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Abstract

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1 Introduction

Imagine to randomly extract a 25 years old man from the world population in 1950. We would expect this individual to have spent, on average, less than four years of his life in a classroom.[1] If we repeat the same exercise in 2010, we would get a very different answer. On average, a young man in 2010 has spent almost nine and a half years of his life in school. This thought experiment illustrates the dramatic and global increase in schooling observed in the second half of the last century.

Figure I: Global Increase in Average Years Spent in School

Notes: average years of schooling is calculated taking the average, weighted by age-specific population, across all countries the 146 countries present in the dataset.

It is plausible to argue that the steep increase in schooling deeply transformed the labor force. In particular, if the skills learned in school are more useful out of agriculture, as suggested by the extensive evidence on sorting of high-skilled workers across sectors,[2] then the global increase in schooling would have shifted the comparative advantage of many workers away from agriculture, thus effectively reducing – for fixed prices – the amount of agricultural labor. In turn, this reduction in the relative supply of agricultural labor might have affected the aggregate rate of structural transformation.

In this paper, we formally study this hypothesis, with the overarching goal of answering whether schooling increase can cause structural transformation. Towards this aim, we ask three instrumental questions. We study i) whether the supply of agricultural workers decreased and by how much – i.e.

[1] Authors' calculations using Barro and Lee (2013), see Figure I.

[2] See Gollin et al. (2013), Young (2013), and more recently Hicks et al. (2017).

whether the labor force changed becoming more biased towards non-agriculture; ii) whether the increase in schooling played an important role in this change; and iii) the implications, in general equilibrium, for the aggregate rate of labor reallocation out of agriculture.

To answer the *first question*, we need to provide a methodology to measure, in a consistent way across countries and over time, whether and by how much the labor force became more biased towards non-agriculture. We use a revealed preference approach, building on the simple insight that the share of individuals of a birth-cohort engaged in agriculture could provide useful information. In the presence of within-cohort skill heterogeneity, some, but not all, individuals of each birth-cohort should move towards the non-agricultural sector and, as the cohort's average comparative advantage in non-agriculture increases – for example, due to an increase in schooling, – more individuals would find it worthwhile to work in that sector.[3] However, though valuable, the average non-agricultural employment of a birth-cohort does not provide a full mapping into cohort-level characteristics. The reason being that younger cohorts not only differ in their relative return from agricultural production, but they are also exposed to different aggregate economic conditions. Therefore, in order to properly measure by how much did the labor force become more biased towards non-agriculture, we develop a simple model as guide.

We build a dynamic, general equilibrium, overlapping generations model of frictional labor reallocation out of agriculture. The model has three exogenous driving forces: the human capital of new birth-cohorts; the relative sectoral productivity; and an exogenous shifter affecting relative demand for agricultural goods. There are two types of agents in the economy: workers decide in which sector to work, subject to a switching cost; firms, in both sectors, compete for workers. As usual, goods and labor markets clear in equilibrium, determining relative agricultural price and wage. We assume that human capital is more valued in the non-agricultural sector, which implies that the supply of agricultural labor is determined by the average level of human capital of the cohorts in the labor market. The demand for agricultural labor, instead, is determined by changes in agricultural revenue productivity. Changes in the relative supply and demand of agricultural labor determine the equilibrium rate of labor reallocation out of agriculture.

The model provides an analytical map between differences across cohorts in agricultural employment and their comparative advantage towards agriculture. We prove that, if the data are generated by our model, a cohort-level regression of log agricultural employment on year, cohort and age dummies allows us to recover the changes in the cohort average human capital, and thus in the aggregate supply of agricultural workers. The year dummies capture the demand for agricultural labor. The age dummies control for the effect of reallocation frictions. One of the advantages of our revealed preference approach is that we don't need to use relative wages or prices, which are, especially in developing countries, hard to observe and often unreliable. Instead, we prove that data on quantities is enough to identify, leveraging the structure of the model, the objects of interest.

As is well known, we cannot run a fully saturated regression with year, cohort and age dummies. Due to their collinearity, we need to impose at least one linear restriction. The model implies that

[3]Throughout the paper, we use "sectors" to refer to agriculture and non-agriculture.

we should restrict the age effects to be identical in the first two periods that a cohort is working.

We bring the model-implied empirical specification to the data. We use micro-level data available from IPUMS International for 52 countries around the world. For each country, the data are either censuses or large sample labor force surveys representative of the population, and we have at least two repeated cross-sections, which allow us to compute labor reallocation over time. On average, for each country there are 28 years from the oldest to the most recent cross-section. For some countries, such as Brazil, our data cover half a century of labor reallocation. The 52 countries cover two thirds of the world population, and span five continents and the income distribution from Liberia to the United States.

We run the year-cohort-age regression separately for each country, which allows the structural parameters to be country-specific. The regressions recover country-year effects, which are a measure of the demand for agricultural labor, and country-cohort effects, which are a measure of cohort-level comparative advantage towards agriculture. Using the estimates, we can statistically decompose the observed aggregate rate of labor reallocation into changes in the year effects, and changes in cohort effects of the active cohorts. The statistical decomposition has a structural interpretation through the lens of the model. The cohort component captures the aggregate effect of changes in the supply of agricultural labor, for fixed prices. The year component captures the aggregate effect of changes in the demand of agricultural labor, which depends on the relative prices and productivities, but might also be affected by changes in the supply, through its effect on the relative agricultural price.

The rate of labor reallocation out of agriculture was, on average across countries, approximately 2% in the period of our study. The year effects declined on average at a rate of 1.20%, and the cohort effects at a rate of 0.80%. While there is some heterogeneity across countries, the cohort effects substantially declined in the overwhelming majority of them. Interpreting this statistical decomposition through the model, we learn that the decrease in the supply of agricultural workers would generate, keeping prices fixed, as much as 40% of the observed global reallocation out of agriculture. Overall, these results unveil a sizable decrease in the supply of agricultural labor in most countries.

We next turn to the *second question*: did the schooling increase play a role in the decrease of the supply of agricultural workers? To answer this question we need to address the apparent causal inference concern. We would ideally measure the effect of an exogenous schooling shock on labor reallocation across sectors. However, we are not aware of any credible instrument for schooling that is available in all (or even most) countries in our sample. We thus follow a second best strategy: we exploit three distinct sources of variation to draw a broad picture on the role of schooling in shaping cohort-level comparative advantage towards non-agriculture.

First, following the identification strategy of Duflo (2001), we exploit school construction in Indonesia as a shock to cohort-level schooling. We find evidence supporting a causal link between schooling and the supply of agricultural workers: individuals in the cohorts affected by the school construction are less likely to be employed in agriculture. While appealing, this result is limited to only one country in our sample.

Therefore, we then use within-country cross-cohort variation in average schooling and agricultural employment. We run, separately for each country in our sample, a regression of the cohort dummies identified from the previously described regressions on cohort-level average schooling, controlling for a cubic trend. In almost all countries in our sample, we uncover a significant negative relationship: cohorts that are relatively more educated than the trend, have also lower cohort dummies – i.e. a lower comparative advantage for agriculture. The magnitude of the relationship is sizable: when pooling all countries together, an additional year of schooling is associated with a 17% decrease (not 17 percentage points) in agricultural employment relative to the baseline.

We should be cautious in interpreting this result as causal. Direct reverse causality is not an issue since we measure agricultural employment after schooling is completed. Selection of higher skilled individuals into schooling and out of agriculture is also not an issue since we are studying cohort-level outcomes. However, two other relevant concerns remain. First, parents may decide to invest more in their children's education if they expect a higher future return from school (see Adukia et al. (2017)). Second, schooling may be a signal of other cohort-level characteristics, such as early-life human capital investment, rather than the determinant of returns from non-agricultural production. We can alleviate the first concern, but at the cost of making the second one possibly more severe, by instrumenting for schooling using exposure to the cyclical component of GDP during youth. Results using this specification have comparable magnitude to the benchmark ones.

Third, we use variation across countries. We show that countries that have experienced a faster increase in aggregate schooling have also experienced a larger decrease in the supply of agricultural workers, as measured by the change in the cohort effects.

While each one of the three strategies have limitations, we conclude that the overall evidence points to a relevant role of schooling in explaining the decrease in the supply of agricultural workers.

Finally, we address the *third question* and study the aggregate implications of the decrease in the supply of agricultural labor. The model provides analytical equations that map the empirically estimated changes in the supply of agricultural workers to their aggregate effects. The map is modulated by several parameters capturing the strength of the general equilibrium in the labor and goods market, and the relationship between observed cohort effects and unobserved human capital stocks. Since these parameters are likely to vary across countries, for example, as a function of trade-openness, we provide a range of estimates for the aggregate effects of the changes in supply.

First, we consider the simplest benchmark, where both the labor and goods' markets are in partial equilibrium. In this case, the estimated cohort component of labor reallocation directly maps into the aggregate counterfactual of no change in the supply of agricultural workers. We would thus conclude that the decrease in the supply of agricultural workers explained, on average, 40% of total labor reallocation out of agriculture. Second, we consider a small open economy with no trade frictions – i.e. we let the path for relative agricultural prices be exogenous. We show that the contribution of the supply of agricultural labor to aggregate reallocation decreases from the previous 40% to 16-36%, depending on parameter estimates. Third and last, we show that when also the goods market is in general equilibrium, a decrease in the supply of agricultural labor could actually pull workers *into* agriculture, as long as the price elasticity is sufficiently large – i.e. if the elasticity of substitution across sectors is below one – and the demand effect is sufficiently small.

This conclusion is, in fact, not surprising, and mirrors the result in Matsuyama (1992a): changes in relative productivity may have opposite implications in an open and a closed economy.

We return to our main question: does schooling cause structural transformation? We have shown that the increase in schooling transformed the labor force by shifting their relative comparative advantage towards non-agricultural production. However, the aggregate implications of such a shift probably differ across countries, spanning a large range, from at most minor to very significant. While we don't provide a definitive answer to the main question we posed, we nonetheless argue that any credible quantitative estimation of the drivers of structural transformation cannot fail to consider – as has been mostly done in the literature so far – both the changes in the supply of agricultural workers, and the role of schooling in determining it.

The paper is organized as follows. In Section 2, we develop a simplified framework to illustrate how we measure cohort characteristics using a revealed preference approach. In Section 3, we describe the data and lay out the basic statistical decomposition of aggregate labor reallocation into cohort- and year-effects. In Section 4, we build a general equilibrium OLG model of frictional labor reallocation out of agriculture. In Section 5 we use the model as a measuring tool to back out from the data how much the global comparative advantage of the labor force shifted away from the agricultural sector. In Section 6, we establish the role of schooling in changing the characteristics of the labor force. In Section 7, we study how the changes in the characteristics of the labor force affect structural transformation, in general equilibrium.

Related Literature. We build on the work of Caselli and Coleman II (2001) and Acemoglu and Guerrieri (2008). To our knowledge, Caselli and Coleman II (2001) first argued that the supply of agricultural workers might be relevant to understand structural change. It noticed that non-agriculture is more skill-intensive than agriculture, and, therefore, an aggregate increase in schooling raises the relative supply of non-agricultural workers. It focused on the effect of human capital increase on relative wages, and argued that taking it into account is necessary to match the path of relative agricultural wages. Acemoglu and Guerrieri (2008) formalized the general insight that changes in the relative prices of inputs – in our case, agricultural and non-agricultural workers – may lead to structural transformation if sectors vary in the intensity with which they use inputs.

These two papers developed the notion that changes in the supply of agricultural workers could contribute to reallocation out of agriculture. Our contribution is to develop and apply a methodology to measure the actual changes in the supply of agricultural workers for many countries, link them to changes in schooling, and quantify their aggregate impact.

With respect to this aim of separating the role of labor demand and supply as drivers of sectoral reallocation, our work is, in fact, most closely related to Lee and Wolpin (2006). Lee and Wolpin (2006) devised and structurally estimated a rich model to study the process of labor reallocation from manufacturing to services in the United States. We see our work as complementary, to the extent that we are interested in a similar question, but we tackle it from a radically different perspective. Specifically, our approach aims to impose the minimal structure to interpret the data, closer in spirit to the accounting literature.

