Rural-Urban Migration and Structural Change: A Reinterpretation

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Abstract

Structural change and urbanization are often viewed as a single reallocation process. Using two decades of panel data on Indonesian workers, I present evidence challenging this view. I document that workers switch from agriculture to non-agriculture within rural areas, rather than through migration to urban areas, suggesting that rural-urban migration is not central to structural change. Yet, rural-urban migration places future cohorts of workers in cities, where access to education and non-agricultural labor demand are higher, thereby contributing to the cohort component of structural change. Consistent with this mechanism, the offspring of migrants acquire more education and are less likely to work in agriculture. To quantify the forces behind these patterns, I build an overlapping generations model in which workers choose their sector and location of work considering that switching sectors or locations is costly and that locations differ in the access to education for their offspring. Contrary to the standard view, I find that rural-urban migration has limited effects on structural change, as the rural non-agricultural sector is able to absorb most workers leaving agriculture. I also uncover that sectoral switching costs—not differences in education—explain most of the variation in the agricultural share across cohorts. Taken together, these findings imply that frictions limiting migration are not the main barrier to structural change.

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1 Introduction

Structural change 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 non-agricultural jobs. Under this view, frictions that prevent migration constitute a large barrier to structural change and, as a consequence, hinder economic development. However, we lack direct evidence on whether workers' 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 structural change and, ultimately, economic development.

In this paper, I revisit the relationship between rural-urban migration and structural change by explicitly differentiating the reallocation of employment across locations from the reallocation of employment across sectors. My analysis draws on a panel survey of Indonesian households spanning two decades, during which the country experienced large reallocations of employment out of agriculture and from rural to urban areas. The data track both the location and the sector of work of individuals, and how these two choices change over time, which allows me to distinguish and relate each reallocation process. I first use this information to document the worker-level patterns of reallocation across locations and sectors, linking them to the aggregate processes of urbanization and structural change. Then, I build a model in which workers choose their location and their sector of work, which I use to study the forces and frictions behind these patterns and to quantify their implications for macroeconomic development.

I start by documenting that, contrary to common wisdom, most workers leave agriculture within rural areas, rather than through migration to urban areas. Indeed, rural-urban migrants are typically already working in non-agriculture before moving to cities. Taken at face value, this evidence suggests that rural-urban migration is not central to structural change. This interpretation, however, misses an important fact: aggregate structural change is mainly driven by younger cohorts entering the labor market in non-agriculture, rather than by workers switching from agriculture to non-agriculture over their working-life.

The limited movement of workers out of agriculture points to initial conditions at labor-market entry as key determinants of their sector of work (Hobijn et al., 2018; Porzio et al., 2022). Rural-urban migration modifies these initial conditions by placing future cohorts of workers in cities, thereby changing their location and shaping their human capital. As the non-agricultural sector has a larger presence in urban areas and a higher demand for skilled workers, rural-urban migration may still contribute to structural change, even though migration is not a common way workers leave agriculture. Consistent with this mechanism, I show that the offspring of rural-urban migrants acquire more education and are less likely to work in agriculture than the offspring of rural stayers.

To interpret these patterns and quantify their underlying mechanisms, I build an overlapping generations model with two locations (rural and urban) and two sectors (agriculture and non-agriculture). In the model, individuals choose their location and sector of work, and bear a cost when they switch either sectors or locations over their life-cycle. Importantly, workers take into account that the location they choose determines the place where their offspring will get educated and begin their working-life. This affects their offspring's sector of work due to differences in the demand for human capital across sectors and differences in the access to education across locations. Across cohorts, differences in their agricultural share may arise as a result of sectoral switching costs—which are not paid by young workers upon entering the labor market—, differences in human capital—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. Over time, structural change and urbanization are mainly driven by asymmetric productivity growth across locations and sectors, which changes relative prices and real income, affecting the expenditure allocated to each sector in each location.

I calibrate the model to match the patterns of employment reallocation across locations and sectors documented for Indonesia between 1983 and 2013, while being consistent with its growth in output per worker. Using the micro-data, I construct bilateral switching flows across location-sector pairs that, together with relative wages, 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 productivity and switching costs. I calibrate the parameters that control how educational investment translates into human capital in each location to match the evolution of the local stock of high-skill workers. Importantly, my calibration rests on an estimate of the income elasticity of sectoral demand that I obtain from micro-data on households' consumption expenditure.

The calibrated model recovers a general increase in productivity over the sample period, larger in agriculture than in non-agriculture. This pattern of productivity growth generates structural change due to income effects, as the estimated income elasticity of agricultural goods is smaller than one, and due to price effects, as the calibrated elasticity of substitution across goods is also 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 substantial costs of switching from rural to urban areas and from agriculture to non-agriculture, which help sustain the income differences across locations and sectors in equilibrium. Lastly, the calibration recovers an access to education higher in urban than in rural areas.

To assess the role of rural-urban migration in structural change, I study a counterfactual economy in which migration is not possible. In this economy, the only ways to reallocate labor out of agriculture are switches of incumbent workers to the local non-agricultural sector or the entry of new local cohorts into non-agriculture. Remarkably, the agricultural share falls almost as much in this counterfactual as in the benchmark economy (26 *vs.* 28 percentage points). The rural non-agricultural sector is able to absorb most of the workers released by agricultural productivity growth in rural areas. In particular, for incumbent workers, migration is not a common way to leave agriculture, so preventing it does not change their patterns of sectoral reallocation. For new cohorts, being raised in rural rather than in urban areas reduces their educational attainment. However, this does not limit the expansion of rural non-agriculture, which is less skill-intensive than its urban counterpart. Structural change towards rural non-agriculture is, nonetheless, detrimental for aggregate output, which is at every point in time lower than in the benchmark economy (by 8% in 2013, the last period). Without migration, non-agricultural activity does not develop where it is most productive. In this way, rural-urban migration arises as an essential force for economic growth, rather than for structural change, as it allows the economy to relocate labor to the location with a comparative advantage in non-agriculture.

Next, I analyze a set counterfactual economies to isolate the drivers of the cohort effects in structural change. I find that sectoral switching costs account for most of the differences in the agricultural share across cohorts. When incumbent cohorts are free to move across sectors, they leave agriculture at a similar rate to new cohorts, despite being less educated. Differences in educational attainment across cohorts are therefore not a major determinant of their gap in agricultural employment, as differences in the demand for skills across sectors are not strong enough. Similarly, rural-urban migration plays a limited role for the cohort effects, as differences in non-agricultural labor demand across locations shrink in an economy without migration, in which the rural non-agricultural sector expands to compensate for the lack of growth of non-agriculture in urban areas.

Taken together, these findings imply that frictions to leave agriculture, rather than spatial frictions, are the main impediment to structural change. In the model, these frictions are captured in reduced form by sectoral switching costs, which do not have a specific counterpart in the data. I show that switchers from agriculture to non-agriculture are less likely to hold land, less likely to be self-employed, and have accumulated less experience in the sector. These observations are consistent with the presence of frictions in land markets (Adamopoulos et al., 2022) and of sector-specific human capital and retraining costs (Hobijn et al., 2018), respectively. Yet, identifying specific frictions that trap workers in the rural agricultural sector deserves further research efforts.

Another lesson from the quantitative exercise is that rural-urban migration, while not essential for structural change, is an important force of long-run growth. In particular, it allows the economy to accumulate human capital and to relocate labor to the location with a comparative advantage in non-agriculture. As workers have incentives to migrate for their offspring's education, policies affecting educational access in each location have effects on the spatial allocation of employment. Indeed, I show that in a counterfactual economy in which urban areas have the same access to eduction as rural areas, urbanization and growth are lower.

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 migration 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 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, Porzio et al. (2022) and Hobijn et al. (2018), 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. They interpret this cohort component of structural change as the result of increases in educational attainment and of the presence of retraining costs, respectively. I offer a new and complementary interpretation 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 reallocations with between-cohort reallocations out of agriculture (through generations). These 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 in two dimensions. First, I explicitly distinguish between the reallocation of employment across sectors and the reallocation of employment across locations, which allows me to study the role of frictions to switch sectors and locations separately. Second, I focus on the contribution of movers to the long-run process of structural transformation, while these papers focus on sectoral or spatial gaps at a given point in time. Given this longer run focus, 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) and Hnatkovska et al. (2023). Different from these authors, I use a dynamic model to explore how frictions affect workers choices of location and sector along the development path. Using a dynamic model is important because these choices determine the initial conditions of the entering cohorts of workers, who play a central role in aggregate reallocations. Similarly, the paper is also related to a literature that explores the role of barriers to structural change or to rural-urban migration and their aggregate implications (Ngai et al., 2019; Gai et al., 2021; Lagakos et al., 2023; Donovan and Schoellman, 2023).

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

2 Context and Data

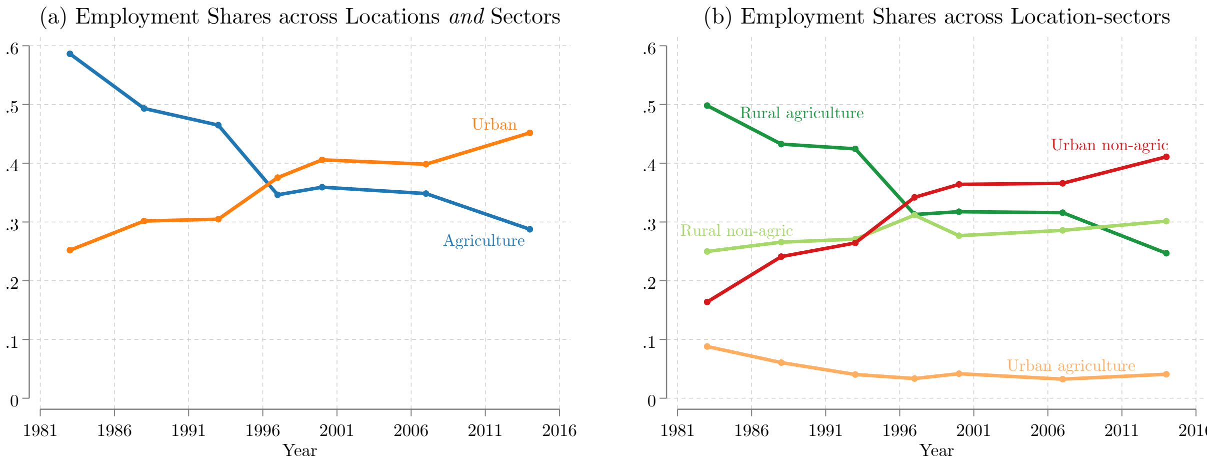
My analysis focuses on the development experience of Indonesia. Since the 1980s, the country has undergone a substantial reallocation of employment out of agriculture and from rural to urban areas, the two aggregate trends of interest, see Appendix Figure A.1 panel (a). These reallocation processes have come together with sustained population and GDP per capita growth, see Appendix Figure A.1 panel (b). More importantly, the availability of a panel dataset recording worker's location and sector for a long time-span allows me to study the aggregate relationship between rural-urban migration and structural change building on observed individual-level transitions across locations and sectors.

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 unfolded in 1997, 2000, 2007 and 2014.[1] While the first wave interviewed 22,019 individuals in 7,224 households, this number has grown to 58,337 by 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 dataset to explore the reallocation of workers across locations and sectors as well as its intergenerational dimension, 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 reallocation, in a similar fashion to what Hicks et al. (2020), Lagakos et al. (2020) and Pulido and Świecki (2021) have done with this same dataset. Notably, I focus not only on the returns to these individual-level transitions, 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 A.1. To that end, I use information on workers' sector of work and

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

Figure 1: Employment Shares in the IFLS



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

rural/urban status[2] 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 of Indonesia in Figure A.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 how these two trends are related is the main goal of next Section.

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 a large share of the fall in the aggregate agricultural share is 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.

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

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 who 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 the transitions from rural to urban areas (the upper, right quadrant of the matrix), we can see that these are more likely for workers in the rural non-agricultural sector than for workers in the rural agricultural sector, as the conditional probability of moving to urban areas next period is 1.4 + 13.4 = 14.8% for RN workers compared to 2.0 + 2.7 = 4.7% for RA workers. This difference in conditional probabilities does indeed get 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.[3]

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.2 shows that just 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.2 shows that just 11.7% of them were earlier in both rural agriculture and rural non-agriculture. These numbers suggest that the quantitative relevance of rural non-agriculture as a stepping stone towards urban non-agriculture is limited.

Heterogeneity and robustness. Matrix (1) is an average of all the observed transitions across location-sectors 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.1. First, I show that the transition probabilities are stable over time. Next, I note that the pattern of transitions across location-sectors is virtually the same if I restrict my sample to prime-age males (between 25 and 59 years old). I then explore the heterogeneity by gender, age, and educational attainment. I find that the transition probabilities are very similar for males and females, that location-sector states are more persistent for older than for younger workers, and that agriculture is more persistent for low- than for high-skill workers. I further analyze workers' transitions by splitting non-agriculture into industry and services, showing that it is more common for individuals who leave agriculture to work in rural services than to work in rural industries, with sales being their main occupation. Relatedly, I document the differences in the sectoral and occupational composition between rural non-agriculture and urban non-agriculture. I also show, crucially, that the reallocation patterns across location-sectors are robust to alternative definitions of rural/urban as well as to the exclusion of workers that hold a job in both sectors. Finally, I consider the possible bias induced by sample attrition or switches to non-employment. All robustness exercises point in 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. At the worker-level, rural-urban migration does not mean leaving agriculture.

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

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 with leaving the agricultural sector or with 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 on earnings. Yet, if significant, they may be informative about the presence of factors preventing the equalization of incomes across sectors and locations.[4] 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 identified by switchers. Table 1 reports the estimation results for the same sample used to build matrix (1), with income measured as log household earnings per adult, omitting the rural-agriculture category.[5] 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, 11 and 12 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, 26 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 correlated with geographical distance, limiting the sample to moves that happen within district (column 2 of Table 1) reduces the estimates for rural-urban migration gains, while estimates for the gains from leaving agriculture

[4] 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.

[5] In Table B.1 in the Appendix, I show that the results are similar if I use alternative outcomes, such as individual earnings or consumption expenditure, to quantify the returns to transitions.

Table 1: Returns to Switching Location-sector

	log household earnings per adult	
	(1)	(2)
Rural Non-agriculture	0.110***	0.090***
	(0.021)	(0.023)
Urban Agriculture	0.122**	0.032
	(0.048)	(0.053)
Urban Non-agriculture	0.262***	0.124***
	(0.039)	(0.041)
N	65,002	55,539
R-squared	0.63	0.65
Individual FE	Yes	Yes
Only within district	No	Yes

Note: individual-level controls include age, years of education and household size, in levels and squared. SEs clustered at the sampling unit level (enumeration area) in parenthesis. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

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 enter the labor market and others retire, the aggregate share of employment in agriculture may change, as sectoral employment shares may differ systematically across cohorts.

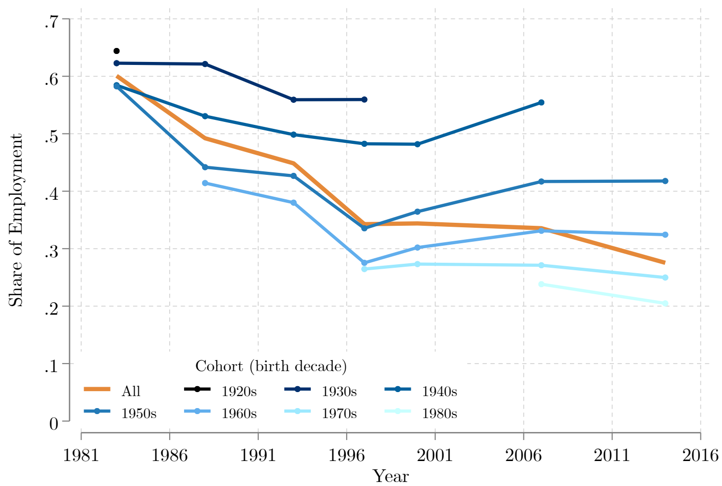
In the case of Indonesia, the persistence of location-sector states at the worker-level in matrix (1) already suggests that younger cohorts may be responsible for an important part of aggregate reallocation out of agriculture.[7] Following Porzio et al. (2022), Figure 2 plots the evolution of the agricultural share for different birth-decade cohorts. We can see that, in general, the lines for each cohort do not overlap, and that they are much flatter than the orange line, which registers the evolution of the aggregate agricultural share. At any given point in time, younger cohorts have a lower agricultural share than older cohorts, with the difference between the youngest and the oldest cohort being consistently 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-

[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.

