitative Appendix

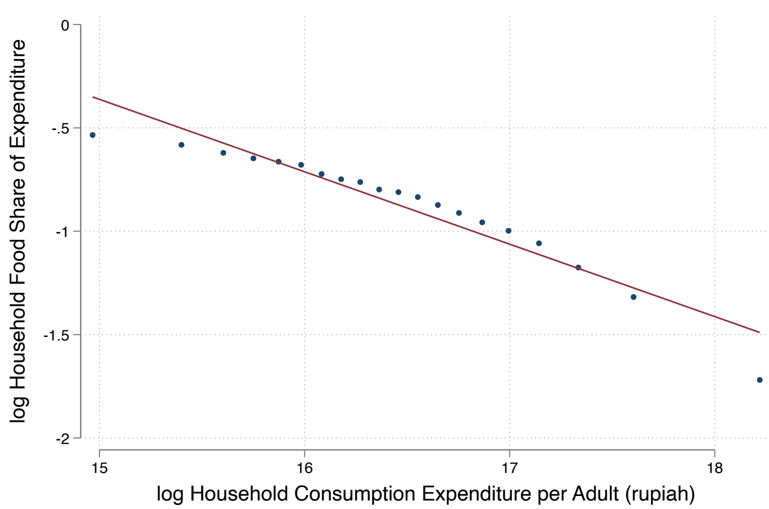
E.1 Income elasticity

TABLE E.1: Income Elasticity of Sectoral Demand

Dependent var:	$\log\left(\varphi^s_{\ell j} - \phi\right)$						
Value of ϕ	0.00	0.01	0.02	0.03	0.04	0.05	0.06
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log household expenditure per adult	-0.302***	-0.314***	-0.328***	-0.343***	-0.362***	-0.385***	-0.420***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
N	50,147	50,147	50,147	50,147	50,147	50,147	50,147
R-squared	0.43	0.42	0.42	0.42	0.42	0.41	0.39

Controls: district, sex, household share of elder memebers, household share of children members.
SEs clustered at the sampling unit level in parenthesis. $^{*}p < .1, ^{**}p < .05, ^{***}p < .01$

FIGURE E.1: Engel curve



E.2 Remaining parameters calibrated in the SMM

(a) Trade costs in agriculture $\tau_{\ell\ell' a}$ (b) Trade costs in non-agriculture $\tau_{\ell\ell' n}$

$$\begin{array}{c} \\ R \\ U \end{array} \begin{array}{c} \begin{array}{cc} R & U \end{array} \\ \begin{bmatrix} 1.00 & 1.16 \\ 1.46 & 1.00 \end{bmatrix} \end{array} \qquad \begin{array}{c} \\ R \\ U \end{array} \begin{array}{c} \begin{array}{cc} R & U \end{array} \\ \begin{bmatrix} 1.0 & 1.67 \\ 1.99 & 1.0 \end{bmatrix} \end{array} \tag{E.1}$$

Table E.2: Remaining calibrated parameters

SUMMARY OF CALIBRATED PARAMETERS						
Par	Description	Value	Method	Target/Source	Model	Data
ϕ	Asymptotic agr expenditure sh	0.0	Regression			
η	Income elasticity of demand	0.302	Regression			
ι	Elasticity of subs across goods	0.002	SMM			
ν	PIGL parameter	0.242	SMM			
κ	Inverse switching elasticity	1.10	SMM	γ in regression (22)	0.85	0.82
β	Discount factor	0.65	Standard	Model period of 10 years		
ω_a^H	High-skill CES sh agriculture	0.39	SMM and Eq (23)	High-skill sh of agr employment	0.17	0.12
ω_n^H	High-skill CES sh non-agr	0.77	SMM and Eq (23)	High-skill sh of non-agr employment	0.61	0.60
σ	Elasticity of subs across skills	2.5	Literature	Acemoglu and Autor (2011)		

Table E.3: Other targeted moments

OTHER MOMENTS TARGETED BY THE SMM ALGORITHM		
Target	Model	Data
Average wage gap across sectors	0.61	0.53
Average wage gap across locations	0.43	0.50
Growth in VA per worker agiculture 1993-2003	0.09	0.10
Growth in VA per worker agiculture 2003-2013	0.45	0.44
Growth in VA per worker non-agiculture 1993-2003	0.05	0.02
Growth in VA per worker non-agiculture 2003-2013	0.33	0.29