More broadly, our work is related to a rich literature that studied the contribution of human capital, as measured by years of schooling, to growth and development. This literature showed that the level of human capital is significantly correlated with consequent growth (See Nelson and Phelps (1966), Barro (1991), Mankiw et al. (1992), and more recently Valencia Caicedo (2018)). To our knowledge, we are the first to measure the effects of changes in human capital on the supply of agricultural workers and the reallocation of labor out of agriculture.

Our model combines elements and insights already presents in Matsuyama (1992b), Lucas (2004), and more recently in Herrendorf and Schoellman (2017) and Bryan and Morten (2017). To the best of our knowledge, we are the first to provide a tractable framework to analytically characterize labor reallocation by cohorts in a context with general mobility frictions. Hsieh et al. (2016) also exploits year and cohort effects to calibrate a model of allocation of talent. It uses them to discipline the relative role, for the aggregate efficiency of the allocation of talent, of changes in frictions that affect human capital investment and frictions that distort the labor market. Relative to this paper, we focus on a simpler framework that allows us to analytically consider fixed-cost-type frictions, which turn out to be crucial to correctly identify the role of changes in the supply of agricultural workers.

Finally, our work relates to a growing literature that uses longitudinal wage data to reconsider the agricultural productivity gaps and that shows that these gaps are more consistent with sorting across-sectors than with large mobility frictions; (Alvarez (2017), Herrendorf and Schoellman (2017), and Hicks et al. (2017)). We contribute to this literature in two ways: we provide a model that highlights when wage data can be informative on frictions; and we show, without relying on wage data, additional evidence corroborating the sorting explanation and casting doubts on the presence of large mobility frictions.

2 The Simple Benchmark: Frictionless and in Partial Equilibrium

We build a simplified framework and use it to illustrate how changes in cohort-level characteristics can be measured through a revealed preference approach. Further, the framework provides a structural interpretation to the empirical regressions in Section 3.

2.1 Simplest Model of Labor Reallocation out of Agriculture

Time, indexed by a subscript t, is discrete and runs infinitely from time 0. We consider a dynamic economy inhabited by $N+1$ overlapping cohorts, indexed by the subscript c. Each cohort is made of a mass $\frac{1}{N+1}$ individuals, indexed by ε, which determines their relative return from non-agricultural production, or comparative advantage. Therefore, each individual is fully characterized by a couple (c, ε). We let ε be distributed as a $\text{Beta}\,(v, 1)$, whose CDF we label $F\,(\varepsilon)$. There are two sectors in the economy: agriculture and non-agriculture. Wages per efficiency unit in each sector are exogenous and are given by $w_{A,t}$ in agriculture and $w_{M,t}$ in non-agriculture. Wages grow over time at rates $g_{A,t}$ and $g_{M,t}$. Each individual supplies inelastically one unit of labor if he works in agriculture and $h\,(c, \varepsilon)$ units of labor if he works out of agriculture. Therefore, he would receive income $w_{A,t}$ in agriculture and $w_{M,t}h(c,\varepsilon)$ in non-agriculture. Individuals use income to buy an aggregate consumption good, which is supplied inelastically and for which they have a non-satiated utility. $h(c,\varepsilon)$ should be interpreted as the individual relative comparative advantage of non-agricultural activity and takes the form

$$h(c,\varepsilon) = \kappa h_c^{\gamma} \varepsilon^{1-\gamma},$$

where κ is a scale constant that we assume to be large enough to guarantee that for each cohort, as we observe in the data, at least some worker is not-employed in agriculture; h_c is a cohort-specific shifter that modulates the average cohort-level non-agricultural bias; and γ modulates the relative importance of between- and within-cohort heterogeneity since when γ is equal to 1 all individuals within a cohort are identical and when γ is equal to 0 all cohorts are identical. We will refer to $h(c,\varepsilon)$ as human capital.

Individuals choose frictionlessly, in each period in which they are alive, in which sector to work. We define $\omega_t(c,\varepsilon)$ to be occupational choice function of individual (c,ε) at time t, where $\omega_t(c,\varepsilon)$ is equal to 1 if the individual chooses to work in agriculture and 0 otherwise. Given the assumptions, individuals choose in each period the sector that provides them with the higher income. As a result the occupational choice is given by

$$\omega_t(c,\varepsilon) = \begin{cases} 1 & \text{if } w_{M,t}h(c,\varepsilon) < w_{A,t} \\ 0 & \text{otherwise} \end{cases}$$

and generates a cutoff policy within each cohort, such that all the individuals with $\varepsilon \leq \hat{\varepsilon}_t(c) = (w_{A,t})^{\frac{1}{1-\gamma}} (\kappa h_c^{\gamma} w_{M,t})^{-\frac{1}{1-\gamma}}$ are employed in agriculture.

Cohort-Level Agricultural Employment. The model implies that the share of individuals of a cohort c employed in agriculture at time t – $l_{A,t}(c) \equiv \log \int \omega_t(c,\varepsilon)\, dF(\varepsilon)$ – is given by:

$$\log l_{A,t}(c) = \hat{\kappa} + \underbrace{\frac{v}{1-\gamma} \log\left(\frac{w_{A,t}}{w_{M,t}}\right)}_{\text{Market Conditions}} - \underbrace{\frac{v\gamma}{1-\gamma} \log h_c}_{\text{Cohort Characteristics}}, \tag{1}$$

where $\hat{\kappa}$ is a time and cohort invariant function of parameters.

Changes in Aggregate Agricultural Employment. The aggregate share of employment in agriculture at time t is $L_{A,t} = \sum_{c=t-N}^{t} l_{A,t}(c)$, and its change between two periods is given by[4]

$$\log \frac{L_{A,t+1}}{L_{A,t}} = \underbrace{\frac{v}{1-\gamma}\left(\log \frac{g_{A,t}}{g_{M,t}}\right)}_{\text{Change in Demand}} + \underbrace{\log\left(\frac{\sum_{c=t+1-N}^{t+1} h_c^{-\frac{v\gamma}{1-\gamma}}}{\sum_{c=t-N}^{t} h_c^{-\frac{v\gamma}{1-\gamma}}}\right)}_{\text{Change in Supply}}. \tag{2}$$

[4]The model presented in this section is a special case of the model presented in Section 4. In that section we provide the derivation for all the analytical expressions.

Aggregate labor reallocation out of agricultural can be driven either by a change in market conditions which make agricultural labor paid less or by a change in the characteristics of the labor force which is biased towards non-agriculture. The first mechanism is a decrease in the demand for agricultural labor, while the second is a decrease in the supply of agricultural labor.

The literature interested in structural transformation has focused on several mechanisms, either working through non-homothetic utility or unbalanced productivity growth, that generate changes in the demand for agricultural workers. The goal of this paper is, instead, to empirically isolate and quantify the changes in the supply of agricultural workers, relate them to the global increase in schooling, and study whether and under which conditions they can lead to aggregate labor reallocation. The simple insight of the paper is that agricultural-employment by birth-cohort can reveal such changes. We next illustrate this argument with an example.

2.2 Inference Through Cohort-Level Agricultural Employment

In Figures IIa and IIb we plot labor reallocation out of agriculture by cohort for two hypothetical countries that have identical aggregate labor reallocation, but opposite patterns at the micro level.

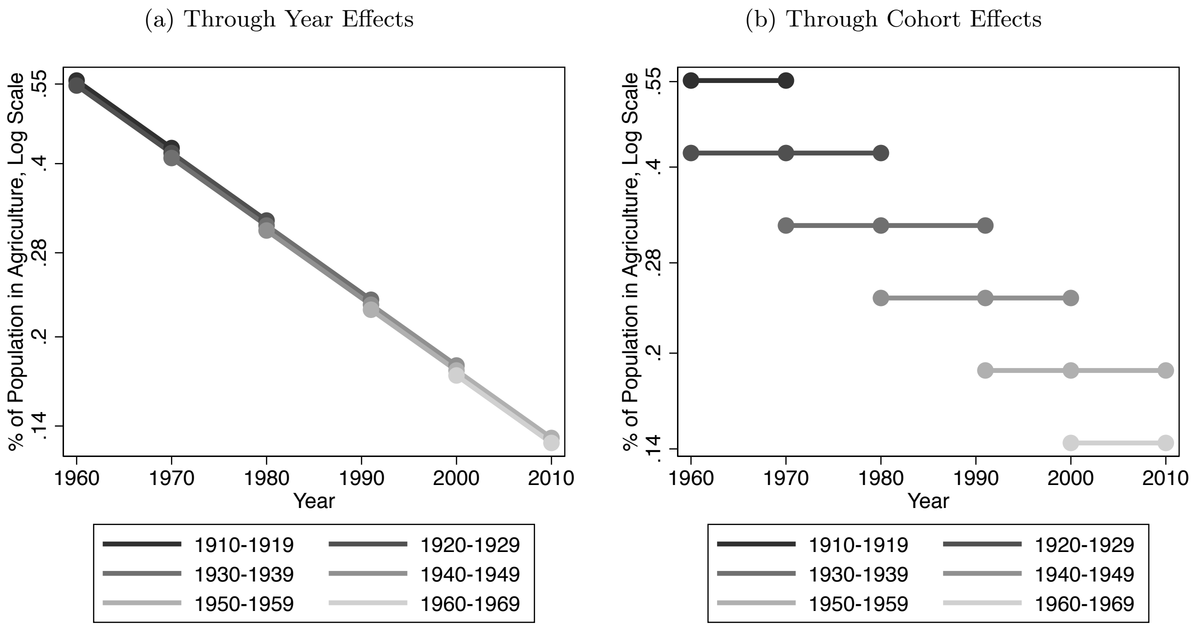
In Figure IIa, all birth cohorts have, in a given year, an identical share of agricultural employment, and over time some individuals from each cohort move out of agriculture. Interpreted through equation (1), we would infer from this figure that all cohorts must be identical, or $h_c = h_{c'}$ for all (c, c'). All cohorts behave identically at each point in time, indicating that only aggregate changes in the demand for agricultural labor can be responsible for the observed reallocation.

In Figure IIb, instead, the agricultural employment for each cohort is constant over time, and aggregate reallocation is driven by younger cohorts having a smaller share of workers in agriculture. From this figure we would infer that cohorts are different, but market conditions are identical in each period, or otherwise we should observe some within-cohort labor reallocation over time. In this second case, we would conclude that the demand for agricultural workers has not changed over time. In fact, more individuals of younger cohorts find it worthwhile to move out of agriculture, suggesting that the composition of the workforce, hence the supply of agricultural workers, is changing.

Remarks. The one to one maps between cohort-level agricultural employment, cohort characteristics and aggregate labor reallocation is an artifact of the assumptions of this simple model. The more general setting of Section 4 will highlight two shortcomings of the current analysis. Frictions in the labor reallocation will spoil the map between agricultural employment and cohort characteristics, since age effects will play a role. General equilibrium will affect the map between changes in the supply of agricultural workers and aggregate labor reallocation, since prices and wages will adjust and possibly reverse the direct effect of a decrease in supply highlight here.

Nonetheless, the simple insight is robust: cohort-level agricultural employment can shed light, under some assumptions, on cohort characteristics, and both demand for and supply of agricultural workers can play a major role for aggregate labor reallocation.

Figure II: Labor Reallocation By Cohort, Two Opposite Cases



Notes: the two figures depicts two hypothetical countries with identical aggregate reallocation out of agriculture, but specular micro patterns. Each solid line depicts the agricultural share of a birth-cohort. Darker lines are for older cohorts. Each ten year cohort is followed for the years in which all its members would show up in our dataset – i.e. the age of the younger individual of the cohort is larger than 25 and the age of the older one is lower than 60.