[7] Indeed, taking the initial distribution of employment across location-sectors and iterating matrix (1) forward produces a 12 percentage points fall in the agricultural share between 1983 and 2014, compared to a 29 percentage points fall in the data.

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 birth-decade. The orange line shows the evolution of the aggregate agricultural share.

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 68% of the fall in the agricultural share in Indonesia between 1983 and 2014 to the between component, and 32% to the within component.[8] Alternatively, using the Porzio et al. (2022) decomposition, I compute in Appendix B.2 that 72% of structural change out of agriculture can be attributed to younger cohorts disproportionately working in non-agriculture.

The between-cohort component of aggregate reallocation is much smaller for the increase in the urban share of employment over time. In a decomposition as the one above, it actually contributes negatively to the increase in the urban share over time, while in a decomposition as in Porzio et al. (2022), cohort effects account for 29% of the total urbanization, see also Appendix B.2.

[8]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). I compute each component for every pair of subsequent years, and then report the average share accounted for by the between-cohort component.

3.3 Rural-urban migration and the cohort effects in structural change

As emphasized by the previous fact, reallocation out of agriculture over an individual's working-life is limited. This points to the role of worker's initial conditions as determinants of her sector of work. An important initial condition may be the location where a worker is raised and located upon entering the labor market. In particular, in the presence of spatial frictions, working in non-agriculture upon entering the labor market may be easier for workers raised in urban areas, where non-agriculture is more present. Additionally, if access to education is higher in urban than in rural areas, urban-raised workers may be able to acquire more education than rural-raised workers, which may generate further differences in their initial sector of work, as the demand for human capital is higher in non-agriculture.

Rural-urban migration, by modifying the location where future workers are raised, may have an effect on the sector of work of future cohorts. In particular, the migration of young workers will affect the initial conditions of their offspring, who will be raised in urban areas. To explore the role of the location where workers are raised, I make use of information on workers' family linkages and compare the descendants of rural-urban migrants to the descendants of rural stayers. Specifically, I follow a group of young rural workers,[9] of whom some migrate to urban and some do not. Then, I compare the offspring of migrants to the offspring of stayers in terms of educational attainment, probability of working in agriculture, and earnings. Specifically, I run regressions like

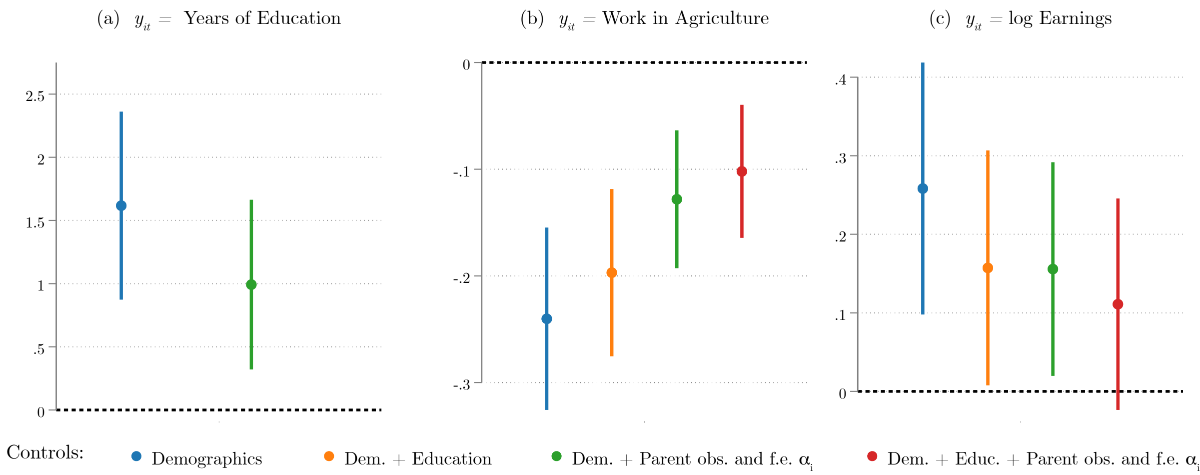
$$y_{it} = \alpha_t + \beta \text{ R-U Mig Offspring}_i + X_{it}\Gamma + \varepsilon_{it} \tag{4}$$

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, we can see that unconditionally (other than in standard demographic controls), the offspring of migrants have 1.61 more years of education, 24 percentage points lower probability of working in agriculture, and 26 log points higher earnings. Once we control for education, the offspring of migrants still have a significantly lower agricultural share (20 percentage points) and higher earnings (16 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.[10] Therefore, I also present estimates for β in which I control for parents' education, sector, and unobserved permanent characteristics (as captured by the individual fixed effect of an earnings regression like (2)). The finding that the offspring of rural-urban migrants attain higher education, work less in agriculture, and earn more remains

[9] 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) at some point become household heads. This is a sample of 2,912 individuals and 11,520 individual-year observations. See Appendix B.3.1 for further details on this sample.

[10] 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's 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 unobservables (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 4,492, of panel (b) 4,440, and of panel (c) 3,355.

true. While this cannot be interpreted as the causal effects of being raised in an urban area—as parents migration may be driven by unobservable shocks correlated with offspring outcomes—, it suggests that the location where workers grow up is an important determinant of their labor market outcomes, including their initial sector of work.[11]

3.4 Taking stock

This section has presented evidence on the relationship between rural-urban migration and structural change building on individual-level longitudinal data on worker's location and sector. First, I have documented that, for most workers, rural-urban migration does not entail a move out of agriculture. Indeed, most switches from agriculture to non-agriculture happen within rural areas. I have also documented that switches out of agriculture and out of rural areas are both associated with substantial earnings gains for switchers, which is suggestive of the presence of switching costs across sectors and across locations. Next, I have shown that a large share of the aggregate reallocation out of agriculture is driven by younger cohorts entering the labor market directly in non-agriculture, rather than by the reallocation of workers across sectors over their working-life.

[11] I make progress on the causal identification using a subset of the sample of migrants' offspring for whom I observe their educational attainment before and after their parents' migration. An event-study design comparing the outcomes of movers with yet-to-move children shows that parental rural-urban migration increases children's educational attainment by around 1.1 years of schooling, see Appendix B.3.2. More generally, the findings in this section are in line with van Maarseveen (2025), who finds that childhood urban residency increases future earnings, and with Nakamura et al. (2021), who highlight the intergenerational returns to migration.

This suggests that differences in initial conditions across cohorts may be an important determinant of their different sectoral employment shares. I have explored the role of rural-urban migration in shaping these initial conditions. In particular, I have shown that the offspring of rural-urban migrants have higher educational attainment, a lower agricultural share, and higher earnings than the offspring of rural stayers. In this way, rural-urban migration of a given cohort, by increasing the share of members of future cohorts raised in urban areas, emerges as a driver of the cohort effects in structural change.

Given this evidence, I next build a model that allows me to quantitatively assess the role of rural-urban migration for structural change. In the model, the reallocation of employment across locations and sectors arises from individual-level choices that spill over to future generations through the effects of the location where workers are raised on their initial conditions. Importantly, the model incorporates elements that govern how educational attainment and production patterns would evolve in the absence of urbanization.

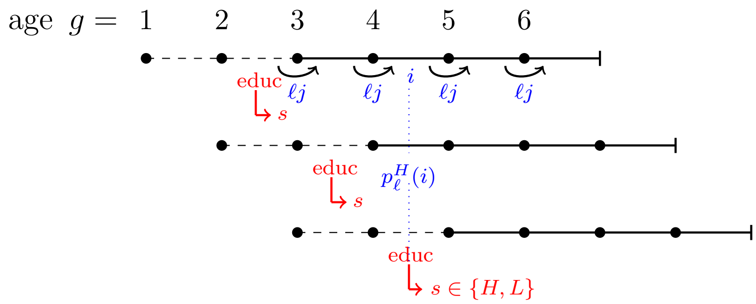
4 Model

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 or between-cohort reallocations 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). The economy is populated by overlapping generations of individuals who live for six 10-year periods. The first two periods of their life, individuals are children, acquire education, and do not work. Then, at age 21, their skill level $s = L, H$ (low and high) is realized, and individuals 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 $g = 1, \ldots, 6$.

On the production side, there is a final good in each sector j which is a composite of intermediate varieties indexed by x in the continuum $[0, 1]$. Sectoral intermediate varieties are produced within locations by competitive producers, combining high- and low-skill labor, and are tradable across locations subject to transport costs. Locations differ in their sectoral productivity to pro-

Figure 4: Life-cycle of individuals.



Notes: this figure provides a graphical summary of the life-cycle of individuals in the model. Each line represents the life-cycle of one generation. The first two periods, represented by dashed lines, correspond to childhood, where individuals do not make choices. The remaining periods correspond to adulthood, where choices are represented in blue.

duce intermediate varieties. Additionally, locations differ in the access to education they provide to their residents.

4.1 Workers

Timing, demographics, and choices. Figure 4 provides a graphical representation of an individual's life-cycle, which I describe in detail here. Individuals are born in the location of their parents, with whom they spend their first two periods of life, until they become 20 years old. During childhood, at age $g = 2$ (from 11 to 20 years of age), they acquire education. The moment they turn 21 years old ($g = 3$), individuals become high-skill workers with probability $p_{\ell t}^H(i)$, which is a (location-specific) function of the investment i made by their parents in the previous period. Immediately after, they leave their parents' household and enter the labor market by choosing in which location-sector ℓj to live and work in that period. They also give birth to a child. Individuals choose again location-sector as they turn 31 years old ($g = 4$). Their decision of where to spend this period takes into account that the investment in their children's education is shaped by the location-specific function $p_{\ell t}^H(i)$, and that their chosen location determines the place from which their children will start youth. Next, individuals become age $g = 5$ (41 years old) and choose one more time their location-sector of work, while their children become age $g = 3$ (21 years old) and leave the household to start their working-life. Finally, they turn 51 years old ($g = 6$) and decide for the last time where to live and work.

At any point in their life-cycle, individuals' choice of a location-sector ℓj considers the flow utility derived from consumption in ℓj and the access location-sector ℓj provides to any other location-sector $\ell' j'$ next period, as switching across locations and sectors is costly. The flow utility that individuals derive from consumption in a given period depends on the income they receive in location-sector ℓj and on the prices of the final agricultural and non-agricultural goods in location ℓ, which determine the share of expenditure they allocate to each final good according to their preferences for consumption.

Preferences for consumption. Following Boppart (2014), individuals have PIGL (Price-Independent Generalized Linear) preferences represented by the indirect utility function

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

where $e^{g\,s}_{\ell j\,t}$ is the total expenditure of a worker of age g and skill s in location-sector ℓj at time t, and $P_{\ell j\,t}$ the price of final good j in location ℓ at time t. This class of preferences features non-unitary income and substitution elasticities, so changes in income and in relative prices 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 age g and skill s working in sector j of location ℓ is given by

$$\varphi^{g\,s}_{\ell j\,t,a} \equiv \phi + \nu\left(\frac{P_{\ell a\,t}}{P_{\ell n\,t}}\right)^{\iota}\left(\frac{e^{g\,s}_{\ell j\,t}}{P^{\phi}_{\ell a\,t}P^{1-\phi}_{\ell n\,t}}\right)^{-\eta}, \tag{6}$$

where ϕ, η, $\iota \in (0,1)$ and $\nu \geq 0$. This expression shows that ι and η control how changes in relative prices and in real income translate into changes in relative sectoral expenditure, respectively. The importance of both forces depends on parameter ν. Parameter ϕ, in turn, determines the share of expenditure on agriculture as real income tends to infinity.

Given how individuals allocate their expenditure across sectors in a given period to maximize their flow utility, we can now turn to their choice of location-sector.

Location-sector choice. Individuals choose where to live and in which sector to work in each period of their working life. As switching across locations and sectors is costly, this decision is dynamic, as individuals understand that their choice of location-sector in a given period affects their access to other location-sectors next period. Moreover, *parenting* 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 a worker of skill s and age group $g \neq 4$ at time t. This value is given by the flow indirect utility associated to ℓj at t and the option value of starting next period in ℓj,

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

where β is the rate at which individuals discount the future. Importantly, the option value associated to location-sector ℓj, $\Psi^{g+1\,s}_{\ell j\,t+1}$, varies by age. In particular, for individuals aged $g = 6$, $\Psi^{g+1\,s}_{\ell j\,t+1} = 0$, as period t is their last period alive and there is nothing to bequest. For individuals aged $g = 3$ or $g = 5$,

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

where $V^{g+1\,s}_{\ell' j'\,t+1}$ is the value of being in location-sector $\ell' j'$ next period, $\mu_{\ell j\,\ell' j'\,t+1}$ 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 $\{\epsilon_{\ell' j'\,t}\}$ are 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

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

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 in the flow utility and option value that ℓj provides for them, but also in the opportunities it provides for their offspring. In particular, $V^{4\,s}_{\ell j\,t}$ reflects that parents make an investment in the education of their children. This investment i affects the probability $p^H = p^H_{\ell t}(i)$ that their children become high-skill agents. The mapping of investment i to p^H is controlled by the function $p^H_{\ell t}(i) = 1 - \exp\{-\lambda_{0\ell\,t}\, i^{\lambda_{1\ell\,t}}\}$, 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 change over time.[12] Investing in their children's education is costly for parents, as it reduces their disposable income. Specifically, i carries the price of the local non-agriculture good, so the total expenditure for parenting agents becomes $e^{4\,s}_{\ell j\,t} = w^s_{\ell j\,t} - P_{\ell n\,t} \cdot i$. Additionally, the choice of parenting agents also factors in that the location they choose is the place from which their offspring will start youth and enter the labor market, which is relevant in the presence of switching costs. Then, the value of location-sector ℓj for an individual of age $g = 4$ and skill s at time t is given by

$$V^{4\,s}_{\ell j\,t} = \max_i \left\{ \mathcal{V}(e^{4\,s}_{\ell j\,t}, P_{\ell a\,t}, P_{\ell n\,t}) \;+\; \beta\,\Psi^{5\,s}_{\ell j\,t+1} \;+\; \beta\left(p^H_{\ell t}(i)\,\Psi^{y\,H}_{\ell\,t+1} \;+\; \left(1 - p^H_{\ell t}(i)\right)\ \Psi^{y\,L}_{\ell\,t+1}\right)\right\} \tag{10}$$

$$\text{s.t.}\ \ p^H_{\ell t}(i) = 1 - \exp\{-\lambda_{0\ell\,t}\, i^{\lambda_{1\ell\,t}}\}$$

$$e^{4\,s}_{\ell j\,t} = w^s_{\ell j\,t} - P_{\ell n\,t} \cdot i$$

where $\Psi^{5\,s}_{\ell j\,t+1}$ is the individual continuation value of the parenting agent, given by (8), and $\Psi^{y\,s}_{\ell\,t+1}$ is the value of her offspring upon joining the labor market, $\Psi^{y\,s}_{\ell\,t+1} \equiv \mathbb{E}\left[\max_{\ell' j'}\left\{V^{3\,s}_{\ell' j'\,t+1} - \mu_{\ell\,\ell'\,t+1} + \epsilon_{\ell' j'\,t+1}\right\}\right]$.[13]

[12] Broadly speaking, $\lambda_{0\ell\,t} \geq 0$ controls the average probability of becoming high-skill in location ℓ, while $\lambda_{1\ell\,t} \in [0, 1]$ determines how differences in i translate into differences in p^H within location ℓ.

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

Note that $\Psi^{y\,s}_{\ell\,t+1}$ reflects that young agents pay location switching costs if they decide to leave location ℓ ($\mu_{\ell\ell'}$), but do not pay any sectoral switching costs, given that the moment they enter the labor market they are not yet working in any sector.

The solution to the investment problem for a parenting agent of skill s in location-sector ℓj at time t satisfies the FOC

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

which simply equalizes the marginal cost of investing in the education of children (in terms of individual flow utility), to the expected returns of this investment, as captured by the difference in the values of high- and low-skill young agents. Importantly, both the costs of and the returns to investing in education are location-specific.

Once we have expressed how the value functions associated with each location-sector vary by age, we can set up the discrete-choice problem that individuals face when choosing where to live and work. Specifically, an individual of skill s that just became age g in location-sector ℓj at time t chooses a location-sector $\ell' j'$ to solve

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

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 age g, skill s individuals that move from location-sector ℓj to location-sector $\ell' j'$ as they turn age $g+1$ is

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

where we can see that κ attenuates the importance of the economic value of each location-sector in determining employment flows. The problem for individuals that just became young ($g = 3$) in location ℓ is analogous to (12), with the difference that they pay location switching costs (if they move to a different location ℓ' in order to enter the labor market), but not sectoral switching costs (as they are not yet working in any sector).

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

$$L^{s\mathcal{S}}_{\ell' j' t} = \underbrace{\sum_{\ell} \rho^{y\,s}_{\ell\,\ell' j' t} L^{c\,s}_{\ell\,t-1}}_{\substack{\text{skill-}s\text{ children who become}\\ \text{young and choose } \ell' j'}} + \underbrace{\sum_{g \neq y} \sum_{\ell} \sum_{j} \rho^{g\,s}_{\ell j\,\ell' j' t} L^{g-1\,s}_{\ell j\,t-1}}_{\substack{\text{rest of skill-}s\text{ agents that}\\ \text{turn age } g\text{ and choose } \ell' j'}} \tag{14}$$

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

4.2 Production and trade

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

$$y_{\ell j}(x) = A_{\ell j\,t}(x) \left({\omega^{H}_{\ell j}}^{1/\sigma} L^{H}_{\ell j}(x)^{\frac{\sigma-1}{\sigma}} + {\omega^{L}_{\ell j}}^{1/\sigma} L^{L}_{\ell j}(x)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{15}$$

where σ is the elasticity of substitution between high- and low-skilled labor, $\omega^{s}_{\ell j}$ is a parameter controlling the skill-s intensity of sector j in location ℓ, and $A_{\ell j\,t}(x)$ denotes the productivity of location ℓ in the production of variety x of sector j in period t. Hence, sectors in each location differ both in their productivity and in their skill intensity. Following Eaton and Kortum (2002), productivity $A_{\ell j\,t}(x)$ is a random variable drawn from an independent location-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 dispersion of productivity in the production of sector j varieties. The scale parameter $T_{\ell j\,t}$ is location-sector specific and controls the average level of local efficiency in the production of sector j varieties in period t. Trade across locations 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 location ℓ producers to location ℓ' consumers is $p_{\ell\ell' j}(x) = \frac{c_{\ell j\,t}}{A_{\ell j\,t}(x)} \tau_{\ell\ell' j}$ where

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

is the unit cost of an input bundle. Consumers in location ℓ' only purchase variety x from the location that can provide it 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 properties of the Fréchet distribution, this implies that the price $P_{\ell j}$ of the sector j

composite good (the price index of sector j varieties) in location ℓ at time t is given by

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

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

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

Hence, location ℓ''s expenditure in sector j varieties produced by location ℓ at time t is higher if location 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 at every period t. Then, I provide formal definitions of a static competitive equilibrium, a sequential competitive equilibrium, and a Steady State competitive equilibrium of the economy.

4.3.1 Market clearing

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

$$P_{\ell j\,t} Y_{\ell j\,t} = \sum_{\ell'} \pi_{\ell \ell' j\,t} X_{\ell' j\,t} \quad \forall\, \ell j,\, t \tag{16}$$

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 the varieties produced in ℓj. Note that $X_{\ell' j\,t}$ is the total expenditure in sector j varieties of location ℓ' consumers at time t. As consumers in a given location differ by age, skill, and sector of work, $X_{\ell' j\,t}$ is given by

$$X_{\ell' a\,t} = \sum_{k,g,s} \varphi^{g\,s}_{\ell' k\,t} e^{g\,s}_{\ell' k\,t} L^{g\,s}_{\ell' k} \qquad \text{and} \qquad X_{\ell' n\,t} = \sum_{k,g,s} (1 - \varphi^{g\,s}_{\ell' k,t}) e^{g\,s}_{\ell' j\,t} e^{g\,s}_{\ell' j} L^{gs}_{\ell' k,\,t} + \sum_{k,s} P_{\ell' n\,t} \cdot i^{*\,s}_{\ell' j,t} \cdot L^{4s}_{\ell' k,t}$$

for agriculture and non-agriculture, respectively, and where we can see that the investment in education of parenting agents $i^{*\,s}_{\ell' j,t}$ is included in the expenditure of non-agriculture goods.

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

$$L^{s\mathcal{S}}_{\ell j\,t} = L^{s\mathcal{D}}_{\ell j\,t} \quad \forall\, s,\, \ell j,\, t \tag{17}$$

where labor supply $L^{s\mathcal{S}}_{\ell j\, t}$ is given by equation (14) and labor demand $L^{s\mathcal{D}}_{\ell j\, t}$ is implied by the goods market clearing condition in equation (16), 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

$$L^{s\mathcal{D}}_{\ell jt} = \frac{1}{w^s_{\ell jt}}\xi^s_{\ell jt}\sum_{\ell'}\pi_{\ell\ell' jt}X_{\ell' jt} \tag{18}$$

where $\xi^s_{\ell jt}$ is the share of skill s in total labor payments[14]

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

which depends on the relative wage across skills and the skill intensity of location-sector ℓj.

4.3.2 Definitions

For the purpose of formally defining the equilibrium, I call $\Theta_t \equiv \left\{\mu_{\ell j\,\ell' j'\, t}, \lambda_{0\ell\, t}, \lambda_{1\ell\, t}, \omega^L_{\ell j}, \tau_{\ell\ell' j}, T_{\ell jt}\right\}$ 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 $\left\{L^{g\,s}_{\ell j\, t}\right\}^{g=3,\ldots,6;s=H,L}_{\ell=r,u;j=a,n}$, a *static competitive 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 (16) holds), and labor markets clear for each skill in each location-sector (so equation (17) holds).

Note that, in a static competitive equilibrium, for a given allocation of workers across location-sectors (so for a given labor supply), wages are pinned down by the downward sloping labor demand, see equation (18).

Definition 2. Given an initial distribution of workers of each age-skill group across location-sectors $\left\{L^{g\,s}_{\ell j\, 0}\right\}^{g=3,\ldots,6;s=H,L}_{\ell=r,u;j=a,n}$ 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 parenting 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

[14] Note that while we can differentiate the labor supply from different generations, we cannot do the same for labor demand, as workers of different ages of a given skill level are perfect substitutes in production.

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 competitive 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 parenting agents of each skill in each location-sector; and value functions for each age-skill group in each location-sector $\left\{V^{g\,s}_{\ell jt}\right\}_{\ell j,g,s,t}$ are constant.

Note that, in a Steady State equilibrium, fundamentals Θ_t do not change ($\Theta_t = \bar{\Theta}$) and as a consequence the economy does not grow and employment allocations are constant over time. Net employment flows across location-sectors are zero, and hence there is neither structural change nor urbanization.

4.4 Discussion

In the empirical analysis presented in Section 3.1, the focus lies on the reallocation of employment across sectors and locations. In the model developed in this section, this reallocation can arise as a result of changes in fundamentals Θ_t along the transition towards a Steady State.[15] In particular, the model can generate structural change due to symmetric and asymmetric sectoral productivity growth, which change income and relative prices and, given the PIGL preferences, the allocation of expenditure (and employment) across sectors. Moreover, if the urban location has a comparative advantage in the production of non-agriculture goods, these changes in sectoral productivity may generate urbanization as well. Importantly, how changes in productivity translate into flows of workers across location-sectors depends on the magnitude of switching costs at every point in time.

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, incumbent workers in agriculture after an increase in the value of working in non-agriculture. Second, younger cohorts may have more skills than older cohorts, which are more in demand in non-agriculture. The model can endogenously generate this increase in the share of high-skill workers across cohorts if the value of being a high-skill worker increases over time or, alternatively, the costs of becoming a high-skill worker decrease over time. Lastly, rural-urban migration may also generate cohort effects in structural change by increasing the stock of agents raised in urban areas, where access to education and the demand for non-agricultural workers are

[15] To solve for the equilibrium allocations along 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 $V^{g\,s}_{\ell jT}$ to solve for the full transition given that at $t = T - 1$ we know that $V^{g\,s}_{\ell jt+1} = V^{g\,s}_{\ell jT}$. Appendix C.1 provides a detailed description of the solution algorithm.

potentially higher. The quantitative importance of each mechanism is assessed in the following Sections.

Finally, as the model allows different locations to have different sectoral specialization, access to education, and wages, it can also be used to assess the importance of intergenerational incentives for rural-urban migration.

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.

5.1 Timing and Measurement Adjustments

Timing adjustments. I have data for 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 into 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[16] and the average years of education in the data —around 7—, I classify as high-skill any individual with 8 or more years of completed education.

[16] Primary education in Indonesia lasts for 6 years. Secondary education is divided into 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, compulsory education was raised to 9 years (primary plus junior highschool).

5.2 Calibration strategy

To present the calibration of model parameters, I classify them into 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 simulate 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 this procedure in more detail towards the end of the Section.

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 $\varphi^{g\,s}_{\ell j\,t}$ minus parameter ϕ are a log-linear function of income and relative prices:

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

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 $\varphi^{g\,s}_{\ell j}$ and on total expenditure $e^{g\,s}_{\ell j}$, adding location-time fixed effects $\alpha_{\ell t}$ to control for differences in prices across locations 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 C.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 falls slightly 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 C.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. In the data, aggregate sectoral productivity increases more in agriculture than in non-agriculture, while aggregate employment moves in the opposite direction. Conditional on income effects, this will require a low elasticity of substitution, so a low ι, to match the data.

5.2.2 Labor supply parameters

Switching costs and switching elasticity. In line with the evidence of Section 3.1 on the income gaps across sectors *and* 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 $\mu_{\ell j\, \ell' j'\, t} = \mu^{\text{loc}}_{\ell\, \ell'\, t} + \mu^{\text{sec}}_{j j'\, t}$. This means that there is a different cost for workers who change only location ($\mu^{\text{loc}}_{\ell\, \ell'\, t}$), only sector ($\mu^{\text{sec}}_{j j'\, t}$), or both ($\mu^{\text{loc}}_{\ell\, \ell'\, t} + \mu^{\text{sec}}_{j j'\, t}$). 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 $\mu^{\text{sec}}_{j j'\, t}$ to vary by bilateral pairs and over time.[17]

I calibrate switching costs internally. The main moments in the data to discipline the values of switching costs are the bilateral flows across location-sectors $\rho_{\ell j\, \ell' j'\, t}$. Intuitively, for a given value of choosing a location-sector $\ell' j'$ —targeted by productivity parameters, see next section—, the size of bilateral flows from each location-sector ℓj to $\ell' j'$, $\rho_{\ell j\, \ell' j'\, t}$, is controlled by the bilateral switching costs $\mu_{\ell j\, \ell' j'\, t}$. 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 expression 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

$$\log\left(\frac{\rho^{g\, s}_{\ell j\, \ell' j'\, t}}{\rho^{g\, s}_{\ell j\, \ell j\, t}}\right) = \frac{1}{\kappa}\Big(\mathcal{V}(e^{g\, s}_{\ell' j'\, t}, P_{\ell' a\, t}, P_{\ell' n\, t}) - \mathcal{V}(e^{g\, s}_{\ell j\, t}, P_{\ell a\, t}, P_{\ell n\, t})\Big) + \beta \log\left(\frac{\rho^{g+1\, s}_{\ell j\, \ell' j'\, t+1}}{\rho^{g+1\, s}_{\ell' j\, \ell' j\, t+1}}\right) + \tilde{C} \qquad (19)$$

where $\tilde{C}$ is a pair-specific constant within year t. 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 at this stage, equation (19) cannot be directly used to estimate κ. Alternatively, we can use the following auxiliary model, which in

[17] Note that, while flexible, this specification does not allow a full *model inversion*, as it is common in dynamic spatial economics (see, e.g. Caliendo et al., 2019). To achieve that, switching costs would need to vary also by age and skill groups. I prefer a more restrictive form of switching costs to be able to discuss sectoral and spatial frictions in a more transparent way.

essence captures the same idea as equation (19), but is amenable to direct estimation in the data:

$$\log\left(\frac{\rho^{g\,s}_{\ell j\,\ell' j'\,t}}{\rho^{g\,s}_{\ell j\,\ell j\,t}}\right) = \alpha_g + \alpha_t + \alpha_s + \gamma \log\left(\frac{w^{s}_{\ell' j'\,t}}{w^{s}_{\ell j\,t}}\right) + u^{g\,s}_{\ell j\,\ell' j'\,t}\,, \tag{20}$$

where α_g, α_t, and α_s are age, time and skill fixed effects—as γ does not vary by age, time or skill—, and $u^{g\,s}_{\ell j\,\ell' j'\,t}$ an estimation error term. I estimate γ in equation (20) by PPML regression.[18] Then, in the internal calibration of the model, I run the same regression and target the value of γ estimated in the data, 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 young workers 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.[19]

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

Productivity, trade costs and trade elasticity. The evolution of location-sector productivity $T_{\ell j\,t}$ is the main force of structural change, urbanization, and growth in the model. Hence, for every period of my observation window (1993, 2003 and 2013), I allow $T_{\ell j\,t}$ to freely take a different value in each location-sector. In terms of identification, I recover the relative productivity across locations and sectors every period by targeting the relative wage across locations and across sectors, which is informative of the relative value of choosing a location or sector. Additionally, I target the evolution of real output per worker in each sector to recover the growth in productivity 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

[18] Unlike OLS, the PPML estimator of gravity equations like (20) accommodates zeros in the outcome variable and is immune to heteroskedasticity in the error term, see Silva and Tenreyro (2006).

[19] 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.

local level are informative about their magnitude.[20] For simplicity, I keep trade frictions constant over time and symmetric across bilateral pairs. 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 an elasticity of substitution σ and intensities $\omega^s_{\ell j}$ that differ by location-sector ℓj. 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

$$\frac{L^H_{\ell j\,t}}{L^L_{\ell j\,t}} = \frac{\omega^H_{\ell j}}{1-\omega^H_{\ell j}} \left(\frac{w^H_{\ell j\,t}}{w^L_{\ell j\,t}}\right)^{-\sigma} \quad \forall \ell j,\, t \tag{21}$$

to retrieve a value for $\omega^H_{\ell j}$, where I impose that $\omega^L_{\ell j} = 1-\omega^H_{\ell j}$. In particular, I use data on relative employment $L^H_{\ell j\,t}/L^L_{\ell j\,t}$ and relative wages $w^H_{\ell j\,t}/w^L_{\ell j\,t}$ and take the average of equation (21) over time for each location-sector. This procedure delivers $\omega^H_{ra} = 0.33$ and $\omega^H_{ua} = 0.68$ for agriculture in rural and urban, and $\omega^H_{rn} = 0.66$ and $\omega^H_{un} = 0.84$ for non-agriculture in rural and urban, respectively. These values mean that, for the same relative wages, high-skill labor is used more intensively in non-agriculture than in agriculture (in both locations), and in urban than in rural areas (in both sectors). To be consistent with this imputation, I target within the SMM algorithm the average $L^H_{\ell j\,t}/L^L_{\ell j\,t}$ across time in each location-sector, such that on average (21) 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 $\left\{L^{g\,s}_{\ell j\,1983}\right\}^{s=H,L;g=1,\ldots,6}_{\ell=r,u;j=a,n}$, and the values for η, ϕ, β, θ_j, σ, and $\omega^s_{\ell j}$ (already calibrated or assigned), the algorithm searches for values of

(a) preference parameters ι and ν,

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

(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 symmetric trade costs in each sector $\tau_{\ell\ell' j}$ (2 parameters),

[20] 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).

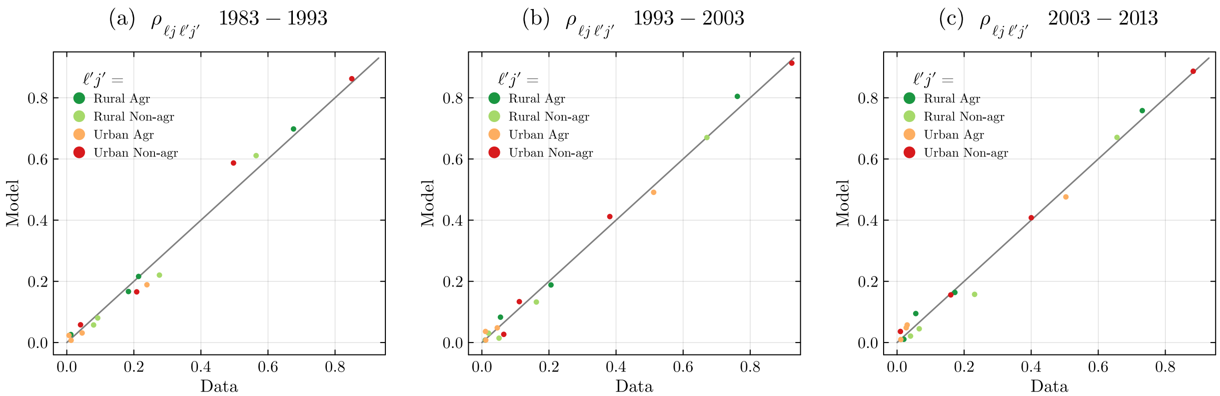
to minimize the distance between a set of model moments and their data counterparts in 1993, 2003, and 2013 during a transition to a Steady State equilibrium.