3 The Basic Empirical Decomposition: The Role of Cohort and Year Effects

We use micro level data from 52 countries and document patterns on labor reallocation out of agriculture by birth-cohorts. Most of the evidence available to date only covers aggregate rates of reallocation, we are among the first to document micro level evidence on the behavior of different cohorts of workers in the process of structural transformation[5].

3.1 Data

We use micro level data from the Integrated Public Use Microdata Series (IPUMS)[6]. The data are either censuses or large samples from labor force surveys that are representative of the entire population. We include in our analysis all IPUMS countries for which we have available at least two or more repeated cross-sections with available information on age, gender, and working industry, and which span in total at least ten years. This gives us a sample of fifty two countries covering about two thirds of the world population. For twenty three countries, we observe four or more

[5] Kim and Topel (1995), Lee and Wolpin (2006), and Perez (2017) document sectorial reallocation by cohort but limit their focus to, respectively, South Korea and United States and Argentina. Hobijn et al. (2017) in ongoing work are also using the IPUMS dataset to document patterns on reallocation by cohort. In particular, they document results consistent to our Fact 1 below, but considering reallocation between three sectors.

[6] Integrated Public Use Microdata Series, International: Version 6.5 [dataset], see(King et al. (2017)).

cross-sections, for seventeen we observe three or more. On average, we observe countries over a period of 28 years. For some countries, such as United States and Brazil, our data cover a long time span of half a century or more of labor reallocation.

Table A.I in the online appendix[7] lists the countries in our sample, the income level of each country, in 2010, relative to the one of United States, the years of coverage, the agricultural employment shares, and the number of observed cross-sections. In Figure A.I in the appendix, we show that the aggregate agricultural shares from our data are comparable to the same results from the World Development Indicators, which are an often used source of data on agricultural employment, for example by the handbook chapter Herrendorf et al. (2014).

The countries in the sample comprise a wide range of income levels, from the United States to Liberia and El Salvador. Eight countries are high-income countries, twenty five are middle-income countries and the remaining nineteen are low-income[8]. Our sample also spans a large geographical area, covering Asia and Oceania (nine countries), Africa (twelve countries), Central and South America (nineteen countries), and Europe and North America (twelve countries).

We focus on males and restrict our attention to those aged 25 to 59. This is meant to capture working age individuals and identify the period after education investment is completed. We exclude women from the current analysis given the large cross-country differences in female labor force participation.

3.2 Measurement

In each country j, for each cross section t, and for each cohort c, we compute the share of the population in agriculture, $l_{A,t,c,j}$. We normalize the values c to be equal to the birth year plus 25, so that a birth cohort first enters into our dataset when $c = t$ and it is last in the dataset when $c = t + N$, where $N = 59 - 25 = 34$. We define $k_{t,j}$ to be the number of years between cross-section t and the next cross-section in our data for country j.

We specify the log of the agricultural share to depend on a year and a cohort dummies:

$$\underbrace{\log l_{A,t,c,j}}_{\text{AGR SHARE OF COHORT } c \text{ AT TIME } t} = \underbrace{\mathbb{Y}_{t,j}}_{\text{YEAR DUMMIES}} + \underbrace{\mathbb{C}_{c,j}}_{\text{COHORT DUMMIES}} + \varepsilon_{t,c,j}. \tag{3}$$

This specification mirrors equation (1), which derived the observable empirical object in the simple framework. The simple framework therefore provides a structural interpretation of the year and cohort dummies as capturing market conditions and cohort characteristics.

This statistical decomposition restricts age to have no effect on agricultural share. It is well known that year, cohort and age are collinear, hence – even with panel data – it is not possible to separately identify them.[9] In order to include age dummies, we need to impose an additional linear restriction. We will do so in Section 5, when we include the linear restriction which is consistent

[7]The online appendix is available at https://sites.google.com/view/tommaso-porzio. We next refer to it as, simply, the appendix.

[8]By high-income (low-income) countries we mean those with income per capita greater (smaller) than 45% (10%) of the one of the United States at PPP, in 2010.

[9]See Deaton (1997), and more recently Lagakos et al. (2017a).

with the assumptions of the framework of Section 4.

The overall share of the population employed in agriculture in country j at time t is equal to the sum of cohort-specific agricultural share, $l_{A,t,c,j}$, weighted by the overall percentage of individuals in each cohort, $n_{t,c,j}$:[10]

$$L_{A,t,j} = \sum_{c=t-N}^{t} n_{t,c,j} l_{A,t,c,j}.$$

Using this last equation, the aggregate yearly rate of labor reallocation between two periods t and $t + k_{t,j}$ – $\log g_{L_A,t,j} \equiv \log \frac{L_{A,t+k_{t,j}}}{L_{A,t}}$ – can be shown to be given by a year component that captures the change in the year effects estimated from the year dummies, and a cohort component that captures the change in the composition of cohort effects of the active workforce

$$\underbrace{\frac{1}{k_{t,j}}\left(\log L_{A,t+k_{t,j},j} - \log L_{A,t,j}\right)}_{\text{RATE OF LABOR REALLOCATION}} = \underbrace{\log \bar{\psi}_{t,j}}_{\text{YEAR COMPONENT}} + \underbrace{\log \bar{\chi}_{t,j}}_{\text{COHORT COMPONENT}} + \upsilon_{t,j}, \quad (4)$$

where

$$\log \psi_{t,j} \equiv \frac{1}{k_{t,j}}\left(\mathbb{Y}_{t+k,j} - \mathbb{Y}_{t,j}\right) \quad (5)$$

$$\log \chi_{t,j} \equiv \frac{1}{k_{t,j}} \log \left(\frac{\sum_{c=t+k_{t,j}-N}^{t+k_{t,j}} n_{t+k,c,j} \exp\left(\mathbb{C}_{c,j}\right)}{\sum_{c=t-N}^{t} n_{t,c,j} \exp\left(\mathbb{C}_{c,j}\right)} \right). \quad (6)$$

This decomposition mirrors equation (2) previously derived. Under the assumptions of Section 2, the year and cohort components, which can be computed in the data, map directed into changes in the demand and supply of agricultural workers. While this simple mapping may not hold in general, it provides a useful benchmark. The results could also be also interpreted a-theoretically as a simple statistical decomposition which highlights the role of cohort effects in generating labor reallocation, thus motivating the rest of the paper.

We next decompose, for each country, labor reallocation according to specification (4), and summarize their joint distributions across countries. Practically, for each country, we estimate equation (3);[11] we compute, for each pair of cross-sections, the annualized year and cohort components, and calculate their average across all cross-sections.[12] Formally, the average year and cohort components are given by

$$\log \bar{\psi}_j = \tfrac{1}{|\mathbb{T}_j|} \textstyle\sum_{t\in\mathbb{T}_j} \log \psi_{t,j}, \qquad \log \bar{\chi}_j = \tfrac{1}{|\mathbb{T}_j|} \textstyle\sum_{t\in\mathbb{T}_j} \log \chi_{t,j}$$

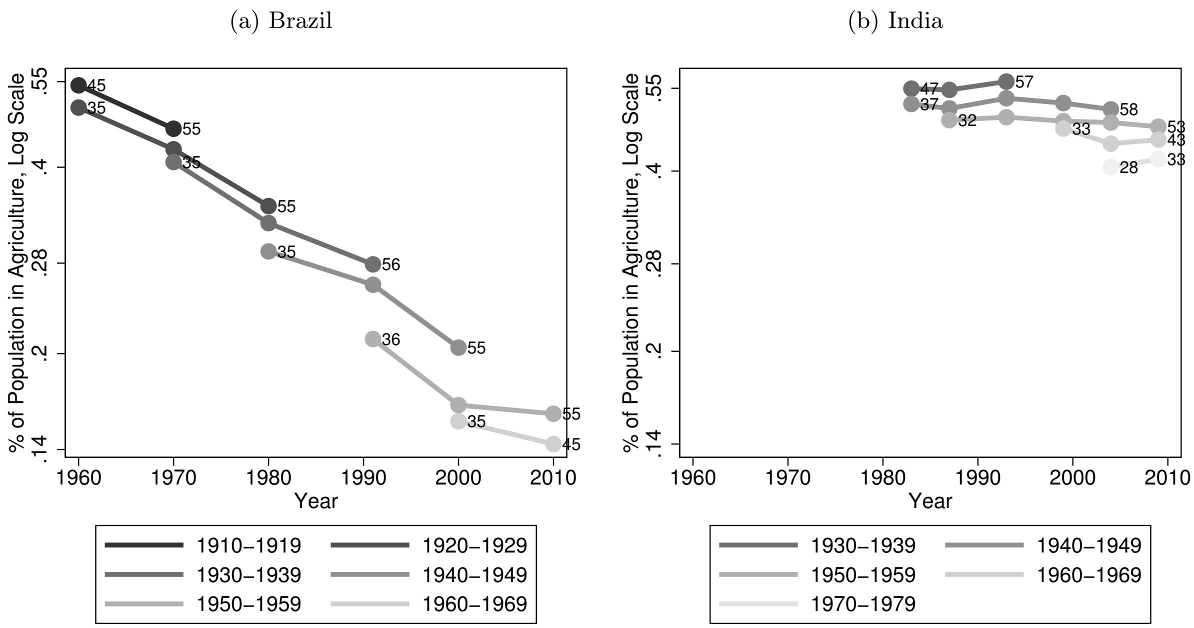
[10] For few countries, notably India, we observe age-heaping. We adjust for it by smoothing out $n_{t,c,j}$ with a quadratic equation. In Section C.1, we show that for all countries, but India, the adjustment is inconsequential.

[11] We estimate equation (3) in first differences to provide a tight map with the results of the model in section 4.

[12] We use this approach to assign to each country an equal weight, irrespective on the number of available cross-sections of data. In Appendix (C), we report the disaggregated results for each country cross-section.

where $\mathbb{T}_j$ is the set of all cross-sections available for country j excluding the most recent one, for which we cannot calculate the reallocation rate.

Figure III: Labor Reallocation By Cohort, Two Examples



Notes: the two figures plot agricultural employment by birth cohorts in Brazil and India over time. Each ten year cohort is followed for the years in which all its members would show up in our dataset – i.e. the age of the younger individual of the cohort is larger than 25 and the age of the older one is lower than 60. The average age of the cohort in a given year is reported for the first and last year a cohort is observed.

3.3 Results

In Figures IIIa and IIIb we plot agricultural employment by cohort for two countries with different reallocation experiences, Brazil and India, to illustrate our methodology. Graphically, the average year effect, $\log \bar{\psi}_j$, is given by the average slope of the cohorts' paths; while the average cohort effect, $\log \bar{\chi}_j$, is roughly given by the average within year vertical gaps across birth cohorts, properly annualized to reflect that in the figure we plot ten years birth cohorts. The year effect is -1.9% for Brazil and -0.2% for India. The cohort effect is -0.9% for Brazil and -0.4% for India. These numbers provide a quantitative statement for the qualitative evidence that emerges by comparing the figures: over time cohorts move out of agriculture much faster in Brazil than in India; on the other hand, for both Brazil and India, at any given point in time younger cohorts are employed in agriculture to a smaller extent.

Table A.II in the Appendix includes the rate of labor reallocation and the average year and cohort effects for each country. We here succinctly summarize their joint distribution across countries into two novel facts.

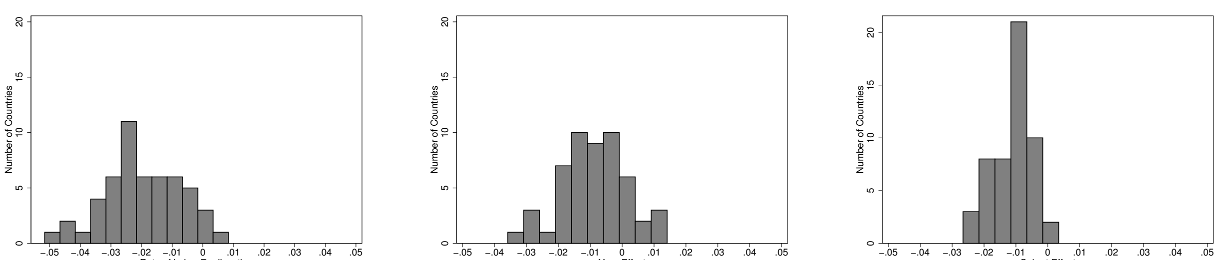
Fact 1: Decomposition of Average Reallocation Rate out of Agriculture. In Figures IVa, IVb and IVc, we plot the cross-cross-country distribution of, respectively, the rate of reallocation out of agriculture, the average year effect and average cohort effect. For almost all countries, the rate of reallocation out of agriculture is negative, suggesting, unsurprisingly, that most countries in our sample underwent reallocation from agriculture to non-agriculture. We can also observe that in most countries both the year and cohort effects are negative, indicating that they both positively contributed to structural change. The key pattern to notice is that the two distributions have similar means, namely, -0.9% and -1.1%. Equation (4) shows that the total rate of reallocation out of agriculture can be decomposed in the sum of year and cohort effects. That is, we can write

$$\mathrm{E}\left[\log g_{L_A,j}\right] \quad = \quad \mathrm{E}\left[\log \bar{\psi}_j\right] + \mathrm{E}\left[\log \bar{\chi}_j\right],$$

where the expectation is taken across countries j. Similar cross-country means for year and cohort effects suggest that, on average, they have a similar contribution, in a purely statistical sense, to reallocation out of agriculture. Specifically, cohort effects account, on average for all countries, for 56% of overall labor reallocation. If we restrict the attention only to low-, middle-, or high-income countries we obtain that cohort effects account for respectively 64%, 52%, and 57% of the overall labor reallocation.

Figure IV: Distribution Across Countries (Fact 1)

(a) Rates of Structural Change (b) Year Effects (c) Cohort Effects



Notes: the three figures plot the distributions of reallocation rates, cohort components, and year components across countries.

Fact 2: Decomposition of Cross-Country Variance of Reallocation Rates. In Figures Va and Vb, we plot, respectively, year and cohort effects as a function of the rate of labor reallocation out of agriculture. Two patterns emerge: (i) the year effects are strongly positively correlated with the rate of labor reallocation, while (ii) the cohort effects are more similar across countries and weakly correlated with the rate of labor reallocation. In other words, countries experiencing both slow and fast structural transformation have quite similar cohort effects, while countries undergoing fast reallocation have much larger year effects. This is consistent with what the Brazil vs. India case suggested: Brazil experienced fast structural transformation and displays large year effects.

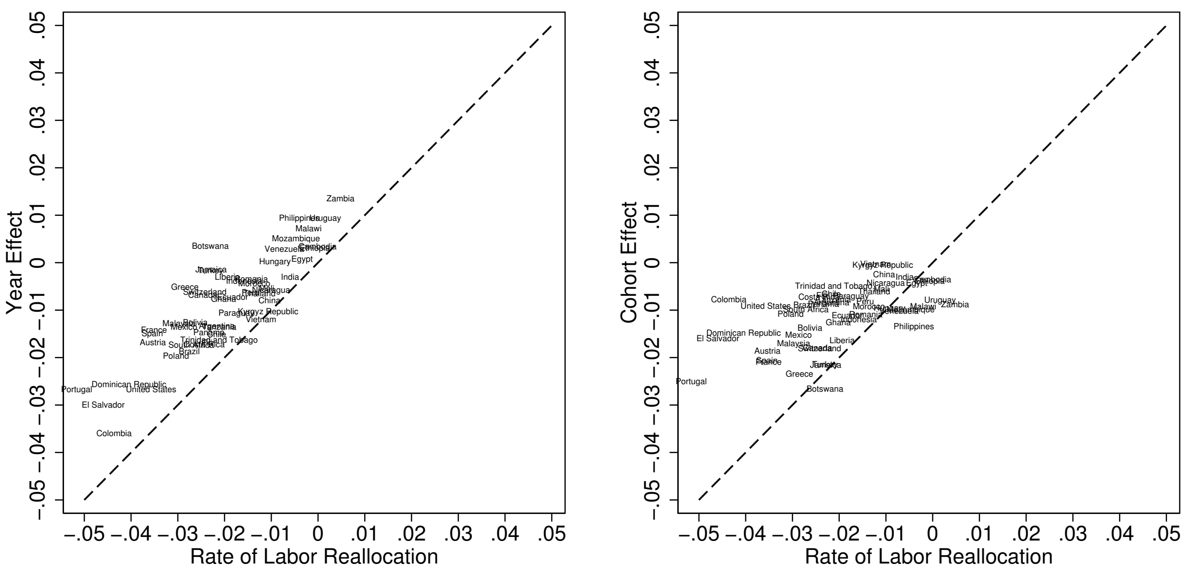
To make this discussion formal, we decompose the cross-country variation in the rate of reallocation out of agriculture as follows

$$\text{Var}\left[\log g_{L_A,j}\right] \quad = \quad \text{Cov}\left[\log g_{L_A,j}, \log \bar{\psi}_j\right] + \text{Cov}\left[\log g_{L_A,j}, \log \bar{\chi}_j\right].$$

We obtain that, on average across all countries, the cohort-effects component accounts for 28.9% of the dispersion of reallocation rates. If we focus to only low-, middle-, or high-income countries, we obtain that the across-cohorts component contribution to total variance is respectively 20.6%, 18.5%, and 16.5%.[13]

Figure V: Variance Decomposition (Fact 2)

(a) Year Effects (b) Cohort Effects



Notes: the left figure plots, across countries, the year effects as a function of the reallocation rates. The right figure plots the cohort effects as a function of the reallocation rates.

3.4 Interpretation and Discussion

These results can be interpreted structurally through the simple model of Section (2). Taking literally equation (2), we would conclude that changes in the supply of agricultural workers explain, on average across countries, more than half of the labor reallocation out of agriculture, and accounting for roughly one quarter of cross-country differences in rate of labor reallocation. We would thus conclude that changes in the supply of agricultural workers are a key determinant

[13]Notice that the average contribution of the within-cohort component does not need to be a weighted average of the contributions within each income group. In fact, the overall variance of reallocation rates takes into account also the differences across income groups.

of global patterns of structural transformation. This conclusion is appealing, but premature since the benchmark model does not take into account possibly important forces; namely, reallocation frictions and general equilibrium. Nonetheless, we find these results suggestive of a relevant role of the supply of agricultural workers, and thus they motivate us to develop the richer model of Section (4), which will provide a guide for proper measurement.

Finally, before moving forward, we briefly discuss further analysis, included in Appendix (C), aimed at exploring the robustness of the empirical results. First of all, we could expect that changes in the demographic composition, due to cohorts having different sizes, and cohort sizes changing over time due to mortality, could affect the estimated cohort and year effects. We show through a series of exercises that, in fact, demographic composition does not mechanically drive our estimates. Second, we use the geographical information at the sub-national level (e.g. states or districts), and show that Facts 1 and 2 hold also if we study regional variation within countries, in the spirit of recent work, such as Gennaioli et al. (2013).

4 The Measurement Framework: with Frictions and in General Equilibrium

We develop a general equilibrium model of frictional labor reallocation out of agriculture by cohort. We build on the stylized model of Section 2, and add two main features: wages and prices are determined in equilibrium, and workers face mobility frictions to move out of agriculture.[14] The model serves as the measurement tool to infer changes in the supply and demand of agricultural workers from data on agricultural employment by birth-cohort. Further, it provides a framework to compute their aggregate effects in general equilibrium.

4.1 Environment

We next describe the economic environment. Time is discrete and runs infinitely from time 0. Markets are complete and competitive, and individuals have perfect foresight.

4.1.1 Demographics, Preferences, and Individual Traits

Each period a cohort, indexed by c, is born. A cohort is composed by a continuum of mass one of individuals. Individuals of cohort c enter into the labor market at time c and they work for a total of $N+1$ periods; therefore, they work each period in $\{c, ..., c+N\}$. Individuals face an increasing and non-satiated utility for an agricultural and a non-agricultural good, possibly changing over time, as we further discuss below. They have no disutility of labor.

All individuals have identical returns from agricultural production. Instead, the returns from non-agricultural production are heterogeneous and determined by two characteristics: the cohort c in which an individual is born, and his idiosyncratic returns ε. We assume that ε is distributed according to Beta with parameters $(v, 1)$, where v captures the concentration of non-agricultural returns within cohorts. We aggregate the two characteristics (c, ε) into one non-agricultural returns

[14] The model of Section 2 is a special case of the model in this section. Nonetheless, we repeat, for clarity the description of all features of the economy, even those that are present even in the stylized model.

$h(c,\varepsilon)$ through a Cobb-Douglas

$$h(c,\varepsilon) = \kappa h_c^{\gamma} \varepsilon^{1-\gamma},$$

where κ is a scale constant; h_c captures a cohort-c specific shifter; $\gamma \geq 0$ is the elasticity of non-agricultural returns with respect to the cohort shifter and $1-\gamma$ with respect to individual returns. The non-agricultural returns $h(c,\varepsilon)$ account for both the relative non-agricultural productivity, and any other non-monetary value of non-agricultural production: we let $h(c,\varepsilon)^{\tau}$ be the non-agricultural productivity, where τ is a constant parameter that modulates the relative role of productivity as opposed to non-monetary values.

Notice that when either $h_c = h$ for all c, or $\gamma = 0$, all cohorts are identical, when instead $\frac{h_{c+1}}{h_c} > 1$ and $\gamma > 0$, then, the distribution of non-agricultural returns of cohort $c+1$ first order stochastic dominates the one of cohort c.

4.1.2 Production and the Problem of the Firms

There are two sectors in the economy, We call them agriculture, indexed by A, and non-agriculture, indexed by M. Production of agricultural good requires land X and labor input $L_{A,t}$, while production of non-agricultural good only requires labor $L_{M,t}$. We assume that land is owned collectively by all individuals, who share the profits, and use them to finance consumption. Productivity in agriculture, $Z_{A,t}$, may differ from productivity in non-agriculture, $Z_{M,t}$. The relative price of agricultural goods in equilibrium is given by p_t, which we describe below. Production functions are Cobb-Douglas in each sector. Summing up, the revenue functions of agriculture and non-agriculture are given by

$$\begin{aligned} p_t Y_{A,t} &= p_t Z_{A,t} X^{\alpha} L_{A,t}^{1-\alpha} \\ Y_{M,t} &= Z_{M,t} L_{M,t}. \end{aligned}$$

All individuals are equally productive in agriculture, while non-agricultural productivity of an individual (c,ε) is given – as discussed – by $h(c,\varepsilon)^{\tau}$, where $\tau \in \left(0,1\right]$.

We assume that individuals of all cohorts are perfect substitutes and we let $\omega_t(c,\varepsilon)$ be the occupational choice function, that is equal to 1 if individual (c,ε) at time t works in agriculture, and 0 otherwise. As a result, agricultural and non-agricultural labor are simply given by

$$\begin{aligned} L_{A,t} &= \sum_{c=t-N}^{t} \int \omega_t(c,\varepsilon)\, dF(\varepsilon) \\ L_{M,t} &= \sum_{c=t-N}^{t} \int h(c,\varepsilon)^{\tau} \left(1-\omega_t(c,\varepsilon)\right) dF(\varepsilon), \end{aligned}$$

where $F(\varepsilon)$ is the distribution of ε within a cohort. A simple interpretation of this functional forms is that $h(c,\varepsilon)$ reflects the human capital of individual (c,ε) and non-agriculture is more skill intensive to human capital.[15] We will thus refer to $h(c,\varepsilon)$ as either human capital or non-

[15] This assumption is consistent with sorting of high skilled workers to non-agriculture, as widely documented in the data (e.g. Gollin et al. (2014), Young (2013) Porzio (2017)); with the documented larger returns to skills in

agricultural returns.