The full set of 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 wage gap across locations and across sectors (2 moments per time period), the average high-skill share of employment in each location-sector (4 moments), and growth in real output 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 36 parameters (as I normalize $T_{ra\, 1993} = 1$) to match 58 moments. Importantly, I assume that all parameters except productivity $T_{\ell j\, t}$ remain unchanged after 2013. For productivity, I allow it to grow for five more periods after 2013, until the year 2063 ($2013 + 5 \times 10$). In particular, I compute the growth in sectoral output per worker in Indonesia between 2003 and 2013 using information from the Economic Transformation Database, and apply this growth rate to the values of $T_{\ell j\, t}^{1/\theta}$ 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 takes a few more periods given that reallocations across locations and sectors are costly.

A couple of aspects of the internal calibration are worth highlighting. First, by targeting the data on switching probabilities 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 probabilities across ℓj, see equation (14). 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 sectors 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) simulating 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, switching costs, and productivity. As explained above, the parameters of $p^H_{\ell t}(i)$ are assumed to remain constant since 2003.[21] Similarly, I keep switching costs $\mu_{\ell j\, \ell' j'\, t}$ constant since 2013, given that no information on switching flows is available afterwards. Instead, I allow productivity $T_{\ell jt}$ to keep growing for several periods. In particular, by applying the growth rate of the last observed ten years to the next two model periods (corresponding to the years 2023 and 2033), I assume that Indonesia keeps growing at a similar rate that it has done in the recent past. As the country gets richer, however, we may expect that it converges to the growth rate of richer countries. Therefore, I assume that, twenty years after 2013, productivity keeps growing but does so at a 2% yearly rate. Finally, it is worth mentioning

[21] 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 5: 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.

that the economy converges to a Steady State (recall, a situation with no growth) more than five periods after 2013, so far enough to barely affect the moments of 2013.

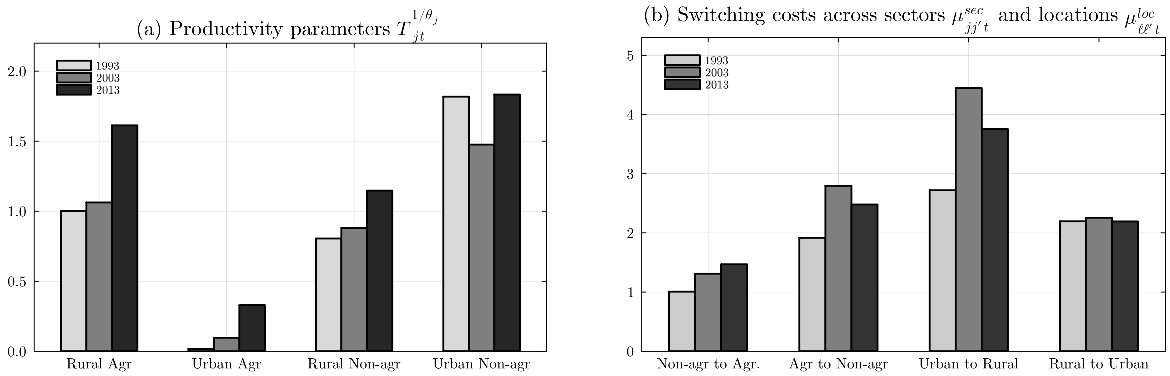
5.3 Calibrated parameters and model fit

This section presents the results of the model calibration outlined above. In the main text, I present the fit of the model to most targeted moments and the estimated values for the main parameters of interest. I present the remaining calibrated parameters and model fit in Appendix C.3, 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 5 that the model does a very good job matching the patterns of gross worker-level reallocations. This is then reflected in the fact that it reproduces very well the aggregate evolution of employment shares across location-sectors observed in the data, see Figure C.3 in the Appendix. The calibrated values for $T^{1/\theta}_{\ell j t}$, $\mu^{\text{loc}}_{\ell \ell' t}$, and $\mu^{\text{sec}}_{j j' t}$ behind these moments are presented in Figure 6 below, while the calibrated values for bilateral trade costs $\tau_{\ell \ell' j}$ are reported in Appendix C.3.

The calibrated model recovers a general increase in productivity, faster in agriculture than in non-agriculture, which matches well the increase in sectoral output per worker in the data, see Table C.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 (as both the income elasticity and the elasticity of substitution are lower than one, see Table C.3) and urbanization (as the urban location has a comparative advantage in non-agriculture, see Figure 6 panel a). To match the worker flows across sectors, the model asks for higher costs of switching from agriculture to non-agriculture than viceversa, see Figure 6 panel (b), consistent with the notion that a barrier is needed to rationalize the wage gap across sectors in equilibrium, which the model matches well,

Figure 6: Evolution of location-sector productivities



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

see Table C.3. Despite also matching the wage gap between urban and rural areas—and for an elasticity of $1/\kappa = 0.75$—[22] the model recovers higher costs of moving from urban to rural than viceversa. This is necessary to match the very small flow of workers leaving urban areas, recall the transition matrix in Section 3.1. Yet, note that the main flow is rural to urban, and that the model also recovers substantial costs for this move. Switching costs are also relatively stable over time, which is consistent with the stability of the transition matrices. It is also relevant to highlight that, while these costs are related to the income gaps for switchers across sectors and locations documented in Section 3.1.2, they are not a direct counterpart. The regression estimates capture an average gap (over time and across switchers), while the value of switching costs in the model regulates the flow of movers and the wage gaps in equilibrium every decade, which depends on all the stream of future values in each location-sector. 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 some 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 $p_{\ell\,t}^{H}(i)$. 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 very well the targeted moments for the share of high-skill young agents in each location, and slightly worse the moments for the differences in the probability of having a high-skill child between high- and low-skill parents within location. The function $p_{\ell\,t}^{H}(i)$ associated with the calibrated values for $\lambda_{0\ell\,t}$ and $\lambda_{1\ell\,t}$ is presented in Figure C.2, 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 greater in urban than in rural areas, the model recovers a $p_{\ell\,t}^{H}(i)$ function that, especially for

[22] This value is in the ballpark of estimates found in the dynamic migration literature, which vary substantially. For instance, Caliendo et al. (2019) find a quarterly elasticity of 0.2, while Artuç et al. (2010) find an annualized elasticity of 0.53. Consistent with the intuition that this elasticity should be larger at lowers frequencies, I find a higher value for the 10-year elasticity.

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. Through the lens of the model, this implies that the costs of acquiring education fall over time.

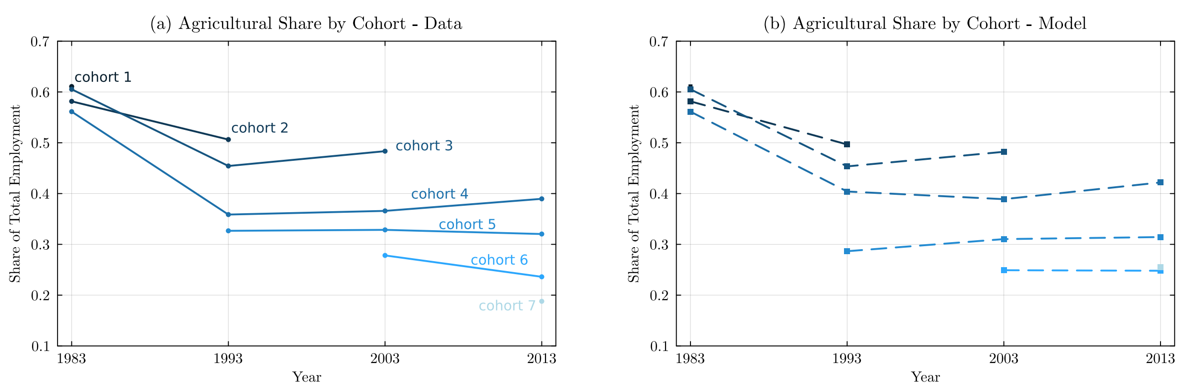
Table 2: Calibrated parameters probability of becoming high-skill function

EDUCATION PROBABILITY FUNCTION PARAMETERS									
Par	Description	Value		Target		Model	Data	Model	Data
		Rural	Urban		Year	Rural		Urban	
$\lambda_{0\ell\,1993}$	Scale of $p^H_\ell(i)$	0.81	1.42	Share of high-skill	2003	0.36	0.37	0.59	0.61
$\lambda_{0\ell\,2003}$		1.01	2.33	young agents in ℓ	2013	0.48	0.52	0.70	0.68
$\lambda_{1\ell\,1993}$	Curvature of $p^H_\ell(i)$	0.26	0.72	Difference in $p^H_\ell(i)$	2003	0.06	0.11	0.21	0.22
$\lambda_{1\ell\,2003}$		0.15	0.84	high- and low-skill parents	2013	0.02	0.05	0.15	0.09

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

Non-targeted moments. Recall that the calibration exercise does not target the employment allocations in each location-sector by age group. Hence, cohort effects in structural change are the result of how incentives and constraints built-in in the model vary over the life-cycle of agents. The fit to these non-targeted moments is presented in Figure 7. Remarkably, the model is able to reproduce the cohort effect in structural change observed in the data.

Figure 7: 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).

6 Quantitative Results

This section presents the results of a number of counterfactual exercises. First, I analyze the role of rural-urban migration in structural change by studying an economy in which migrations are not possible. Second, I explore several economies to quantify the different 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.

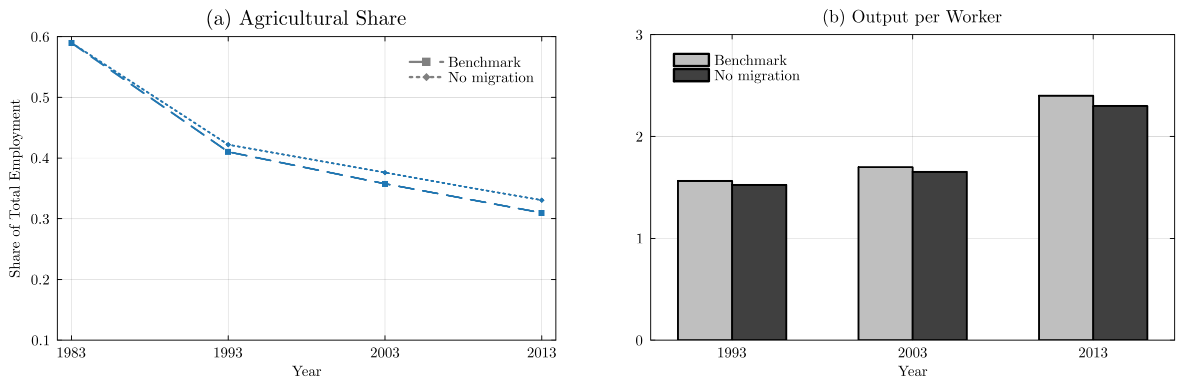
6.1 Rural-urban migration and structural change

To understand the effect of rural-urban migration on structural change, I analyze an economy in which migrations are not possible.[23] In this economy, the only ways to reallocate labor out of agriculture are switches of incumbent workers to the local non-agricultural sector or the entry of new local cohorts into non-agriculture. The results in terms of the evolution of the agricultural share are presented in Figure 8 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. The mechanics behind this result are as follows. On the one hand, recall that in the benchmark economy incumbent workers do not use rural-urban migration to leave agriculture, see transition matrix (1). Hence, not surprisingly, preventing their migration in the counterfactual economy does not prevent them from leaving agriculture either. On the other hand, for new cohorts, rural-urban migration by previous cohorts facilitates their access to non-agriculture. This channel, however, turns out to be quantitatively small. In the no-migration economy, new cohorts are able to access non-agriculture at a similar rate to that of the benchmark economy, despite disproportionately entering the labor market in rural areas. This happens because the difference in the access to education between rural and urban areas is small, such that the share of high-skill agents in the no-migration economy is similar to the benchmark (38% *vs.* 41% by 2013). Moreover, as the non-agricultural sector is less skill intensive in rural than in urban areas, the lower increase in the share of high-skill agents does not limit its growth.

We can also understand this result from the perspective of labor demand, rather than labor supply. As income grows and the relative price of agriculture falls (driven by asymmetric increases in sectoral productivity), the demand for non-agricultural goods (and labor) 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 to a larger local demand. This result hinges on the difference across locations in non-agricultural productivity being relatively small, see Figure 6 panel (a), and on the ability to substitute goods across locations through trade.

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

Figure 8: Agricultural share of employment and output per worker - model *vs.* no migration



Notes: this figure plots the evolution of the agricultural share of employment (panel a) and output 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 output per worker, which is consistently lower in the counterfactual than in the benchmark economy, see Figure 8 panel (b). In particular, the present discounted value of output per worker is 11% lower in the no-migration economy. 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.3 in the Appendix. In sum, 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 to aggregate productivity.

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 7. These 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) from leaving agriculture after changes in the relative value of working in non-agriculture, a mechanism highlighted by Hobijn et al. (2018). Second, younger cohorts 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, compared to older cohorts, younger cohorts are disproportionately born and raised in urban areas, where the demand for non-agriculture is higher and the access to education is better, a new mechanism highlighted by this paper. This section explores several counterfactual economies that help us understand the relevance of each of these mechanisms. Table 3 presents the results in terms of the change in the agricultural share, providing various statistics

Table 3: Drivers of cohort effects in structural change

DRIVERS OF COHORT EFFECTS					
	Benchmark (1)	No sec costs (2)	Fixed p_ℓ^H (3)	$\omega_{\ell a}^H = \omega_{\ell n}^H$ (4)	No migration (5)
ΔAgricultural sh (1983-2013)	-0.28	-0.23	-0.28	-0.3	-0.26
Between cohort %	71	33	73	64	75
Difference agr sh incumbent-new	0.13	0.01	0.12	0.11	0.13
Agricultural sh new cohorts	0.25	0.35	0.26	0.25	0.27

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 reallocations. 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 $p_{\ell j}^H$ is set exogenously such that new cohorts have the same share of high-skill agents as incumbent cohorts. In column (4), of an economy in which all four location-sectors are equally high-skill intensive in production. In column (5), of the economy in which migration is not possible.

that summarize the part of this change accounted for by between-cohort reallocations. Figures with the evolution of the agricultural share for each cohort are relegated to Appendix D.1.

First, I study an economy in which workers bear no costs when switching sector.[24] In this counterfactual, the between-cohort component of a within-between decomposition of the fall in the agricultural share accounts for only 33% of total reallocation, compared to 71% in the benchmark economy, see column (2). Free mobility across sectors allows all cohorts to leave agriculture at a very similar rate, despite their differences in human capital and location. This is also reflected in the average difference in the agricultural share between incumbent and new cohorts, which is reduced to only 1 p.p., compared to 13 p.p. in the benchmark economy. This reduction is driven both by the lower agricultural share of incumbent cohorts and the higher agricultural share of new cohorts, which is on average 10 p.p. larger than in the benchmark economy. In particular, more members of the new cohorts enter the labor market in agriculture because they anticipate that leaving the sector over their life-cycle is costless. Sectoral switching costs arise, hence, as a first-order determinant of the difference in the agricultural share across cohorts. While these costs do not have a direct counterpart in the data, we can look for observables that are consistent with specific frictions identified by previous literature as barriers to structural change. For instance, Adamopoulos et al. (2022) argue that the inability to trade land prevents farmers from leaving agriculture in China, while Hobijn et al. (2018) highlight the role of retraining costs upon switching sectors, which carries the notion that human capital is partly sector-specific. Consistently, I show in Appendix D.2 that workers who switch from agriculture to non-agriculture are less likely to own land and more likely to be self-employed than observationally equivalent workers who remain in agriculture. Likewise, they have accumulated less experience in the agricultural sector.