Firms choose optimally how many workers to hire, and the labor market is competitive. As a result, workers are paid the marginal product of their labor: the individual wages in agriculture and non-agriculture are given by

$$\begin{aligned} w_{A,t} &= (1-\alpha)\, p_t Z_{A,t} X^{\alpha} L_{A,t}^{-\alpha} \\ w_{M,t}(c,\varepsilon) &= Z_{M,t} h(c,\varepsilon)^{\tau} . \end{aligned}$$

4.1.3 Mobility Frictions and the Problem of the Workers

The net labor incomes in agriculture and non-agriculture are given by

$$\begin{aligned} y_{A,t} &= w_{A,t} \\ y_{M,t}(c,\varepsilon) &= h(c,\varepsilon)^{1-\tau} w_{M,t}(c,\varepsilon) \end{aligned}$$

where $h(c,\varepsilon)^{1-\tau}$ is the non-monetary value of non-agricultural production for individual (c,ε). We can interpret $h(c,\varepsilon)^{1-\tau}$ as either a taste for non-agricultural production or an iceberg cost faced by individual (c,ε). We tie together monetary and non-monetary returns from non-agricultural production to stress that – in fact – our methodology does not allow us to distinguish them.

Since we assume that markets are complete and that there is no disutility of labor, each individual (c,ε) chooses her occupation each period – $\{\omega_t\}_{t=c}^{N+c}$ – to maximize the present discounted value of her future income stream, taking as given the path of net incomes in agriculture – $\{y_{A,t}\}_{t=c}^{N+c}$ – and non-agriculture – $\{y_{M,t}(c,\varepsilon)\}_{t=c}^{N+c}$; and taking into account the cost associated with changing sector – $C_t(\omega_{t-1},\omega_t,y_{A,t},y_{M,t}(c,\varepsilon))$. That is, each individual (c,ε) solves

$$\max_{\{\omega_t\}_{t=c}^{N+c}} \sum_{t=c}^{N+c} \beta^{t-c} \left(\omega_t y_{A,t} + (1-\omega_t)\, y_{M,t}(c,\varepsilon) \quad - \quad C_t(\omega_{t-1},\omega_t,y_{A,t},y_{M,t}(c,\varepsilon)) \right)$$

$$\text{s.t.} \qquad \omega_{c-1} = 1;$$

where we are assuming that all individuals are born in agriculture, hence the constraint $\omega_{c-1} = 1$.

The mobility friction takes the following form

$$C_t(\omega_{t-1},\omega_t,w_{A,t},w_{M,t}) \quad = \quad \mathbb{I}(\omega_t = 1)(i y_{M,t}) \quad + \quad \mathbb{I}(\omega_t < \omega_{t-1})\, f y_{A,t} + \mathbb{I}(\omega_t > \omega_{t-1})\, f y_{M,t} \ ,$$

with an iceberg cost that reduces the monetary value of non-agricultural wage in each period by a fraction i, and a fixed cost to be paid to change sectors, which is given by a scalar f that multiplies the current income in the destination sector. The iceberg cost can be interpreted as an amenity cost – as in Lagakos et al. (2017b) – or as any other flow cost from leaving the agricultural

non-agriculture (see Herrendorf and Schoellman (2017)); and with patterns of mobility across sectors (see Hicks et al. (2017)).

sector, for example, generated by the exclusion from risk-sharing community – as in Munshi and Rosenzweig (2016) and Morten (2016). The fixed cost can be interpreted as a one time mobility cost, which might be driven by the actual moving expenses, if a move is necessary to change sector, or by any other associated costs, such as retraining, idle time in between jobs, or even one time emotional/distress costs.

Notice that we have assumed that the mobility frictions are constant over time and across cohorts. Moreover, they are bounded above by $\bar{i}$ and $\bar{f}$, which are explicit functions of the parameters – included in the appendix – that guarantee that at least some workers reallocate out of agriculture.

Assumption 1. *Mobility frictions are constant over time, across cohorts, and across individuals within cohorts: for all t and (c, ε)*

$$\begin{aligned} i_t(c,\varepsilon) &= i \in [0, \bar{i}] \\ f_t(c,\varepsilon) &= f \in \left[0, \bar{f}\right]. \end{aligned}$$

This is an important assumption. We discuss its role for the identification and interpretation of the results at the end of this section.

4.1.4 Closing the Model: the Price of Agricultural Goods

To close the model we would need to describe how the goods' market clears. This would require taking a stand on the individual utility functions, the degree of openness of the economy, and the relative world prices of agricultural and non-agricultural goods. We sidestep the full specification of the model, and state a log-linear functional form for the relative agricultural price, which could be interpreted as a log-linear approximation of a fully specified model.

Specifically, we let

$$\underbrace{\log p_t}_{\text{Agr Price}} = \underbrace{\eta}_{\text{Elasticity}} \left(\underbrace{\log \theta_t}_{\text{Demand}} - \underbrace{\eta_z \log z_t}_{\text{Supply}} - \underbrace{\eta_L \log L_{A,t}}_{\text{Agr Labor}} + \underbrace{\eta_H \log H_t}_{\text{Human Capital}} \right),$$

where $\log \theta_t$ is a demand shifter that captures the relative demand for agricultural goods; $\log z_t$ is the relative agricultural productivity, $z_t \equiv \frac{Z_{A,t}}{Z_{M,t}}$; $L_{A,t}$ and H_t are aggregate agricultural labor and non-agricultural labor productivity, or human capital, – with $H_t \equiv \frac{1}{N+1} \sum_{c=t}^{t+N+1} \int h(c,\varepsilon)^{\tau} \, dF(\varepsilon)$. The parameters η, η_z, η_L, and η_H modulates the relative role of each variable in determining the agricultural price. In particular, $\eta = 0$ is the case of a small open economy with no trade frictions – i.e. of an economy that takes the prices of agricultural and non-agricultural goods as given. For brevity, we will refer to this case as simply "small open economy". Instead, when $\eta > 0$, an increase in demand increases the relative price, while an increase in supply of agricultural goods, either due to an increase in agricultural productivity or more labor allocated to agriculture, should decrease the price, thus η_z and η_L are assumed to be positive. An increase in human capital, instead, should have two opposing effects on the agricultural price. It makes people richer, thus decreasing the demand for agricultural goods, and pushing down the agricultural price. It also makes people relatively more productive in non-agriculture, thus possibly increasing the agricultural price. The sign of η_H is thus a priori ambiguous.

We follow this reduced form approach because, as the theoretical results will clarify, for our main purpose of identifying the changes in supply of agricultural workers and relating them to schooling, we don't need to pin down the full structure of the model. At the same time, the endogenous agricultural price is needed to compute the aggregate effects of changes in supply. Our research design is not well equipped to pin down the primitive parameters of the price determination and thus we will need to rely instead on estimates from the literature.

Finally, this approach preserves tractability, while encompassing, in reduced form, the different mechanisms suggested in the literature as possible drivers of structural change. To see how this specification encompasses the previously proposed channels of structural change, it is useful to consider a special case with homogenous labor – i.e. when $h(c,\varepsilon) = h$ for all c and ε. Further, normalize $h = 1$, and let – just for the sake of clarity – $\eta_H = 0$. Under these assumptions, in any non-degenerate equilibrium where both sectors are active, wages must be equalized, which requires that $p_t z_t = 1$ for all t. Substituting the expression for price and rearranging gives

$$\log L_{A,t} = \frac{1}{\eta_L} \log \theta_t + \frac{(1 - \eta\eta_z)}{\eta\eta_L} \log z_t. \tag{7}$$

Equation (7) shows that a decrease in demand for agricultural goods over time, for example due to non-homotheticity in demand as in Kongsamut et al. (2001) and Comin et al. (2015), would lead to reallocation of labor out of agriculture. Further, if the economy is sufficiently close to a small open economy – i.e. if η is small – then an increase in relative agricultural productivity would push workers *into* agriculture, as noticed by Matsuyama (1992a). Instead, if the price elasticity is sufficiently large or the economy is sufficiently close to trade – i.e. as η is large enough – a decrease in relative agricultural productivity would push workers out of agriculture, as in Ngai and Pissarides (2007).

4.2 Supply and Demand of Agricultural Workers

The equilibrium agricultural employment is determined by the supply and demand of agricultural workers. The supply of agricultural workers depends on the characteristics of the labor force, which determine the individuals' willingness to supply their labor to agricultural production. The demand for agricultural workers depends on relative price and productivity in the two sectors, which modulate firms' willingness to hire workers in the two sectors. Since both the labor and the goods market clear in equilibrium, the supply of agricultural worker will indirectly effect the demand for them, through the impact on price. We next link the supply and demand of agricultural workers to model's primitive and state assumptions on those primitives to impose that both supply and overall demand weakly decrease over time.

4.2.1 Changes in the Supply of Agricultural Workers

If we keep wages and frictions constant, the change in the mass of agricultural employment between two periods depends only on the change in the average returns from non-agricultural production due to the characteristics of the active labor force – i.e. the supply of agricultural workers. Therefore, we define the change in the supply of agricultural workers simply as the difference between the average return of cohorts in the labor force at time t and $t+1$

$$\begin{aligned}\log \frac{1}{N+1}\sum_{c=t+1}^{t+1+N}\int h(c,\varepsilon)\,dF(\varepsilon) - \log \frac{1}{N+1}\sum_{c=t}^{t+N}\int h(c,\varepsilon)\,dF(\varepsilon) &= \gamma \log\left(\frac{h_{t+N+1}}{h_t}\right)^{\frac{1}{N+1}} \\ &= \gamma \log g_h,\end{aligned}$$

where in the second row we have assumed that the cohort-shifter h_c changes at a constant rate given by g_h. We assume that younger cohorts have higher returns from non-agricultural production, which leads the overall supply of agricultural workers to decrease; that is – keeping fixed the relative wages and prices – each new cohort that enters the labor market would have less and less workers that find it worthwhile to stay in agriculture.

Assumption 2. *The returns from non-agricultural production increase across cohorts at a constant rate*

$$\gamma \log \frac{h_{c+1}}{h_c} = \gamma \log g_h > 0.$$

4.2.2 Changes in the Demand for Agricultural Workers

From the perspective of each individual, the relative demand for labor in agriculture matters to the extent that it affects the relative wage per efficiency unit – i.e. $\frac{w_{A.t}}{Z_{M,t}}$. In turn, the relative wage depends on the share of labor already in agriculture, and on the relative revenue productivity, which is itself driven by three exogenous drivers: the demand shifter θ_t, the relative productivity z_t, and the level of human capital H_t. We have already assumed that human capital grows at a constant rate. We further assume that also the demand shifter and relative productivity change at a constant rate and that, combined, they lead relative agricultural wage per efficiency unit to weakly decay.[16] It is simple to verify, as we do while proving the propositions below, that in order for $\frac{w_{A.t}}{Z_{M,t}}$ to decrease over time, we need the following restriction to be satisfied.

Assumption 3. *Demand shifter θ_t and relative productivity z_t change at constant rates g_θ and g_z such that*

$$\eta \log g_\theta + (1-\eta\eta_z)\log g_z \leq \max\{0, -\Psi \log g_h\},$$

where $\Psi \equiv \frac{\upsilon\gamma(\alpha+\eta\eta_L)+(1-\gamma)\tau\eta\eta_H}{(1-\gamma)}$.

[16] This assumption does not imply that the relative agricultural wage decreases. In fact, as agricultural wage per efficiency units decreases, the average non-agriculture worker becomes relatively less-skilled, thus pushing down the non-agricultural wage. The key distinction is between wages and wages per efficiency unit provided.

We define $\log g_{\theta z} \equiv \eta \log g_\theta + (1 - \eta\eta_z) \log g_z$. The change in the relative agricultural wage is affected by both $\log g_{\theta z}$, and, through general equilibrium, by $\log g_h$. However, we label $\log g_{\theta z}$ *demand* for agricultural workers, to distinguish the direct demand channel, from the change in agricultural wage due to changes in the supply. We refer to the composite effect of $\log g_{\theta z}$ and $\log g_h$ as the *overall demand* for agricultural workers. Assumption 3, as we will show in Proposition 2, guarantees that the overall demand for agricultural workers decreases, so that the year effects are negative – consistent with the empirical evidence.[17]

4.3 Equilibrium

We define the equilibrium, or more specifically a constant reallocation path, and provide an overview of some of its properties. The following sections will provide a formal characterization of the main results we use for the empirical inference.

Definition: Constant Reallocation Path. *A constant reallocation path is given by a series* $\{L_{A,t}, w_{A,t}, w_{M,t}(c, \varepsilon), \omega_t(c, \varepsilon)$ *for all* $c \in [N - t, t]\}_{t=0}^{\infty}$, *such that, given paths for agricultural demand, sectoral productivities, and cohort-specific non-agricultural returns* $\{\theta_t, Z_{A,t}, Z_{M,t}, h_t\}_{t=0}^{\infty}$, *firms maximize profits taking wages as given, individuals choose optimally their occupation at each point in time taking wages as given, labor market clears in both agriculture and non-agriculture, and the aggregate agricultural labor decreases at a constant rate,* $g_{L_A} = \frac{L_{A,t+1}}{L_{A,t}} < 1$.

Consider first the frictionless case – i.e., $i = 0$ and $f = 0$. An individual (c, ε) would move out of agriculture if he earns a higher net income in non-agriculture, therefore if his non-agricultural returns are sufficiently high with respect to relative agricultural revenue productivity, or if

$$h(c, \varepsilon) \quad \geq \quad \hat{h}_t \quad = \quad (1 - \alpha) p_t z_t X^\alpha L_{A,t}^{-\alpha}. \tag{8}$$

Unsurprisingly, individuals sort to the sector where they have a comparative advantage. Using the expression for $h(c, \varepsilon)$, we can see that there is sorting both within- and across-cohorts. Within any cohort, the ones with high relative returns ε move out of agriculture. Across cohorts, the younger ones, that have higher cohort specific non-agricultural returns h_c, have a larger share of individuals out of agriculture. Over time, as the overall demand for agricultural workers decreases and as the composition of the labor force changes, more and more people move out of agriculture, thus generating aggregate labor reallocation.

The distributional assumption on the idiosyncratic return ε plays an important role in generating a constant rate of labor reallocation, and ensuring tractability. For a given cohort c, we can use equation (8) to find an expression for the ability cutoff – $\hat{\varepsilon}_t(c)$ – that defines the marginal

[17] Assumption 3 can be relaxed in favor of the weaker assumption $\log g_{\theta z} \leq 0$, which could generate positive year effects. Yet, it simplifies the solution of the model when there is a positive fixed cost. We also argue that it comes at little cost, since its direct implication, that year effects are negative, is verified in the data for the overwhelming majority of countries.

individual that moves out of agriculture at time t

$$\hat{\varepsilon}_t(c) = \left[(1-\alpha)\kappa^{-1}p_t z_t X^{\alpha} L_{A,t}^{-\alpha} h_c^{-\gamma}\right]^{\frac{1}{1-\gamma}}.$$

The mass of workers from cohort c – $l_{A,t}(c)$ – in agriculture is then equal to

$$l_{A,t}(c) = F(\hat{\varepsilon}_t) \propto \left[p_t z_t X^{\alpha} L_{A,t}^{-\alpha} h_c^{-\gamma}\right]^{\frac{v}{1-\gamma}}, \tag{9}$$

and the reallocation out of agriculture for a given cohort, after substituting for the law of motion of $p_t z_t$ is given by

$$\log l_{A,t+1}(c) - \log l_{A,t}(c) = \frac{v}{1-\gamma}\left(\log g_{\theta z} + \eta\eta_H \log g_h - (\eta\eta_L + \alpha)\log g_{L_A}\right), \tag{10}$$

where $\log g_{L_A} \equiv \log L_{A,t+1} - \log L_{A,t}$.

Equation (10) shows that the rate of labor reallocation for a given cohort is constant over time – as long as the aggregate g_{L_A} is constant, as we will prove to be the case. In doing this derivation, we used the fact that the CDF of a $\mathrm{Beta}(v,1)$ – over the relevant domain – is homothetic.

Last, use equation (9) to notice that the ratio between agricultural employment at time t of cohort c and $c+1$ is given by

$$\frac{l_{A,t}(c+1)}{l_{A,t}(c)} = \left(\frac{h_{c+1}}{h_c}\right)^{-\frac{\gamma v}{1-\gamma}} = g_h^{-\frac{\gamma v}{1-\gamma}}:$$

the faster human capital grows across cohorts, the bigger the difference in their agricultural employment. Summing up, the aggregate constant reallocation rate hides substantial heterogeneity within and across cohorts. The assumptions made guarantee tractability despite the rich heterogeneity along two dimensions: age and ability.

Next, we discuss the role of mobility frictions. The iceberg cost i introduces a constant wedge between agricultural and non-agricultural wages; as such, it does not affect reallocation rates, but only the level of agricultural employment at each point in time. The fixed cost f is more consequential since it may constraint *some* workers, but not others, from reallocating. If a relatively young worker finds it worthwhile to move out of agriculture, then the fixed cost is unlikely to bind, since it is discounted over his whole future life. Instead, if a worker is still in agriculture when old, thus having only few periods left to work, then even a small fixed cost may trap him there. In fact, the fixed cost divides cohorts into two groups, the constrained and the unconstrained, based on their age.

4.4 Aggregate Labor Reallocation

We start by characterizing the aggregate rate of labor reallocation.

Proposition 1: Two Drivers of Labor Reallocation

Labor reallocation out of agriculture is given by

$$\log g_{L_A} = \underbrace{\left(\frac{v}{1-\gamma}\right)}_{\text{Skill Distr.}} \left(\left(1 + \underbrace{\Theta_D}_{\text{GE}}\right) \underbrace{\log g_{\theta z}}_{\text{Demand}} + \left(1 + \underbrace{\Theta_S}_{\text{GE}}\right) \underbrace{-\gamma \log g_h}_{\text{Supply}} \right),$$

where $\Theta_D \equiv -\frac{v(\alpha+\eta\eta_L)}{1-\gamma+v(\alpha+\eta\eta_L)}$ *and* $\Theta_S \equiv -\frac{v(\alpha+\eta\eta_L)+(1-\gamma)\tau\eta\eta_H}{1-\gamma+v(\alpha+\eta\eta_L)}$.

Proof. *See Appendix.* □

Labor reallocation out of agriculture – i.e. $\log g_{L_A} < 0$ – can be triggered by two distinct forces: (i) decrease in the demand for agricultural labor, either due to changes in relative demand or productivity; (ii) decrease in the supply of agricultural labor, through the entrance of new cohorts in the labor market. The direct effect of each term is mediated by general equilibrium forces and by the within cohort distribution of skills, which determines the mass of marginal workers that would leave agriculture for a small change in relative wages. The decrease in demand for agricultural labor has an unambiguous effect since $\Theta_D \in [0, 1)$. The decrease in supply, instead, could either pull people out of agriculture or into agriculture depending on parameters' values, in particular on the price elasticity η.[18] We will further discuss general equilibrium forces in Section (7). Mobility frictions are irrelevant for the aggregate *rate* of labor reallocation, even though they do affect the *level* of agricultural employment in each point in time.[19]

Finally, notice that the model of Section (2) is a special case when general equilibrium is muted – i.e. $\Theta_D = \Theta_S = 0$.

4.5 Labor Reallocation by Cohort

While the mobility frictions do not impact the aggregate rate of labor reallocation, they do have an effect on how this rate is partitioned into year and cohort effects.[20] Nonetheless, as the next proposition shows, controlling for age effects is sufficient to restore the simple insight illustrated in Section 2; namely that cohort effects allow us to identify the changes in the supply of agricultural workers.

Proposition 2: Decomposition of Labor Reallocation

Consider the regression

$$\underbrace{\log l_{A,t,c}}_{\text{agr share of cohort } c \text{ at time } t} = \underbrace{\tilde{\mathbb{T}}_t}_{\text{year dummies}} + \underbrace{\tilde{\mathbb{C}}_c}_{\text{cohort dummies}} + \underbrace{\tilde{\mathbb{A}}_{t-c}}_{\text{age dummies}} + \varepsilon_{t,c}$$

[18] In a small open economy – when $\eta = 0$ – the effect of a decrease in supply is unambiguous and pulls people out of agriculture.

[19] We are assuming that frictions are sufficiently small as to generate positive reallocation. Trivially, if $f \to \infty$ or $i \to \infty$, there would be no reallocation. Proposition 1 thus shows that, in general, the reallocation is either zero, or does not depend on f and i. Our parametric restriction excludes the case in which reallocation is zero.

[20] We can always statistically decompose the aggregate reallocation rate into year and cohort effects.

estimated using model-generated data and imposing the linear restriction that $\tilde{\mathbb{A}}_0 = \tilde{\mathbb{A}}_1$ *– i.e. that the first two age effects are identical.*[21] *Further, define*

$$\begin{aligned}\log\tilde{\psi}_t &\equiv \tilde{\mathbb{T}}_t - \tilde{\mathbb{T}}_{t-1}\\ \log\tilde{\chi}_t &= \log L_{A,t} - \log L_{A,t-1} - \log\tilde{\psi}_t.\end{aligned}$$

The estimated year and cohort components are, for all t*,*

$$\begin{aligned}\log\tilde{\psi}_t &= \left(\frac{v}{1-\gamma}\right)\left((1+\Theta_D)\log g_{\theta z} - \Theta_S\gamma\log g_h\right)\\ \log\tilde{\chi}_t &= -\left(\frac{v}{1-\gamma}\right)\gamma\log g_h.\end{aligned}$$

Proof. *See Appendix.* $\square$

The next corollary shows that omission to include the age effects would bias the estimates.

Corollary 1: Bias in the Basic Decomposition

*Consider, instead, to run with model-generated data the regression of Section (*3.1*). The estimated year and cohort components would be*

$$\begin{aligned}\log\bar{\psi} &= \left(1-\lambda(f)\right)\log\tilde{\psi}\\ \log\bar{\chi} &= \log\tilde{\chi} + \frac{\lambda(f)}{1-\lambda(f)}\log\tilde{\psi}\end{aligned}$$

where the friction parameter $\lambda(f) \in \left[0,1\right)$ *is increasing in the size of the fixed cost* f *and does not depend on the iceberg cost* i*.*

Proof. *See Appendix.* $\square$

Including age effects in the regression, under the identifying assumption that they are identical in the first two periods that a cohort is working, allows us to use the cohort effects to recover the partial equilibrium effect of changes in the supply of agricultural workers on aggregate reallocation. The same regression provides, using the year effects, the change in the overall demand for agricultural workers, given by the direct demand effect in general equilibrium – $\left(\frac{v}{1-\gamma}\right)(1+\Theta_D)\log g_{\theta z}$ – and the general equilibrium component of the supply changes – $\left(\frac{v}{1-\gamma}\right)\Theta_S\gamma\log g_h$.[22]

As Corollary 1 shows, if we don't control for age effects – as was done in Section (3.1) – we would recover biased estimates. The reason is that the fixed mobility cost f constraints individuals in older birth-cohorts. As shown in Corollary 2, there exists a marginal age $\hat{a}(f)$ such that all

[21] *As it is well known, we need to impose at least one linear restriction to estimate a regression with year, cohort, and age dummies.*

[22] The year effect is negative if and only if Assumption 3 is satisfied: $\eta\log g_\theta + (1-\eta\eta_z)\log g_z \leq \max\{0, -\Psi\log g_h\}$.

individuals in cohorts older than $\hat{a}(f)$ do not reallocate out of agriculture, while all individuals in cohort younger than $\hat{a}(f)$ reallocate at the unconstrained rate, given by $\log \tilde{\psi}_t$.[23] Including the age effects, under the proposed linear restriction, is sufficient to pin down the unconstrained year component, and thus the true cohort component.