Next, I explore the role of the differences in human capital across cohorts for their different agricultural shares. I start by studying an economy in which new cohorts have the same share of

[24] In particular, I set to zero the bilateral switching costs across sectors, this is $\mu_{j\,j'\,t}^{sec} = 0\ \forall j, j', t$.

high-skill agents as cohorts already working in 1993.[25] In this experiment, summarized in column (3), both the between-cohort share of aggregate reallocation and the difference in the agricultural share between incumbent and new cohorts are very similar to the benchmark economy. In a similar vein, I then study an economy in which both sectors are equally high-skill intensive. In particular, I set $\omega^H_{\ell a} = \omega^H_{\ell n} = 0.5$ for both locations in the CES production function, such that labor demand in non-agriculture is not biased towards high-skill workers. Compared to the benchmark economy, the between-cohort share of the total fall in the agricultural share is smaller (64% *vs.* 71%), but still sizeable, see column (4). Likewise, the average difference in the agricultural share between incumbent and new cohorts falls, but remains high at 11 p.p.. Together, both exercises reveal that differences in educational attainment across cohorts are not large enough to explain their different agricultural shares.

Finally, in column (5), I report the results regarding cohort effects in structural change of the no-migration economy. In this counterfactual, the between cohort component of the fall in the agricultural share is moderately higher than in the benchmark, while the average difference in the agriculture share between new and incumbent cohorts remains the same, despite new cohorts taking a higher agricultural share. As discussed in the previous section, the rural non-agricultural sector is able to grow and absorb most of the workers of new rural cohorts who cannot migrate to urban areas. This generates differences in the agricultural share between new and incumbent workers that are as large as in the benchmark economy, and thus limits the role of rural-urban migration for the between cohort component of structural change.

6.3 The role of the intergenerational incentives 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 6.3. In the model, these intergenerational returns to rural-urban migration are internalized by agents when making their location choices, see equation (10). In particular, agents may migrate *because of* their offspring due to the higher access to education or due to the higher access to future non-agricultural demand provided by urban areas. This section explores the role of these two intergenerational incentives to rural-urban migration for aggregate outcomes, presenting the results of the relevant counterfactual economies in Table 4.

In an economy in which access to education in urban areas is the same as in rural areas,[26] the increase in the urban share is 2 p.p. lower than in the benchmark economy, see column (2) of Table 4. This means that the additional incentive to migrate induced by differences in the local access to education can account for approximately 10% of the urbanization observed in the data.

[25] In particular, I study an economy in which the probability of becoming a high-skill agent $p^H_{\ell j}$ is exogenous and fixed such that entering cohorts in each location-sector have the same share of high-skill agents as incumbent cohorts. In this economy, agents do not invest in the education of their offspring, so their only choice concerns their location-sector of work.

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

Table 4: Intergenerational incentives for rural-urban migration

INTERGENERATIONAL INCENTIVES TO RURAL-URBAN MIGRATION			
	Benchmark (1)	Same $p^H_\ell(i)\,\forall\ell$ (2)	Free mob young (3)
PDV of Y/L	1.00	0.98	1.00
ΔAgricultural sh (1983-2013)	−0.28	−0.28	−0.29
Agricultural sh youngs	0.25	0.26	0.25
ΔUrban sh (1983-2013)	0.21	0.19	0.24
Urban sh youngs	0.43	0.41	0.46

Notes: this table presents the results of several counterfactual economies in terms of output per worker and the change in the agricultural share and the 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.

Naturally, the share of young agents that are high-skill workers in this economy is lower, and hence their agricultural share is higher. Yet, changes are small, consistent with the small differences in local access to education already discussed in the no-migration counterfactual of Section 6.1, and negligible for aggregate structural change. Also consistent with this previous counterfactual, the present discounted value of output per worker is lower in the economy with less urbanization and less high-skill workers.

Finally, consider an economy in which young agents can freely choose their location of work upon entering the labor market, regardless of the location where they acquire education.[27] In this economy, parents do not have an incentive to migrate in order to facilitate their children's access to urban areas in the future. While this keeps some parenting agents in rural areas, the fact that young workers can freely migrate dominates, and the urban share of employment increases by 3 p.p. more than in the benchmark economy. Consistent with the analysis so far, differences in migration patterns barely translate into differences in the sectoral composition of employment, and aggregate structural change and output per worker remain almost the same as in the benchmark economy.

7 Conclusion

In this paper, I have revisited the relationship between structural change and urbanization, two fundamental processes in the economic development of nations. Drawing on individual-level panel data from Indonesia, I have first documented that most workers leave agriculture within rural areas, rather than by moving to urban areas, and that these reallocations are associated with large earnings gains. Next, I have shown that the fall in the aggregate agricultural share is mainly driven by new cohorts entering the labor market in non-agriculture, rather than by workers leaving agriculture over their working life. Taken together, these two facts suggest that leaving agriculture is costly for workers, and that their initial conditions can be an important determinant of their sector of work. I have explored the role of location as initial condition, and shown that workers

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

raised in urban areas have a larger probability of working in non-agriculture than workers raised in rural areas, part of it as a result of acquiring more education.

To understand the determinants of these employment reallocation patterns and assess their aggregate implications, I have built a quantitative overlapping generations model of two locations (rural and urban) with two sectors (agriculture and non-agriculture). In the model, workers face costs when switching locations and sectors, and take into account that their location choices affect their offspring, as locations differ in the access to education and in the sectoral composition of labor demand. After calibrating the economy to replicate the development of Indonesia between 1983 and 2013, I have first shown that rural-urban migration has little impact on structural change, particularly in the short run, as the rural non-agricultural sector is able to absorb most of the employment released by agriculture in rural areas. Next, I have uncovered a prominent role of sectoral switching costs for the cohort-level differences in the agricultural share. Taken together, these two findings imply that frictions to leave agriculture, rather than to leave rural areas, should be the target of policies aimed at accelerating structural change. This paper is silent on the specific frictions or barriers that these costs represent, which is an important question left for future research.

Finally, my analysis reveals that rural-urban migration allows economies to reallocate labor to the location where non-agriculture is more productive and where accumulating human capital is easier. As intergenerational motives can be a relevant driver of rural-urban migration, it follows that policies that want to foster urbanization should also target outcomes of migrants' offspring, such as access to education.

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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 heterogeneous 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, 16% of all worker-year observations 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, 5% also work in agriculture. I perform robustness checks in which I only keep workers with one job, see Section B.

Rural/Urban status. The information on the rural/urban status of the household in the IFLS is based on the classification as rural or urban of the administrative unit where the household resides. These administrative units can be part of an official urban district (*kota*) —in which case they are classified as urban— or not —in which case their rural/urban status is based on a number of indicators determined by the Indonesian Central Bureau of Statics (BPS). In particular, the BPS uses a functional definition based on indicators such as population density or the availability of infrastructure (e.g. schools, markets, hospitals and health centers, banks) to determine whether a municipality (*desa*) classifies as rural or urban. Each of these indicators is assigned a number of points, and municipalities scoring above a certain threshold are classified as urban.

The IFLS does not provide information on the specific municipality or urban community where each household resides. Nonetheless, it provides information on some characteristics of the municipality, allowing us to compare administrative units classified as rural or urban. Table A.1 gives numbers for the median and average population in rural and urban communities surveyed in

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.

the IFLS. We can see that the median urban community tends to be 3-4 times more populous than the median rural community, which hosts around 3,500 people. This difference is a lower bound, as 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 IFLS households live is larger.

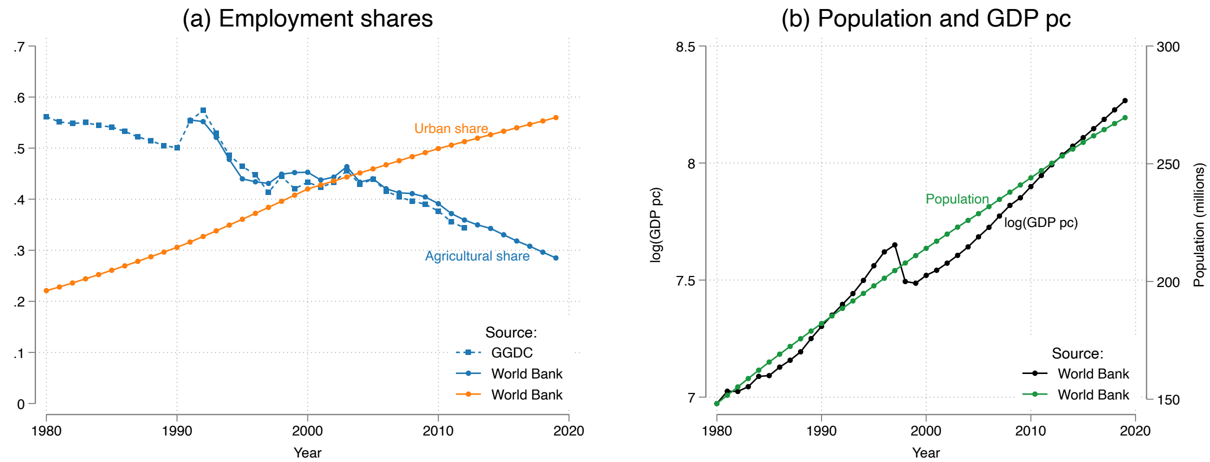
To validate my findings regarding workers sectoral and spatial reallocation, I use alternative definitions of the rural/urban status of the household to the one provided by the BPS. In particular, the migration module of the IFLS asks individuals to categorize the place to which they move to as village, small town, or big city. For individuals who never move, the IFLS asks a similar question regarding the location of the individual at age 12. In this way, I construct a self-reported measure of the rural/urban status of the individuals. Notably, this is the measure used by Hicks et al. (2020) and Lagakos et al. (2020) to construct their rural/urban status in their studies of rural-urban gaps in Indonesia.

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

Consumption expenditure. I aggregate expenditure on different items provided at different frequencies (e.g. monthly for the case of food or housing, yearly for the case of education...) to a yearly frequency. I then aggregate at the household level and divide by the number of adult individuals in the household. I deflate all expenditures by the Indonesian CPI for the corresponding year.

A.1 Macroeconomic aggregates [back]

FIGURE A.1: Main aggregates



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:

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

The standard error associated with 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 transitions.

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

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).

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

Changes over time. Both matrix (1) and matrix (B.3) are averages over time of the transition probabilities observed in 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 into 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

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

Prime-age males. 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. Restricting my sample to prime-age males (between 25 and 59 years old), I obtain very similar transition probabilities to those shown in matrix (1), see matrix (B.5).

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

Heterogeneity by gender. Interestingly, when I explore the heterogeneity by gender, I find that both males and females have similar transition patterns, see (B.6). The most notable difference is that the rural non-agricultural sector is more persistent for females than for males.

$$\text{(a) Males} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 76.7 & 18.2 & 2.2 & 3.0 \\ 23.0 & 61.1 & 1.8 & 14.1 \\ \hline 9.5 & 3.6 & 49.0 & 38.0 \\ 1.1 & 4.3 & 5.1 & 89.5 \end{array}\right] \end{array} \qquad \text{(b) Females} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 75.8 & 20.1 & 1.6 & 2.5 \\ 18.9 & 67.6 & 0.9 & 12.5 \\ \hline 8.4 & 4.7 & 41.9 & 45.0 \\ 0.6 & 4.1 & 3.0 & 92.3 \end{array}\right] \end{array} \tag{B.6}$$

Heterogeneity by age and educational attainment. 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: *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.7). 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.

$$\text{(a) } \textit{Young} \text{ workers} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 66.0 & 25.8 & 1.6 & 6.6 \\ 18.8 & 64.6 & 1.0 & 15.6 \\ \hline 11.6 & 7.8 & 35.1 & 45.4 \\ 1.6 & 7.8 & 3.9 & 86.7 \end{array}\right] \end{array} \quad \text{(b) } \textit{Adult} \text{ workers} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 75.7 & 20.3 & 2.0 & 2.0 \\ 18.6 & 68.5 & 1.0 & 11.9 \\ \hline 8.8 & 2.9 & 46.2 & 42.1 \\ 0.6 & 3.7 & 3.7 & 92.0 \end{array}\right] \end{array} \quad \text{(c) } \textit{Old} \text{ workers} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 83.0 & 13.4 & 2.1 & 1.5 \\ 30.1 & 57.6 & 2.4 & 9.9 \\ \hline 7.6 & 2.5 & 58.7 & 31.1 \\ 0.8 & 1.8 & 7.0 & 90.4 \end{array}\right] \end{array} \tag{B.7}$$

Second, to explore heterogeneity by education, I split my sample into *low-skill* workers (up to 8 years of formal education) and *high-skill* workers (more than 8 years of formal education), consistently with the groups I map my model to. I present these matrices in (B.8), 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.

$$\text{(a) } \textit{Low-skill} \text{ workers} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 79.2 & 17.0 & 1.8 & 2.0 \\ 27.7 & 61.9 & 1.5 & 8.9 \\ \hline 9.0 & 3.5 & 55.4 & 32.1 \\ 1.1 & 3.6 & 7.5 & 87.8 \end{array}\right] \end{array} \qquad \text{(b) } \textit{High-skill} \text{ workers} \quad \begin{array}{c} \\ RA \\ RN \\ UA \\ UN \end{array} \begin{array}{c} \begin{array}{cc|cc} RA & RN & UA & UN \end{array} \\ \left[\begin{array}{cc|cc} 67.6 & 23.9 & 2.8 & 5.7 \\ 12.7 & 66.6 & 1.4 & 19.3 \\ \hline 9.4 & 4.6 & 34.0 & 52.1 \\ 0.8 & 4.5 & 2.8 & 91.9 \end{array}\right] \end{array} \tag{B.8}$$

Split non-agriculture into industry and services. It may be of interest to explore whether workers who leave the agricultural sector in rural areas take up jobs in rural industries or in rural services. To do this, I use the information on the sector of work at the 1-digit level provided by the IFLS and classify as industrial workers those individuals working in the sectors "Mining", "Manufacturing", "Electricity, gas, and water supply", and "Construction". I classify as services workers those individuals working in the remaining non-agricultural sectors.

The transition probabilities across location-sectors with this classification are presented in matrix (B.9). We can see that around two thirds (11.4/(7.3+11.4) = 0.61) of the workers who leave agriculture within rural areas move to rural services, with the rest moving to rural industry. The probability of moving to urban areas is similar for workers in rural services than for workers in rural industry, around 14%. Most rural services workers who migrate to cities keep working in the services sector in urban areas (11.0/(1.2+2.0+11.0) = 0.77), while those coming from rural industry split more evenly between urban industry and urban services.

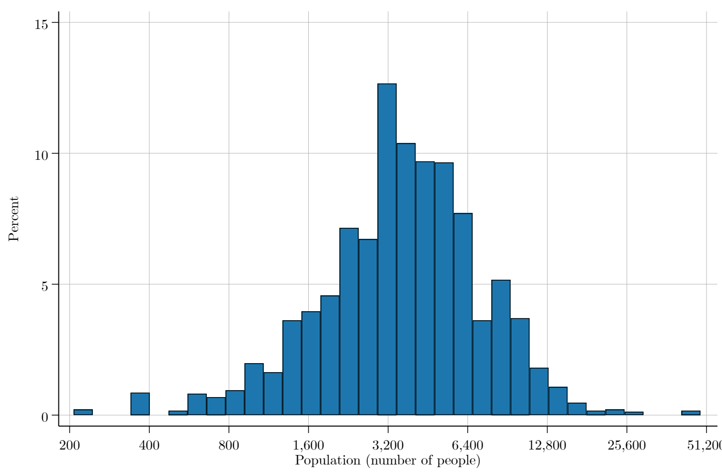
$$\begin{array}{cc}
 & \begin{array}{ccc|ccc} RAgr & RInd & RSer & UAgr & UInd & USer \end{array} \\
\begin{array}{c} RAgr \\ RInd \\ RSer \\ \hline UAgr \\ UInd \\ USer \end{array} & \left[\begin{array}{ccc|ccc}
76.9 & 7.3 & 11.4 & 1.9 & 1.0 & 1.5 \\
27.2 & 39.2 & 20.0 & 1.7 & 6.8 & 5.2 \\
18.9 & 8.5 & 58.4 & 1.2 & 2.0 & 11.0 \\
\hline
9.2 & 1.4 & 2.4 & 47.7 & 13.8 & 25.5 \\
1.1 & 1.8 & 1.7 & 5.8 & 51.6 & 38.0 \\
0.8 & 0.5 & 4.0 & 3.8 & 11.4 & 79.5
\end{array}\right]
\end{array} \tag{B.9}$$

Alternative rural/urban definitions. As explained in the Data Appendix, the workers' rural/urban status used in the main analysis comes from the classification of each municipality as rural or urban by the Indonesian Central Bureau of Statistics. This classification is based on a number of indicators, such as population density or the availability of infrastructure, that change over time and that can potentially affect or be affected by the transitions across sectors that I document. Nonetheless, the IFLS dataset provides information that can help us understand to what extent this classification matters for the main findings. As mentioned in the Data Appendix, from 1997 onwards we know the total population of the municipalities where households reside. Hence, we can see if moves from agriculture to non-agriculture happen within *small* rural locations (with total population below the median total population among rural locations), within *large* rural locations (with total population above the median among rural locations), or across them. This is presented in matrix (B.10), where we can see that moving out of agriculture is common both within small and within large rural locations, but not by moving from small to large rural areas, or from rural to urban areas. We can also see that in both small and large rural areas, moving to urban areas is much more common for workers in the non-agricultural sector.

$$\begin{array}{rc}
 & \begin{array}{cc|cc|cc} \text{R small A} & \text{R small N} & \text{R large A} & \text{R large N} & \text{Urban A} & \text{Urban N} \end{array} \\
\begin{array}{r} \text{R small A} \\ \text{R small N} \\ \hline \text{R large A} \\ \text{R large N} \\ \hline \text{Urban A} \\ \text{Urban N} \end{array} &
\left[\begin{array}{cc|cc|cc}
75.7 & 14.2 & 5.5 & 1.8 & 1.0 & 1.8 \\
23.7 & 55.8 & 2.8 & 10.1 & 0.7 & 6.8 \\
\hline
6.9 & 1.8 & 68.4 & 17.5 & 2.1 & 3.2 \\
1.4 & 4.5 & 15.7 & 63.9 & 1.4 & 13.1 \\
\hline
2.1 & 0.9 & 1.1 & 1.0 & 59.2 & 35.7 \\
0.3 & 1.0 & 0.3 & 1.6 & 4.2 & 92.6
\end{array}\right]
\end{array} \tag{B.10}$$

More directly, we can compute the size distribution (in terms of population) of the rural locations in which we observe workers switching from agriculture to non-agriculture. This is shown in Figure B.1, where we can see that most RA-RN moves happen in locations with population between 2,000 and 6,000 people.