Corollary 2: Reallocation Rates by Age

If the fixed cost is equal to zero, $f = 0$, then individuals of all ages reallocate at identical rate

$$\log \psi_t(c) = \log \tilde{\psi}$$

for all (t, c). If $f > 0$, there exists an age cutoff, $\hat{a}(f)$ such that individuals younger than $\hat{a}(f)$ reallocate at the unconstrained rate, while those older do not reallocate at all. The friction $\lambda(f)$ is given by the share of constrained cohorts

$$\lambda(f) = \frac{N + 1 - \hat{a}(f)}{N + 1}.$$

4.6 Frictions and Wages

As Proposition 2 shows, one advantage of our research design is that we can back-out changes in the supply and demand of agricultural workers without the need to rely on direct measurement of either wages or prices. Nonetheless, as we show next, the model generates predictions for agricultural wages which are consistent with the data. We also clarify that wages are not useful to back-out the size of the frictional parameter $\lambda(f)$.

Proposition 3: Agricultural Wage Gaps

Let $(\hat{c}_t, \hat{\varepsilon}_t)$ be a mover to M at time t and $\bar{w}_{M,t} \equiv \sum_{c=N-t}^{t} \int w_{M,t}(c, \varepsilon)\, dF$ be the average wage in M, then for all periods t

$$\underbrace{\log \bar{w}_{M,t} - \log w_{A,t}}_{\text{Cross-Sectional Wage Gap}} > \underbrace{\log w_{M,t}(\hat{c}_t, \hat{\varepsilon}_t) - \log w_{A,t}}_{\text{Wage Gap for Movers}},$$

and the wage gap for movers is given by

$$\log w_{M,t}(\hat{c}_t, \hat{\varepsilon}_t) - \log w_{A,t} = -\log(1 - i) + \log(1 + (1 - g_{pA}\beta) f) - (1 - \tau) \log \hat{h}_t$$

where g_{pA} is the growth rate of $p_t Z_{A,t}$, and $(1 - \tau) \log \hat{h}_t$ is the non-monetary value of non-agriculture for the movers.

[23] The presence of constrained cohorts may seem surprising given the continuum of heterogeneous individuals in each cohort. The reason this could happen is that the model is dynamic. Consider two marginal types: the lowest ε that is constrained by the fixed cost, and the lowest ε that finds it worthwhile to move out of agriculture. As a cohort ages, the first type increases, while the second decreases. The age $\hat{a}(f)$ corresponds to the time period when the two marginal types cross. After this period, there is no reallocation since the marginal type that would not be subject to the constraint has already moved out of agriculture in a previous period.

Proof. *See Appendix.* □

Proposition 3 shows that observing a low wage gap for movers, as has been shown in recent literature (see Hicks et al. (2017), Alvarez (2017), Herrendorf and Schoellman (2017)), is sufficient to exclude a large iceberg cost or other non-monetary costs, captured by $(1-\tau)\log\hat{h}_t$. However, it is not sufficient to exclude a large fixed cost. In fact, conditional on an individual not being constrained, the fixed cost affects his moving decision only through discounting.[24] Notice that even long panels are not sufficient to back out the size of the fixed cost from wages. We would need to observe the whole wage paths in agriculture *and* in non-agriculture for both movers and non-movers. Such data is simply impossible to generate. For this reason, it is important to provide a methodology that allows us to overcome direct measurement of $\lambda(f)$, which we can, in fact, recover ex-post by comparing our estimates for $\log\tilde{\psi}$ and $\log\bar{\psi}$.

The model replicates another salient empirical fact: in countries where data is available, wage gaps between agriculture and non-agriculture in the cross-section have been shown to be much larger than the wage gaps observed for movers out of agriculture. The model matches this fact since movers are indifferent between agriculture and non-agriculture, and thus they have lower non-agricultural productivity than the average non-agricultural worker.

4.7 Revisiting the Three Questions

The model provides the analytical counterparts to the three questions we ask in this paper, and offers a framework to answer them.

First Question: *Did the supply of agricultural workers decreased over time and by how much?* In order to provide an answer to this question, we want to measure $-\gamma\log g_h$ for each country. Proposition 2 shows that a within-country regression of agricultural employment on year, cohort and age dummies is sufficient to recover $-\left(\frac{v}{1-\gamma}\right)\gamma\log g_h$, which allows to quantify the change in supply of agricultural workers in terms of their partial equilibrium effects on aggregate labor reallocation. We can further use wage variance in non-agriculture to bound $\left(\frac{v}{1-\gamma}\right)$. We tackle this question in Section 5.

Second Question: *Did the increase in schooling cause the decrease in the supply of agricultural workers?* We want to measure whether the average schooling of a cohort is correlated with the measured human capital shifter h_c, and whether this relationship is causal. We tackle this question in Section 6.

Third Question: *Did the decrease in the supply of agricultural workers led to aggregate labor reallocation out of agriculture and by how much?* As Proposition 1 shows, to answer this question we need to use the estimates $-\left(\frac{v}{1-\gamma}\right)\gamma\log g_h$ recovered to answer the first question, and take stand on the strength of the general equilibrium, which is modulated by the Θ_S. We tackle this question in Section 7.

[24]This result is driven by two features of our environment: (i) the decision to move out of agricultural is dynamic, hence individuals can choose to postpone it; (ii) relative wages change over time. As a result of these two features, the fixed cost mainly affects the timing of the movement out of agriculture, and it impacts the wage gap only marginally through discounting.

4.8 Discussion

To conclude this section, we discuss how the model's assumptions might affect inference and interpretation.

We assumed that the frictions are constant over time and across cohorts. This is an identifying assumption. If frictions change across cohorts, we would not be able to distinguish them from a change in relative non-agricultural returns. If frictions change over time, we would not be able – with our data – to distinguish them from a change in the demand for agricultural goods. While we need to keep this caveat in mind for the interpretation of the results, this assumption does not invalidate our main conclusion: a decrease in the friction across cohorts would still lead to a decrease in the supply of agricultural workers. However, in this case schooling would decrease the cost of moving out of agriculture, rather than increasing its returns. As a result, the aggregate implications would be affected.

Similarly, we have let $h(c, \varepsilon)$ to be the product of a monetary and non-monetary return from non-agricultural production, whose respective role is modulated by τ. We have made this assumption to point out that our strategy does not allow us to distinguish between the two (unless we use wage data). Our results are, in fact, compatible with schooling changing either the relative productivity in non-agriculture, or the relative taste for individuals to work there. Again, while this distinction does not matter for the main take-aways on the decrease of the supply of agricultural labor, it does affect the aggregate implications.

We have also abstracted from human capital accumulation over the life-cycle. There could be, in the data, two types of life-cycle effects: i) general human capital – which would make $h(c, \varepsilon)$ increase as a cohort ages; ii) human capital specific to the sector of employment. Recall, that – in order to identify the year effects – we need to impose a linear restriction, and the model suggests to restrict the age effect to be zero in the first years an individual is in the labor market. As a result, if individuals accumulate general human capital while young, thus leading them to move out of agriculture, we would overestimate the year effects – thus underestimate the cohort effect and attenuate our results. Sector-specific human capital is instead more problematic. If individuals accumulate, in the first years on the job, skills which make them more likely to stay in agriculture, then we would underestimate the year effects. In practice, whether our estimates are biased upward or downward depends on whether experience human capital is general or sector-specific. Estimates from Altonji et al. (2013), although admittedly coming from the United States only, suggest that most experience human capital is general. Further, notice that age effects for later periods are controlled for in our regression framework in the next section.

Finally, it is worthwhile to point out that the fixed mobility cost f does not have to represent a monetary migration cost. In fact, it should be interpreted as a reduced form representation of any cost associated with a sector change that is more likely to be binding for old than for young individuals.

5 The Partial Equilibrium Effect of Schooling on Structural Transformation

We now bring the model to the data described in Section (3.1). Our aim is to measure, in each country, whether and by how much the characteristics of the labor force changed, either shifting towards a skill-set which is more valued out of agriculture, or increase the perceived valuation of work outside of agriculture. In other words, we want to measure whether the supply of agricultural workers has decreased.

5.1 Measurement

Proposition 2 provides the framework for measurement: it shows that, assuming that the observable data are generated by our model, we can run a year-cohort-age regression to recover changes in supply of agricultural workers. We cannot run a regression fully saturated with year-cohort-age dummies, due to their collinearity. As shown in Deaton (1997), we need to impose at least one linear restriction. The choice of the linear restriction determines identification and thus need to be guided by theory. In our setting, Proposition 2 shows that we should restrict the age effects to be the same in the first two years that a cohort is employed.

In practice, rather than using a full set of age dummies, we follow recent work (e.g. Card et al. (2013)) and include quadratic and cubic terms for age, centered around a value $\bar{a}$. For each country j of the 52 ones in our sample we run

$$\log l_{A,t,c,j} = \tilde{\mathbb{T}}_{t,j} + \tilde{\mathbb{C}}_{c,j} + \beta_{1,j}\left(a_{c,t,j} - \bar{a}\right)^2 + \beta_{2,j}\left(a_{c,t,j} - \bar{a}\right)^3 + \varepsilon_{t,c,j}, \tag{11}$$

where $\tilde{\mathbb{T}}_{t,j}$ and $\tilde{\mathbb{C}}_{c,j}$ is a full set of year and cohort dummies, and $a_{c,t,j}$ is the age of cohort c at time t (for country j).

The parameter $\bar{a}$ determines the value at which we restrict the age effects to be zero, both in levels and in changes.[25] Following Proposition 2, if we would observe a continuous stream of data as cohort ages, we should set $\bar{a} = 25$ since our sample covers individuals 25 to 59 years old. However, our data comes from repeated cross-sections at several years of distance between one other, and thus we never observe a cohort reallocation behavior around age 25. Therefore, in order to avoid to extrapolate the results from the functional form assumption, we should set $\bar{a}$ to be the average age of the youngest cohort that we observe for two repeated cross-sections. For example, assume that for a country we observe two cross-sections 5 years part, the youngest cohort in the first cross-section would be 30 years old in the second one, thus we should set $\bar{a} = 27.5$. On average across all countries and time-periods, cross-sections are 9 years apart, with a mode and a median of 10 years. Therefore, we set $\bar{a} = 29.5$. We also check that the results are robust to let $\bar{a}$ vary, following the same idea, across countries.[26]

Given the estimates from specification (11), we then compute – following again Proposition 2 – the year and cohort components for each country and cross-section, namely $\log \tilde{\psi}_{t,j}$ and $\log \tilde{\chi}_{t,j}$.

[25] In fact, the omission of the linear term for age is necessary to have the derivative of the age terms to be zero at $\bar{a}$, which is needed for identification of the year trend.

[26] These results are in fact slightly stronger. They are included in appendix Section (C).

Finally, for each country we take the average year and cohort effects across all the observed time periods just as we did in Section (3.2).[27]

5.2 Result: Global Shift in Comparative Advantages away from Agriculture

Table (I) includes the results. Column (3) shows the average cohort component, $\log \tilde{\chi}_j$, for all countries, and separately by income groups. On average the cohort components decreased by 0.81 % per year. There is some heterogeneity across countries: the 20^{th} and 80^{th} percentiles of the distribution across countries are 0.68 % and 1.64 %, and high income countries have on average larger (in absolute value) cohort components. In Section (6.3), we will show that the cross-country heterogeneity is correlated with differences in schooling increase.

In order to interpret the magnitude of the results, it is useful to compare column (3) to columns (1) and (2). Column (1) displays the average rate of labor reallocation out of agriculture. Column (2) displays the cohort components as calculated in Section (3), hence without controlling for the role of frictions. Fact 1 is robust: the cohort component explains a large share of labor reallocation. At the same time, controlling for mobility frictions does attenuate the results, as would be expected.