Figure B.1: Size distribution of locations in which workers switch from RA to RN



Notes: the figure shows the distribution of the total population of all the rural locations in which a worker is observed switching from agriculture to non-agriculture.

Alternatively, using the migration module of the IFLS, we can construct a self-reported measure of rural/urban, as explained in the Data Appendix. This is the information used by Hicks et al. (2020) and Lagakos et al. (2020) to determine the rural/urban status of individuals. In particular, individuals report whether they live in a *village*, a *town*, or a *big city*. Hicks et al. (2020) consider *village* as rural and *town* and *big city* as urban, while Lagakos et al. (2020) consider *big city* as urban and the rest as rural. The transitions across location-sectors with these alternative definitions are presented in (B.11), where I also include a third matrix that keeps the three categories separately. Importantly, we can see in matrix (a) and (b) that alternative definitions of rural areas do not change the fact that workers leave agriculture within rural areas, rather than through migration to urban areas. Indeed, the transitions probabilities conditional on starting a period in rural-agriculture are very similar to those reported in matrix (1) in the main text. As urban areas are a much smaller set of locations in the definition used by matrix (b), the urban non-agricultural sector is much less persistent, and there is much less rural-urban migration. Finally, matrix (c) shows that the same reallocation patterns arise when we allow for three categories of locations: workers leave agriculture within villages or towns, and rural-urban migrants typically work in non-agriculture before moving to cities.

(a) Hicks et al. (2020)

$$\begin{array}{cc} & \begin{array}{cccc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 76.8 & 19.3 & 2.3 & 1.6 \\ 20.0 & 65.8 & 1.2 & 13.0 \\ \hline 17.7 & 7.5 & 39.9 & 35.0 \\ 1.4 & 11.5 & 3.9 & 83.2 \end{array}\right] \end{array}$$

(b) Lagakos et al. (2020)

$$\begin{array}{cc} & \begin{array}{cccc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 74.1 & 24.8 & 0.4 & 0.7 \\ 13.7 & 79.8 & 0.2 & 6.3 \\ \hline 21.5 & 14.2 & 21.0 & 43.2 \\ 1.8 & 28.4 & 1.8 & 68.0 \end{array}\right] \end{array} \tag{B.11}$$

(c) Self-reported

$$\begin{array}{cc} & \begin{array}{cccccc} \text{Village A} & \text{Village N} & \text{Town A} & \text{Town N} & \text{City A} & \text{City N} \end{array} \\ \begin{array}{c} \text{Village A} \\ \text{Village N} \\ \text{Town A} \\ \text{Town N} \\ \text{City A} \\ \text{City N} \end{array} & \left[\begin{array}{cc|cc|cc} 78.4 & 18.9 & 1.3 & 0.9 & 0.1 & 0.4 \\ 23.8 & 68.3 & 0.8 & 5.0 & 0.1 & 2.0 \\ \hline 14.0 & 5.1 & 38.8 & 31.4 & 6.2 & 4.6 \\ 1.0 & 5.4 & 4.3 & 66.2 & 0.8 & 22.5 \\ \hline 9.0 & 3.4 & 6.8 & 5.8 & 37.1 & 37.8 \\ 0.7 & 3.2 & 0.9 & 22.0 & 2.6 & 70.7 \end{array}\right] \end{array}$$

Transitions excluding workers that hold two jobs. In the main text, I include all individuals that are observed working in two consecutive periods, regardless of whether they hold two jobs or not, and compute the transition probabilities using information on the sector of their main job. This may bias the transition probabilities if individuals that hold two jobs in different sectors are more likely switch the sector of their main job. To explore this, I compute the transition probabilities excluding individuals that *ever* hold two jobs (around 17% of all workers, see the data description in Appendix A). The resulting transition matrix is presented in (B.12). The transition patterns are very similar to those presented in matrix (1) in the main text. Not surprisingly, the transition probabilities from RA to RN fall from 18% to 15%, but remain high and, importantly, much larger than from RA to UN.

$$\begin{array}{cc} & \begin{array}{cccc} RA & RN & UA & UN \end{array} \\ \begin{array}{c} RA \\ RN \\ UA \\ UN \end{array} & \left[\begin{array}{cc|cc} 80.0 & 15.0 & 2.1 & 2.9 \\ 17.9 & 64.1 & 1.2 & 16.8 \\ \hline 8.4 & 3.7 & 46.7 & 41.2 \\ 0.8 & 3.9 & 3.3 & 91.8 \end{array}\right] \end{array} \tag{B.12}$$

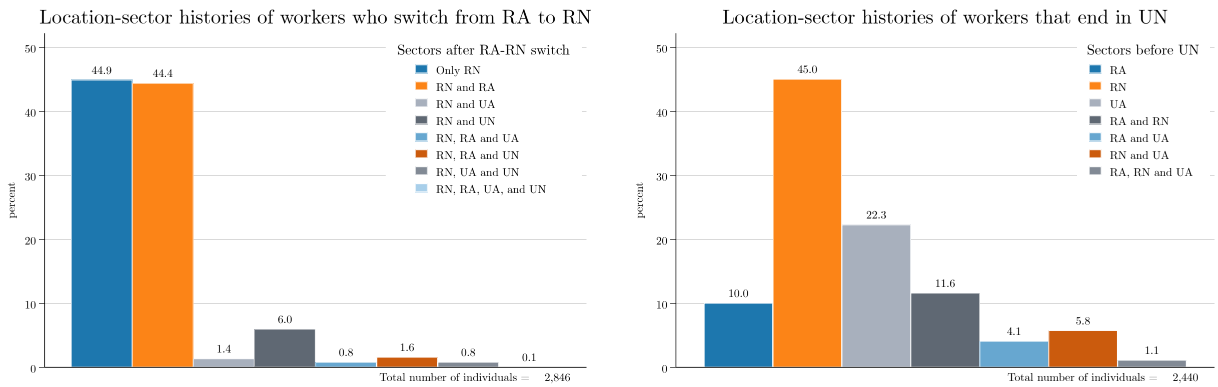
Attrition and transitions to non-employment. Finally, I explore the possible bias induced by transitions to non-employment or sample attrition. Note that, if a worker leaves a sector because of non-employment or not being interviewed in that wave, but comes back to the employment sample the period after, 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.13).[28] The probability of making a transition to non-employment or to leave the sample next period is similar across location-sectors, see the fifth and sixth columns of (B.13), with slightly higher values for urban non-agriculture.

$$\begin{array}{c|cc|cc|cc|}
 & RA & RN & UA & UN & ne & out \\
\hline
RA & 69.2 & 16.8 & 1.6 & 1.7 & 7.1 & 3.6 \\
RN & 18.5 & 59.6 & 1.0 & 10.8 & 6.1 & 4.0 \\
\hline
UA & 8.7 & 3.3 & 42.2 & 35.4 & 7.7 & 2.8 \\
UN & 0.6 & 3.2 & 3.5 & 78.5 & 9.4 & 4.7 \\
\hline
ne & 25.8 & 18.2 & 4.7 & 36.2 & 14.4 & 0.7 \\
out & 22.9 & 25.1 & 3.2 & 37.4 & 3.6 & 7.7
\end{array} \tag{B.13}$$

Location-sector histories. Transitions matrices used in the main analysis to study the reallocations across location-sectors may hide important life-cycle dynamics. The main two patterns of reallocation that we can see in matrix (1) are switches from agriculture to non-agriculture within rural areas, and the rural-urban moves within the non-agricultural sector. This suggests that the rural non-agricultural sector could serve as a stepping stone for rural workers before they can make it to the city. Figure B.2 aims to assess this hypothesis. On panel (a), it shows the distribution of all possible location-sector histories for workers who switch from rural agriculture to rural non-agriculture (and are observed at least a third time). We can see that, among this workers, only 8.5% end up working in urban non-agriculture. Indeed, only 6% move from RN to UN after the RA to RN switch (dark grey bar), with the others experience another location-sector state before reaching UN. On panel (b), it shows the distribution of all possible location-sector histories for workers that start outside UN but end up in UN, i.e. that the last time I observe them have UN as location-sector, and are observed at least three times. We can see that 11.6% of them come from the RA-RN history, while the most common origin of UN workers are individuals who spent their past working history exclusively in rural non-agriculture (45%).

[28] 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, for instance, 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.13) 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.13) focuses on men age 25-59.

Figure B.2: Assessing the role of RN as a 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—.

Different outcomes to quantify the returns to transitions. In the main text, I use annualized household earnings per adult as the outcome to quantify the returns to transitions across location-sectors. In Table B.1, I present the estimation results of regression (2) including as outcomes annualized household consumption expenditure per adult (columns 3 and 4) and annualized individual earnings (columns 5 and 6). Regardless of the outcome, the coefficients associated to leaving agriculture or to leaving rural areas are positive and significant. Compared the coefficients in the main text using household earnings per adult as outcome (columns 1 and 2), the returns to transitions out of agriculture and out of rural areas are higher when the outcome variable is individual earnings and lower when the outcome variable is household consumption expenditure.

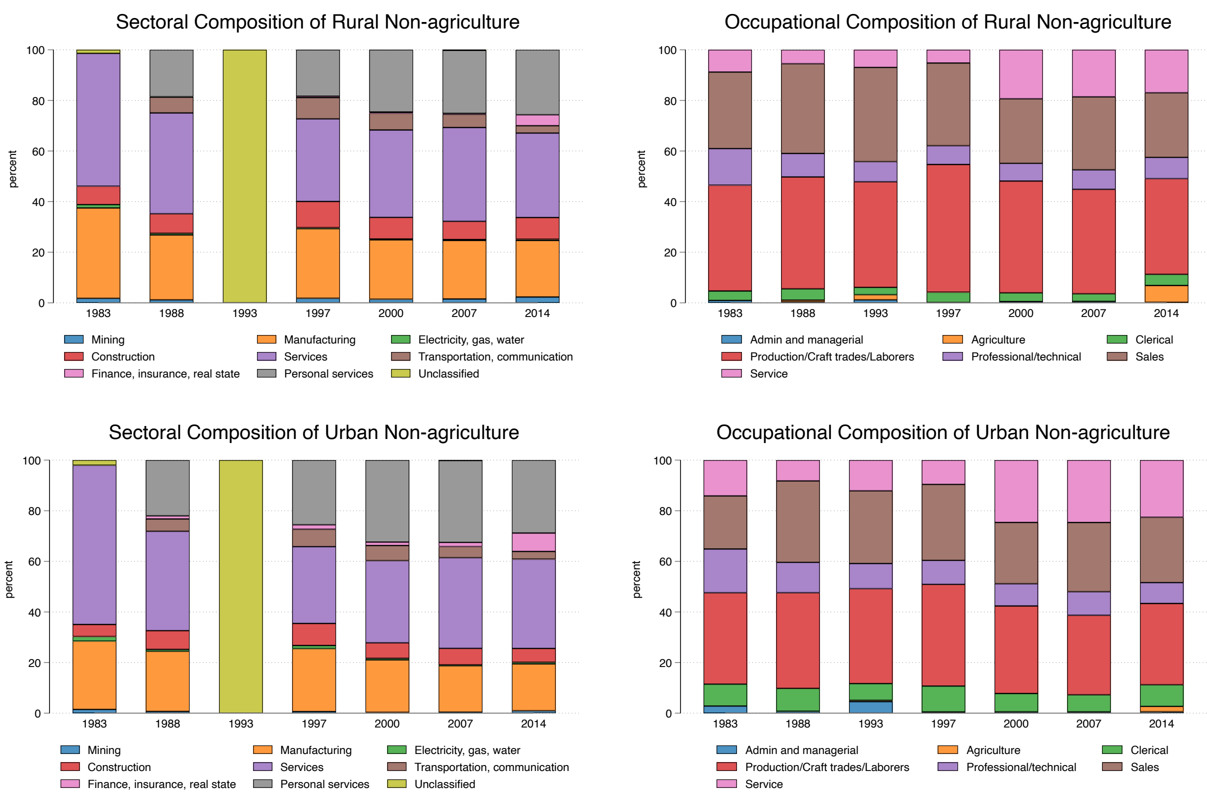
Table B.1: Returns to transitions across location-sectors

y_{it}	log h'hold earnings per adult		log h'hold consumption per adult		log individual earnings	
	(1)	(2)	(3)	(4)	(5)	(6)
Rural Non-agr	0.110***	0.090***	0.064***	0.060***	0.268***	0.242***
	(0.021)	(0.023)	(0.012)	(0.014)	(0.033)	(0.036)
Urban Agr	0.122**	0.032	0.085**	0.045	0.097*	0.034
	(0.048)	(0.053)	(0.036)	(0.038)	(0.057)	(0.062)
Urban Non-agr	0.262***	0.124***	0.190***	0.120***	0.389***	0.278***
	(0.039)	(0.041)	(0.029)	(0.033)	(0.050)	(0.054)
N	65,002	55,539	70,280	60,199	55,819	47,640
R-squared	0.63	0.65	0.72	0.73	0.66	0.67
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Within district	No	Yes	No	Yes	No	Yes

Note: the table presents the estimated coefficients of regression (2) using as outcomes household earnings per adult (as in the main text), household consumption expenditure per adult, and individual earnings. Controls at the individual level include age, education and household size. The sample is restricted to individuals observed at least two times as workers. SEs clustered at the sampling unit (enumeration areas) level in parenthesis. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

Rural non-agriculture *vs.* urban non-agriculture. Figure B.3 displays the sectoral and occupational composition of rural non-agriculture and urban non-agriculture. While differences are relatively small, we can appreciate that urban non-agriculture has more "Personal services", "Finance, insurance, real estate", and "Wholesale and retail trade" than rural non-agriculture, which is composed to a larger extent by "Construction" and "Manufacturing". In terms of occupations, urban non-agriculture has more "Service" and "Clerical" occupations than rural non-agriculture, which is composed to a larger extent by "Production/Craft Trades/Laborers".

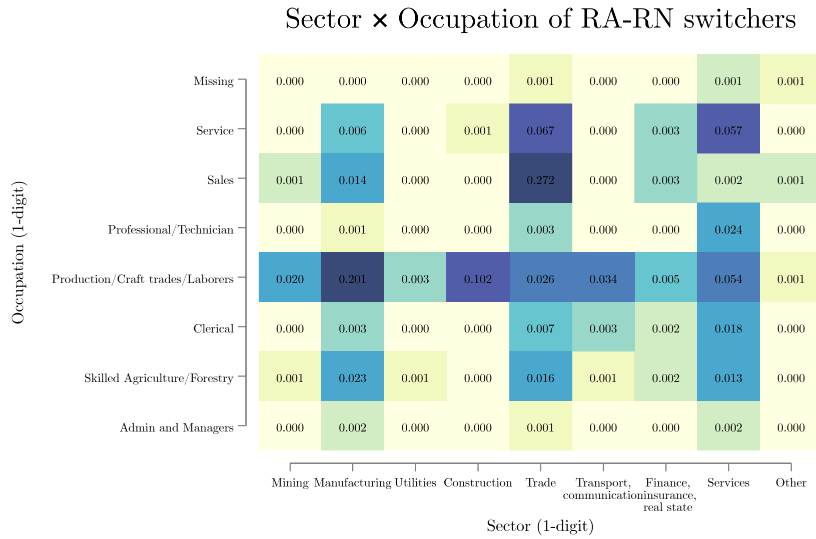
Figure B.3: Composition of Rural Non-agriculture and Urban Non-agriculture



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

Sector-occupation of rural-agriculture leavers. Figure B.4 shows the sector-occupation composition of rural-agriculture leavers in the period after they leave rural-agriculture. The most common sector-occupation categories among rural-agriculture leavers are the combination of the "Trade" sector and "Sales" occupation group and the "Manufacturing" sector and "Production/Craft Trades/Laborers" occupation group. A more casual exploration of the raw responses of the 1993 IFLS wave in text format (literally the verbal response of interviewed individuals) one can find several instances such as "selling snacks" (*kue* in Bahasa Indonesian) or "producing baskets made of bamboo" (*besek* in Bahasa Indonesian), which would fit into these two sector-occupation categories respectively.

Figure B.4: Sector-occupation composition of rural-agriculture leavers



Notes: the figure shows the sector-occupation composition of rural-agriculture leavers in the period after they leave rural-agriculture. The color intensity indicates the fraction of rural-agriculture leavers working in each sector-occupation category.

B.2 Cohort effects in aggregate reallocations

B.2.1 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,

$$\underbrace{\log l_{A,t,c}}_{\text{AGR SHARE OF COHORT } c \text{ AT TIME } t} = \underbrace{\mathbb{Y}_t}_{\text{YEAR EFFECTS}} + \underbrace{\mathbb{C}_c}_{\text{COHORT EFFECTS}} + \varepsilon_{t,c}\,. \tag{B.14}$$

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 a cohort *vs.* a year component

$$\underbrace{\log g_{L_A,t}}_{\text{RATE OF LABOR REALLOCATION}} = \underbrace{\log \psi_t}_{\text{YEAR COMPONENT}} + \underbrace{\log \chi_t}_{\text{COHORT COMPONENT}}\quad , \tag{B.15}$$

where $\log \psi_t = \frac{1}{k_t}\left(\mathbb{Y}_{t+k_t} - \mathbb{Y}_t\right)$ and $\log \chi_t \equiv \log g_{L_A,t} - \log \psi_t$. I run equation (B.14) for several samples (employed and nonemployed individuals, employed and nonemployed males, employed individuals, employed males) for the sake of comparability with these authors. Table B.2 reports the share of the average annual rate of reallocation accounted for by cohort effects in each case. As we can see, the cohort component of aggregate reallocation is high for all samples.[29]

Table B.2: Cohort Effects in Structural Change

All		All males		Employed		Employed males	
avg. $\log g_{L_A}$	sh. $\log \chi$	avg. $\log g_{L_A}$	sh. $\log \chi$	avg. $\log g_{L_A}$	sh. $\log \chi$	avg. $\log g_{L_A}$	sh. $\log \chi$
-2.20	106.67	-2.45	91.14	-2.65	64.70	-2.51	72.38

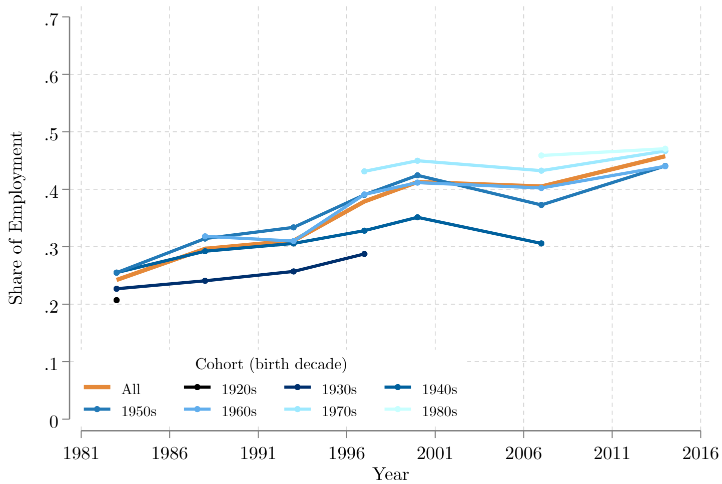
Notes: this table shows the average annual rate of reallocation out of agriculture $\log g_{L_A}$ and the share of it accounted for by cohort effects $\log \chi$ for different samples and groups. Samples: "All" refers to both employed and non-employed individuals between 25 and 60 years old; "All males" refers to employed and non-employed males aged 25-60; "Employed" and "Employed males" refer to all employed individuals and all employed males aged 25-60, respectively.

B.2.2 Cohort effects in urbanization

We can perform a similar decomposition for the evolution of the urban share of employment over time. As we can see in Figure B.5, the differences in the urban share of employment across cohorts are much smaller than the differences in the agricultural share. This suggests that the between-cohort component of the urbanization process is less important than the one of the structural change process. Using again Porzio et al. (2022) decomposition, we can see in Table B.3 that cohort effects

[29]Porzio et al. (2022) find that the cohort effects account for 82% of the average rate of reallocation in Indonesia, similar to what I find when I use their sample restrictions, 91%, see column "All Males" of Table B.2.

Figure B.5: Cohort-level Urban Share



Notes: this figure plots the evolution of the urban share for individuals aged 25 to 60, classifying them into cohorts based on their birth-decade. The orange line shows the evolution of the aggregate urban share.

account for 19-35% of the increase in the urban share during my sample period, a much smaller share of aggregate reallocation than they do for aggregate structural change.

Table B.3: Cohort Effects in Urbanization

All		All males		Employed		Employed males	
$\log g_{L_U}$	$\log \chi$	$\log g_{L_U}$	$\log \chi$	$\log g_{L_U}$	$\log \chi$	$\log g_{L_U}$	$\log \chi$
2.29	19.00	2.13	28.73	2.39	28.87	2.09	35.19

Notes: this table shows the average annual rate of reallocation to urban areas $\log g_{L_U}$ 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 60 years old; "All males" refers to employed and non-employed males aged 25-60; "Employed" and "Employed males" refer to all employed individuals and all employed males aged 25-60, respectively.

B.3 Rural-urban migration and the cohort effects in structural change

B.3.1 Sample selection

To study the contribution of rural-urban migration to the cohort effects in structural change through its effects on workers' initial conditions, I select a sample of young rural workers whom I follow over time to then look at their offspring. As mentioned in the main text, I select individuals that are observed working 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) at some point become household heads. This is a sample of 2,912 individuals and 11,520 individual-year observations. Among this individuals, 23.6% end up in urban areas at some point in time. Then, I compare the offspring of this group of workers with the offspring of rural stayers. While being the offspring of a rural-urban migrant is very correlated with living in urban areas, some individuals may return to rural areas. Likewise, some offspring of rural stayers may move to urban areas. I compute that 92.5% of migrants offspring remain in urban areas, while 10.4% of rural stayers offspring end up moving to urban areas. In terms of the interpretation of results, this would dampen the differences between the two groups generated by location-specific factors. Hence, if anything, the estimates presented in section 3.3 would be a lower bound of the true effect of rural-urban migration on offspring outcomes driven by location-specific factors.

B.3.2 Rural-urban migration and the educational attainment of young cohorts

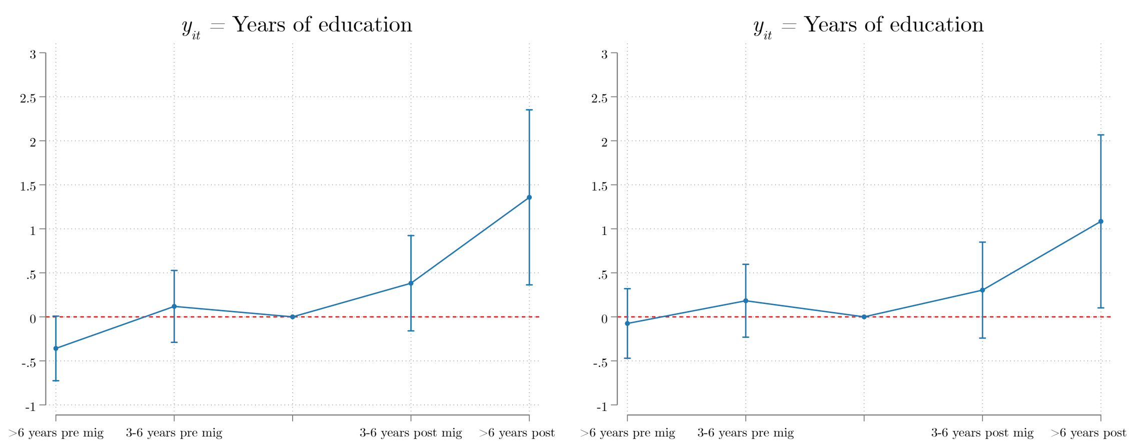
In Section 3.3, I show that the offspring of rural-urban migrants attain higher levels of education than the offspring of rural stayers. While I control for both observable and (time-invariant) unobservable characteristics of parents, it is still possible that part of this difference is driven by selection into migration based on location-specific or time-varying factors that correlate with offspring outcomes. For a subset of the sample, I can complement this analysis by exploiting the panel dimension of the data. In particular, I study whether parental rural-urban migration affects the educational attainment of children that are observed both before and after their parents migrate, in an event study design. By considering only offspring of migrants, I address the concerns related to selection on unobservables. Note that this is something that I cannot do with the other outcomes explored in section 3.3, which unfortunately are only observed after parents migrate.

Specifically, I compare the educational attainment of migrants' offspring before and after their parent's rural-urban migration, exploiting the heterogeneity in the timing of the event. Hence, I compare the outcomes of migrant children to the outcomes of yet-to-migrate children. I exclude from the analysis the offspring of rural stayers who never migrate and the offspring of migrants who are always observed in urban areas. This restricts the sample to 547 individuals and 1746 person-year observations. Moreover, given the gap in the number of years between survey waves, it is not always possible to define the year of the migration event precisely. Hence, I group the years relative to the migration event into five periods: more than six years before migration, between three and six years before migration, between two years before and two years after migration, between three and six years after migration, and more than six years after migration. I then estimate the following event study specification:

$$y_{it} = \alpha_t + \sum_{k=-2}^{2} \beta_k D_{i,t-k} + \Gamma X_{it} + \varepsilon_{it} , \tag{B.16}$$

where y_{it} are the years of education of individual i at time t, $D_{i,t-k}$ are dummies indicating whether individual i is observed in period k relative to the migration event at time t, with periods defined as discussed above and the $k = 0$ dummy suppressed, and X_{it} includes a set of controls. As in section 3.3, I run a specification with individual-level controls that include gender, age, and calendar fixed effects; and a specification that also incorporates parent's sector, years of education and permanent unobserved characteristics. Standard errors are clustered at the individual level. The results from these exercises are presented in Figure B.6. As we can see, there is no differential trend in the educational attainment of migrant children relative to yet-to-migrate children before the migration event. However, after migration, the educational attainment of migrant children increases relative to yet-to-migrate children, setting at around 1.1 extra years of education six years after the migration event (in the specification with both individual-level and parent-level controls). This provides further support to the idea that rural-urban migration has a positive effect on the educational attainment of migrants' offspring.

Figure B.6: Event Study: Educational Attainment of Migrant Children



Notes: this figure plots the estimated coefficients from regression (B.16) for two specifications, one with individual-level controls in X_{it} (left panel) and one with both individual-level and parent-level controls in X_{it} (right panel). The outcome variable is years of education. The omitted category is the period between two years before and two years after the migration event. Error bars represent 95% confidence intervals. Standard errors clustered at the individual level.

Appendix C: Quantitative Model Appendix

C.1 Solution Algorithm

Starting from an initial distribution of workers of each age-skill group across location-sectors $\left\{L_{\ell j\,0}^{g\,s}\right\}_{\ell=r,u;j=a,n}^{g=3,\ldots,6;s=H,L}$ and a converging sequence of fundamentals $\{\Theta_t\}_t$, such that $\{\Theta_t\}_t = \bar{\Theta}$ for all $t \geq T$, the solution algorithm proceeds as follows:

1. Guess an initial sequence of wages $\left\{w_{\ell j\,t}^{s\,0}\right\}_{t=1,\ldots,T}$ for each skill in each location-sector.

2. Given the last element of the sequence of wages $\left\{w_{\ell j\,t}^{s}\right\}_{t=T}$, find the Steady State value functions for each age-skill group in each location-sector $\left\{V_{\ell j\,t}^{g\,s}\right\}_{t=T}$.

3. Given the full sequence of wages and the value functions corresponding to the Steady State, find the value functions for every period $t \leq T$ of the transition to the Steady State $\left\{V_{\ell j\,t}^{g\,s}\right\}_{t}$ using the corresponding Bellman equations.

4. Given the full sequence of value functions, compute the labor supply for each skill in each location-sector at every period of the transition using equation (14) and the initial distribution of workers of each age-skill group across location-sectors $\left\{L_{\ell j\,0}^{g\,s}\right\}_{\ell=r,u;j=a,n}^{g=3,\ldots,6;s=H,L}$.

5. Given the labor supply at every period $\left\{L_{\ell j\,t}^{s\,\mathcal{S}}\right\}_{t=1,\ldots,T}$, find the wage that clears the labor market for each skill in each location-sector at every period using equation (17).

6. Compute a distance between the new wage sequence $\left\{w_{\ell j\,t}^{s\,1}\right\}_{t=1,\ldots,T}$ and the initial wage sequence $\left\{w_{\ell j\,t}^{s\,0}\right\}_{t=1,\ldots,T}$. If this distance is below some tolerance level, stop. Otherwise, update the wage sequence and go back to step 2.

C.2 Estimation of the income elasticity

The expression for the expenditure share in agriculture (6) can be directly estimated using data on expenditure shares and income. In particular, we can arrive at the following estimating equation:

$$\log\left(\varphi_{i\ell t} - \phi\right) = \alpha_{\ell t} - \eta \log e_{i\ell t} + \Gamma X_{it} + \varepsilon_{it}\,. \tag{C.1}$$

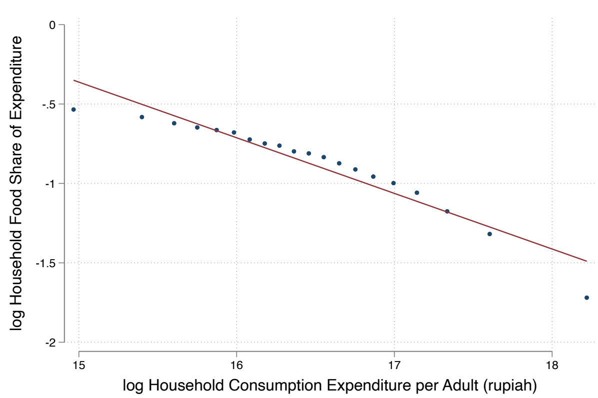
where $\varphi_{i\ell t}$ denotes the agriculture expenditure share of individual i in location ℓ at time t, $\alpha_{\ell t}$ are location-time fixed effects to control for asymmetric changes in prices across locations, $e_{i\ell t}$ is total expenditure, and X_{it} a number covariates at the individual level to control for dimensions that can be relevant to determine $\varphi_{i\ell t}$ but are not present in the model, such as household size or composition. In line with the estimation strategy of Fan et al. (2021), I estimate C.1 by OLS for different values of ϕ. Estimation results are presented in table C.1.

TABLE C.1: Income Elasticity of Sectoral Demand

Dependent var:	$\log\left(\varphi_{i\ell t} - \phi\right)$						
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 members, household share of children members.
SEs clustered at the sampling unit level in parenthesis. $^{*}p < .1, ^{**}p < .05, ^{***}p < .01$

FIGURE C.1: Engel curve



C.3 Remaining parameters ans targeted moments

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

$$\begin{array}{cc} & \begin{array}{cc} R & U \end{array} \\ \begin{array}{c} R \\ U \end{array} & \begin{bmatrix} 1 & 1.004 \\ 1.004 & 1 \end{bmatrix} \end{array} \qquad \begin{array}{cc} & \begin{array}{cc} R & U \end{array} \\ \begin{array}{c} R \\ U \end{array} & \begin{bmatrix} 1 & 1.019 \\ 1.019 & 1 \end{bmatrix} \end{array} \tag{C.2}$$

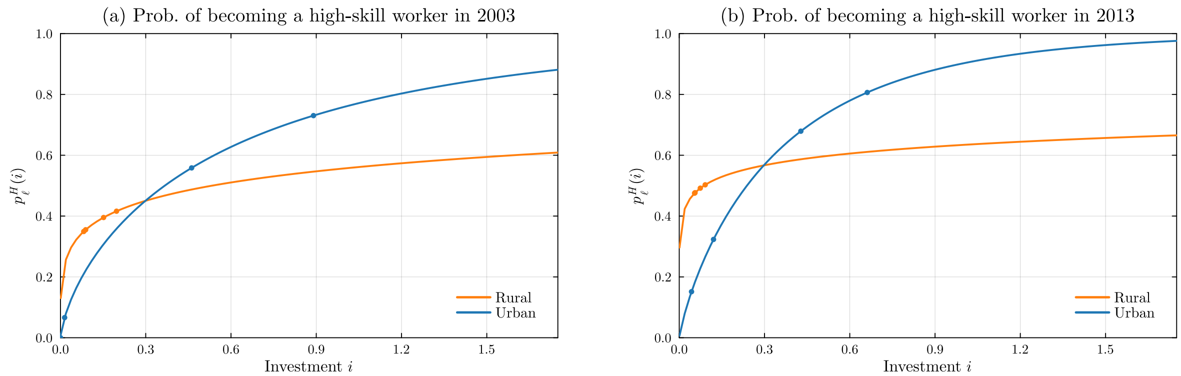
Table C.2: Remaining calibrated parameters

additional 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	0.04	SMM			
ν	PIGL parameter	0.299	SMM			
κ	Inverse switching elasticity	1.35	SMM	γ in regression (20)	0.83	0.82
β	Discount factor	0.65	Standard	Model period of 10 years		
ω^H_{ra}	High-skill CES share RA	0.33	SMM and Eq (21)	High-skill share of RA emp	0.18	0.11
ω^H_{rn}	High-skill CES share RN	0.68	SMM and Eq (21)	High-skill share of RN emp	0.40	0.35
ω^H_{ua}	High-skill CES share UA	0.66	SMM and Eq (21)	High-skill share of UA emp	0.38	0.27
ω^H_{un}	High-skill CES share UN	0.84	SMM and Eq (21)	High-skill share of UN emp	0.87	0.94
σ	Elasticity of subs across skills	2.5	Literature	Acemoglu and Autor (2011)		

Table C.3: Other targeted moments

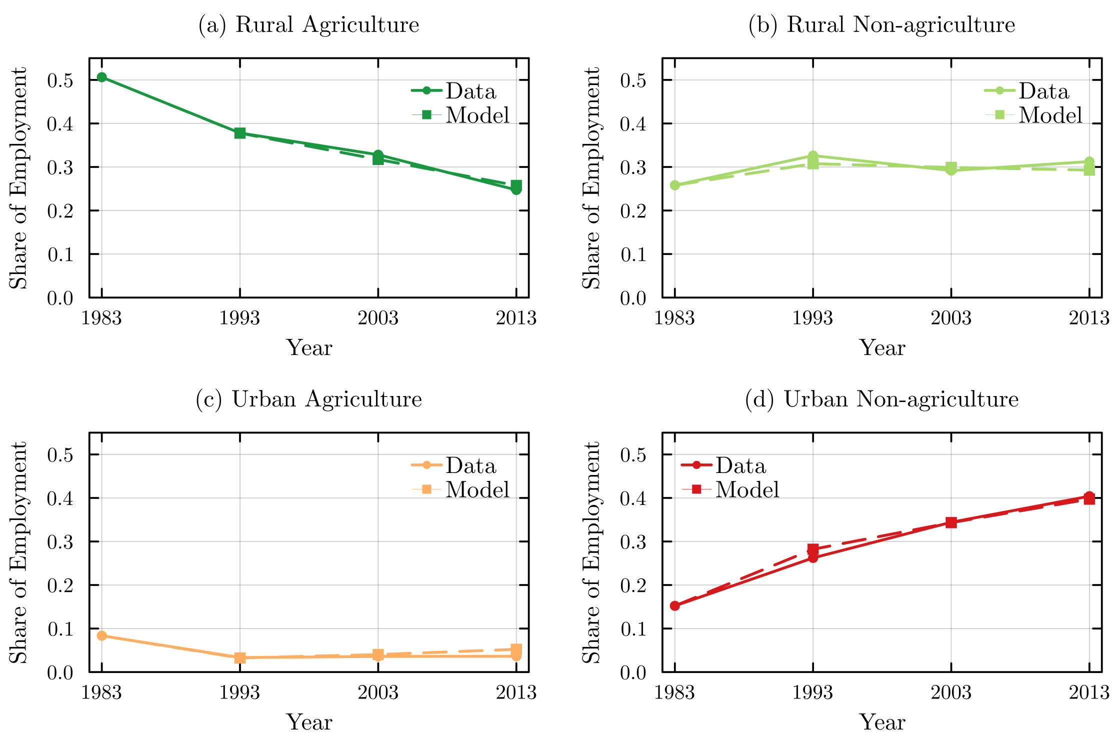
other moments targeted by the smm algorithm			
Target	Time period	Model	Data
Average wage gap across sectors	1993	0.73	0.67
	2003	0.53	0.48
	2013	0.44	0.45
Average wage gap across locations	1993	0.73	0.75
	2003	0.39	0.39
	2013	0.28	0.36
Growth in VA per worker agiculture	1993-2003	0.10	0.10
	2003-2013	0.44	0.44
Growth in VA per worker non-agiculture	1993-2003	0.03	0.02
	2003-2013	0.30	0.29

Figure C.2: 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.

Figure C.3: Evolution of employment shares across location-sectors

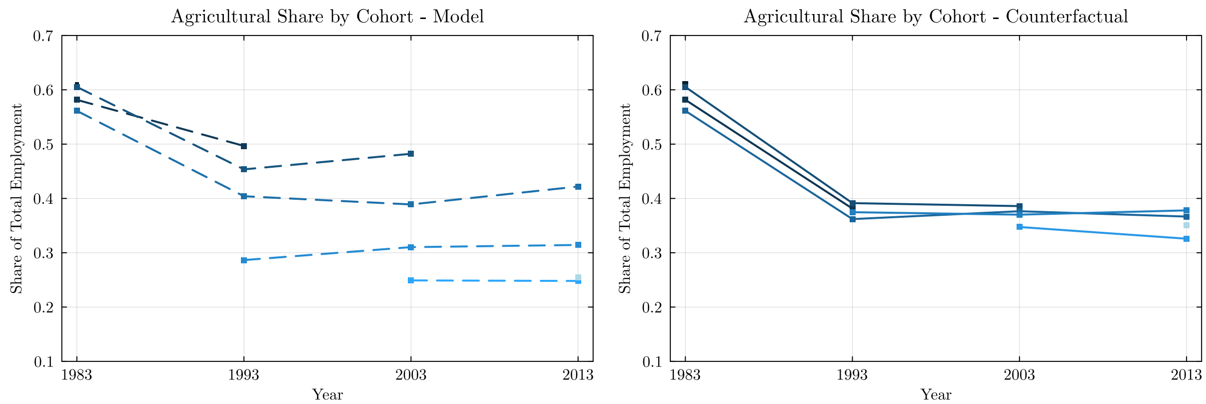


Notes: this figure plots the evolution of employment shares across location-sectors in the calibrated model (dashed lines with squared markers) and in the data (solid lines with circled markers).

Appendix D: Quantitative Analysis Appendix

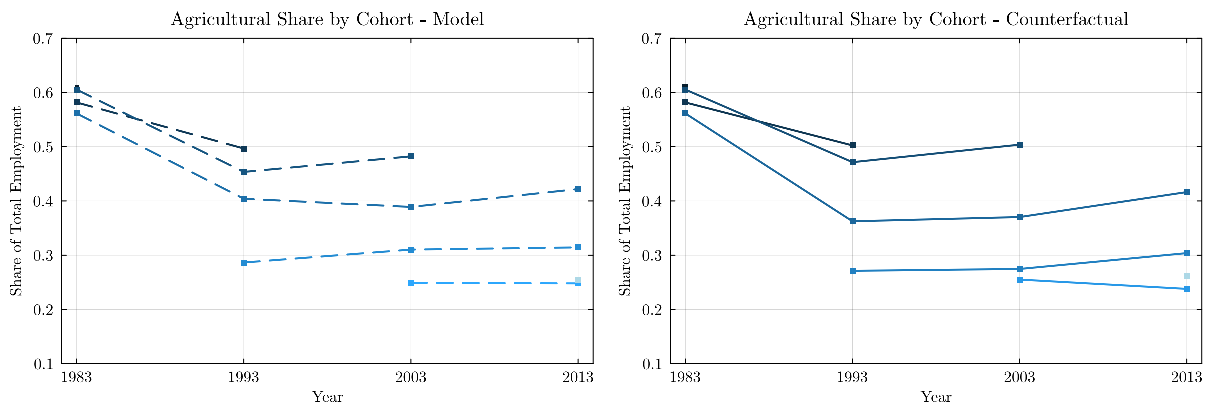
D.1 Drivers of cohort effects

Figure D.1: Counterfactual no sectoral switching costs



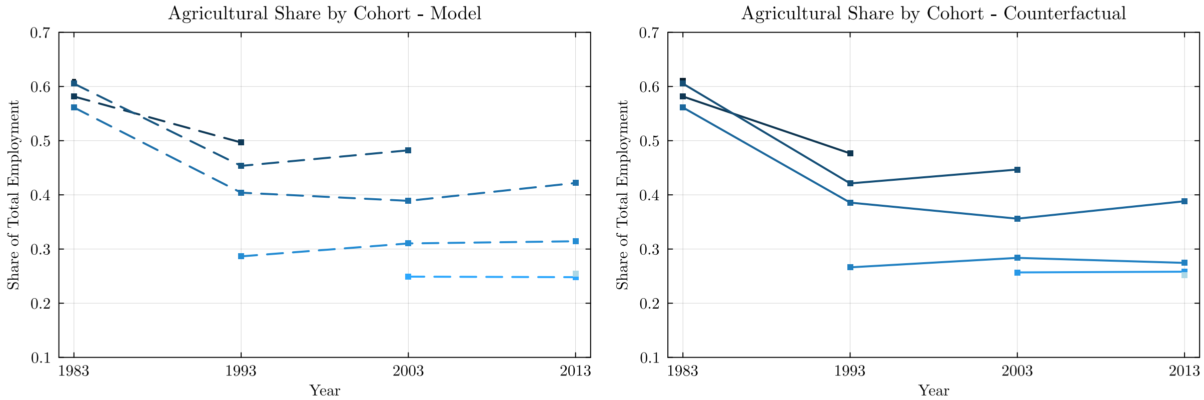
Notes: agricultural share by cohort in the benchmark economy (left panel) and in the counterfactual economy without sectoral switching costs (right panel). Each connected line corresponds to a cohort.

Figure D.2: Counterfactual same educational attainment



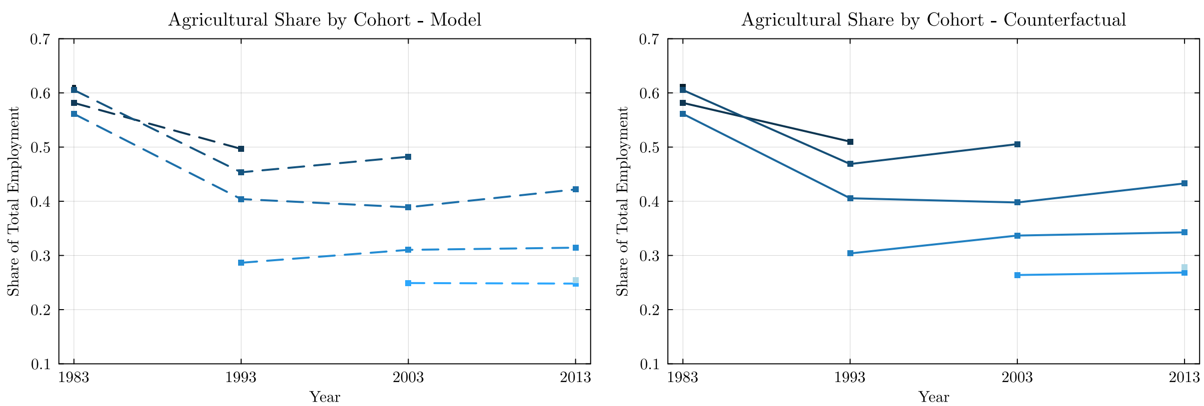
Notes: agricultural share by cohort in the benchmark economy (left panel) and in the counterfactual economy in which educational attainment is the for new than for incumbent cohorts (right panel). Each connected line corresponds to a cohort.

Figure D.3: Counterfactual same skill intensity in the production function



Notes: agricultural share by cohort in the benchmark economy (left panel) and in the counterfactual economy in which all sectors are have the same skill intensity in production (right panel). Each connected line corresponds to a cohort.

Figure D.4: Counterfactual no migration



Notes: agricultural share by cohort in the benchmark economy (left panel) and in the counterfactual economy in which migration is not possible (right panel). Each connected line corresponds to a cohort.

D.2 Observational evidence on sectoral switching costs

Sectoral switching costs are a key driver of the differences in the agricultural share across cohorts, see Figure D.1. On the one hand, they trap incumbent cohorts in agriculture, preventing them from moving to non-agriculture. On the other hand, they make new cohorts disproportionately choose non-agriculture upon entering the labor market, in anticipation of how costly it is to leave the sector. In the model, sectoral switching costs are a residual recovered to match the gross worker flows across location-sectors, and hence do not have a direct counterpart in the data. Yet, we can look for observables that correlate with specific frictions identified by previous literature as barriers hindering the reallocation out of agriculture. In particular, Adamopoulos et al. (2022) argue that frictions in land markets prevent some farmers to leave agriculture. An observation consistent with the presence of such frictions would be that workers who leave agriculture are less likely to hold land than those who stay. Likewise, agricultural leavers may be less likely to be self-employed, as self-employment is typically linked to the ownership of other assets related to farming. Other friction emphasized by the literature is the presence of retraining costs (Hobijn et al., 2018). This follows from the notion that human capital is sector-specific, so switching across sectors requires some retraining. Under this hypothesis, we may expect workers who leave agriculture to have accumulated less experience in the sector (so potentially less sector-specific human capital). I assess these conjectures in regression (D.1) below, where I compare observationally equivalent agricultural leavers with agricultural stayers. As leaving agriculture is not random and may be correlated with unobservable characteristics that also affect the outcomes of interest, the estimates should not be interpreted as causal. Yet, they may provide a first indication of the presence of barriers keeping workers in agriculture. The regression I run is the following:

$$y_{it} = \alpha_t + \beta_1 \text{Agr Leaver}_{it} + \text{X}_{it}\Gamma + \varepsilon_{it} \,, \tag{D.1}$$

where Agr Leaver$_{it}$ is a dummy variable equal to 1 if individual i leaves agriculture between year t and year $t+1$, and X_{it} is a vector of individual characteristics. I run this regression for three different outcomes: whether the individual owns land, whether she is self-employed, and her years of experience in agriculture. The results are shown in Table D.1. As we can see, individuals who leave agriculture are 8 p.p. less likely to own land, 5 p.p. less likely to be self-employed, and have accumulated 0.7 less years of experience in agriculture than those who stay.

Table D.1: Observational evidence on sectoral switching costs

y_{it}	Owns land (1)	Self employed (2)	Exp in agr (3)
Agr Leaver	-0.083***	-0.048***	-0.701***
	(0.010)	(0.009)	(0.168)
Mean y_{it}	0.55	0.52	10.10
N	23,912	24,367	23,656
R-squared	0.42	0.33	0.45

Note: sample includes only agricultural workers. All regressions control for gender, age, age square, education, household size, district, and year. SEs clustered at the sampling unit level (enumeration areas) in parenthesis. $^{*}p < .1,^{**}p < .05,^{***}p < .01$