The model provides a structural interpretation to the cohort components. If the data are generated by our model, then

$$\log \tilde{\chi}_j \quad = \quad -\left(\frac{v_j}{1-\gamma_j}\right)\gamma_j \log g_{h,j}.$$

The cohort component is given by the product of two objects: i) the rate of decay of the supply of agricultural workers, $-\gamma_j \log g_{h,j}$; ii) the elasticity of agricultural labor supply to relative agricultural wage, $\left(\frac{v_j}{1-\gamma_j}\right)$. At the same time, Proposition 1 shows that the product of the two terms, $-\left(\frac{v_j}{1-\gamma_j}\right)\gamma_j \log g_{h,j}$, has a natural interpretation: it is the aggregate effect of changes in supply of agricultural workers on labor reallocation in partial equilibrium. We can thus divide column (1) by column (3) to recover the contribution of changes supply of agricultural workers to labor reallocation, in an hypothetical scenario where the path of relative prices is not affected by changes in supply of agricultural workers. We conclude that, in partial equilibrium, the decrease in supply of agricultural workers would, alone, explain 40% of labor reallocation, on average across all countries. The shift in supply was similarly important across all income groups, with a partial equilibrium contribution to aggregate reallocation of 37%, 35%, and 54% for low, middle, and high income countries. This analysis unveils the first core empirical result of the paper. In the second half the 20^{th} century, we observed – at least in the 52 countries of our study – a dramatic shift in the characteristics of the labor force that moved the comparative advantage away from agriculture.

Finally, in columns (4)-(6) we show the results corresponding to Fact 2 in Section (3). Controlling for friction does not affect Fact 2, and the model provides a structural interpretation to it. Cross-country differences in changes in the supply of agricultural workers explain approximately one quarter of cross-country differences in the rates of labor reallocation out of agriculture.

[27] In Appendix (C), we report the results separately for each time period.

Table I: Decomposition of Labor Reallocation out of Agriculture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fact 1: Average Reallocation			Fact 2: Variance of Reallocation			Friction
	$\mathrm{E}\left[\log g_{L_A,j}\right]$	$\mathrm{E}\left[\log \bar{\chi}_j\right]$	$\mathrm{E}\left[\log \tilde{\chi}_j\right]$	$\mathrm{Var}\left[\log g_{L_A,j}\right]$	$\mathrm{Var}\left[\log \bar{\chi}_j\right]$	$\mathrm{Var}\left[\log \tilde{\chi}_j\right]$	$1-\frac{\mathrm{E}\left[\log \bar{\psi}_j\right]}{\mathrm{E}\left[\log \tilde{\psi}_j\right]}$
All Countries	- 2.05 %	- 1.19 %	- 0.81 %	0.20 ‰	0.05 ‰	0.06 ‰	29%
Low Income	- 1.56 %	- 1.03 %	- 0.58 %	0.26 ‰	0.04 ‰	0.03 ‰	47%
Middle Income	- 2.17 %	- 1.14 %	- 0.77 %	0.12 ‰	0.03 ‰	0.04 ‰	27%
High Income	- 2.77 %	- 1.73 %	- 1.49 %	0.22 ‰	0.08 ‰	0.08 ‰	15%

5.3 Quantifying the Change in Returns from Agricultural Production

As shown, the cohort component captures the joint effect of two objects. Intuitively, a large cohort component may be driven both by large changes in cohort level characteristics, $-\gamma_j \log g_{h,j}$, or by a large effect of cohort characteristics on agricultural employment, $\left(\frac{v_j}{1-\gamma_j}\right)$. To quantify the aggregate effect of changes in the supply of agricultural to labor reallocation, it is not necessary to distinguish between the two. However, it is still useful to directly measure the magnitude of $-\gamma_j \log g_{h,j}$ for interpretation of the results. Recall, in fact, that $-\gamma_j \log g_{h,j}$ is the rate of change of the cohort average relative return from non-agricultural production.

The model provides guidance on how to measure the elasticity $\left(\frac{v_j}{1-\gamma_j}\right)$. First, it shows that it depends on the extent to which overall heterogeneity is explained by cohort components. Recall that non-agricultural return is given by $h(c,\varepsilon) = \kappa h_c^{\gamma} \varepsilon^{1-\gamma}$, where $\varepsilon \sim \mathrm{Beta}(v,1)$. The larger γ_j and v_j are, the smaller is the within cohort heterogeneity of skills. If workers within cohorts have similar returns from working in agriculture, then sorting is mostly across cohorts, and thus small changes in cohort characteristics may lead to large changes in agricultural employment by cohort. Second, it shows that we can use the within-cohort variance of log wages in non-agriculture to bound $\left(\frac{v_j}{1-\gamma_j}\right)$. In fact, the following relationship holds

$$\mathrm{Var}_{\varepsilon}\left[\log w_{M,t}(c,\varepsilon)\right] = \tau^2 (1-\gamma)^2 \, \mathrm{Var}\left[\log \varepsilon \mid \log \varepsilon \geq \log \hat{\varepsilon}_t(c)\right] \leq \left(\frac{1-\gamma}{v}\right)^2, \tag{12}$$

where the equality uses the equilibrium equation for wage, and the inequality is due to the properties of the Beta distribution.[28]

Equation (12) shows that the within cohort standard deviation of log wages in non-agriculture

[28] If $\varepsilon \sim \mathrm{Beta}(v,1)$, then $-\log\varepsilon \sim \mathrm{Exp}(v)$. Also, the variance of a truncated exponential is smaller than the unrestricted variance, which is v^{-2}.

– $\sigma_{M,t,j}$ – can be used to provide an upper bound to $\left(\frac{v_j}{1-\gamma_j}\right)$, and then, given the measured $\log\tilde{\chi}_j$, to obtain a lower bound for the object of interest $-\gamma_j \log g_{h,j}$. The data discussed in Section 3, does not include wages for most countries. However, Lagakos et al. (2017a) made the values of $\sigma_{M,t,j}$ available to us for each one of the eighteen countries in their sample, which span the income distribution from Bangladesh to the United States.[29] On average across all countries, $\mathrm{E}\left(\sigma_{M,t,j}\right) = 0.67$, ranging from 0.38 in France to 0.94 in Brazil. Since we don't have wage data for all countries in our sample and $\sigma_{M,t,j}$ is not systematically correlated with income, we simply use the average value, which gives the bound $\left(\frac{v_j}{1-\gamma_j}\right) \leq 1.5$.

Using the upper bound for $\left(\frac{v_j}{1-\gamma_j}\right)$, we conclude that the relative return from non-agricultural production increase, on average across all countries, by at least 0.5% per year. Compounding over time, our results imply that each generation has roughly 15% higher relative return from non-agricultural production; a modest, but sizable increase, driven purely by the changing characteristics of the labor force.

5.4 The Role of Mobility Frictions and Additional Approaches

Corollary 1 shows that a comparison of the year effects estimated with and without controlling for age can be used to recover the size of the frictional parameter. In fact, rearranging the first equation we get

$$\lambda\left(f_j\right) = 1 - \frac{\log\bar{\psi}_j}{\log\tilde{\psi}_j}.$$

We use this equation, and our estimates of $\log\bar{\psi}_j$ and $\log\tilde{\psi}_j$, to calculate the implied friction in our samples of countries. The results are included in column (7) of Table (I). On average across countries, the friction is approximately 30%, which means that individual's reallocation decision is constrained by the fixed cost in the last 30% of their work-life, or approximately, in our sample, after they turn 45 years old. Rows (1)-(3) report the frictions computed separately for low, middle, and high-income countries. The friction is considerably larger in low income countries, as could be expected.

Finally, we mention that previous versions of this paper used alternative ways to calculate $\lambda\left(f_j\right)$ and then backed out $\log\tilde{\psi}_j$ using $\log\bar{\psi}_j$ and the estimated friction. While the results vary slightly across different methods to impute $\lambda\left(f_j\right)$, they are all broadly consistent and suggest a value of the friction in the 20-30% range. We include these alternative approaches in Appendix (D).

6 The Causal (Partial Equilibrium) Effect of Schooling

In this section, we argue that the global schooling increased played a relevant role in the decrease in the supply of agricultural workers that we just documented. Our argument relies on three

[29] Refer to Lagakos et al. (2017a) for data description and details. Wages are constructed as earnings divided by total hours of work in the period of observation, which is either weekly, monthly, or yearly. We drop the top and bottom 1% of wages to check that the variance estimates are not driven by outliers. For each country, we keep the most recent available cross-section.

separate pieces of evidence that leverage all the data that – to our knowledge – could be brought to bear. We first present a case study for Indonesia, which provides the most credible causal identification. We then use within country variation in schooling and agricultural employment across cohorts. Last, we use across countries and time periods variation in schooling growth and labor reallocation out of agriculture by cohort.

6.1 School Construction in Indonesia

Following the seminal work of Duflo (2001), we use the INPRES school construction program, which built 61,000 primary schools between 1974 and 1978, to provide quasi-experimental variation in schooling. While the intensity of the program, captured by the number of new schools per pupil, was not random, only some cohorts, those younger than 6 at the time the program started, were fully exposed to the program. Therefore, we can run a fairly standard difference-in-difference exercise: we compare cohorts fully exposed to the treatment to those not exposed to it, in districts with higher or lower treatment intensity. The data – the 1995 intercensal survey of Indonesia –, the identification strategy, and the specifications follow closely Duflo (2001). The reader should refer to that article for more details.

We restrict the sample to males born between $1950-1977$. Before showing the IV specification, we focus on the first stage and reduced form. Consider the following specification

$$y_{ijk} \quad = \quad \alpha_{ij} + \eta_{ik} + c_{1k} + \sum_{c=1951}^{1977} \left(T_{ik} \times \mathbb{I}_{ic}\right) \delta_c + \sum_{c=1951}^{1977} \left(c_{ik} \times \mathbb{I}_{ic}\right) \varphi_c + \epsilon_{ijk} \qquad (13)$$

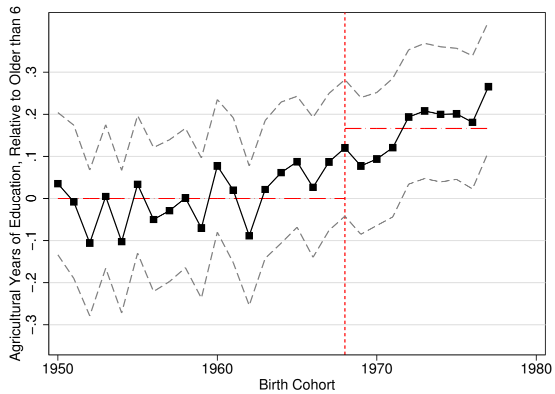
where (i, j, k) is an individual i, born in cohort j, and currently living in district k; α_j is a cohort fixed effect, where the omitted cohort, η_k is a district fixed effect; T_k is treatment intensity, defined as number of school build per 1000 children; $\mathbb{I}_c$ is a dummy that takes value equal to 1 if individual i is born in cohort c, where the control cohort is the one born in 1950; and last c_{ik} is the enrollment in 1972. The coefficients of interest are $\{\delta_c\}_{c=1951}^{1977}$, which be interpreted as an estimate of the effect of the program on a given cohort. We estimate specification (13) for three different left-hand sides: i) years of schooling, which is our first stage; ii) a dummy equal to 1 for agricultural employment, which is our reduced form effect of the program; iii) a dummy equal to 1 for non-agricultural employment, which is useful for ensuring that the program does not simply lead workers to drop out of the labor force, but rather make them more likely to work in non-agriculture.

We report the results on the estimated coefficients and associated standard errors in Figures VIa, VIb, and VIc. The program had a positive effect on education, a negative one on agricultural employment, and a positive one on non-agricultural employment – as expected. The coefficients are normalized to average zero for the control cohorts, that should've been at most marginally affected by the treatment. The figures also build confidence in the exclusion restriction, to the extent that they suggest no differential trend prior to the program.[30] As in the original paper, coefficients are mostly not significant, unless we pool the pre-and post-periods.

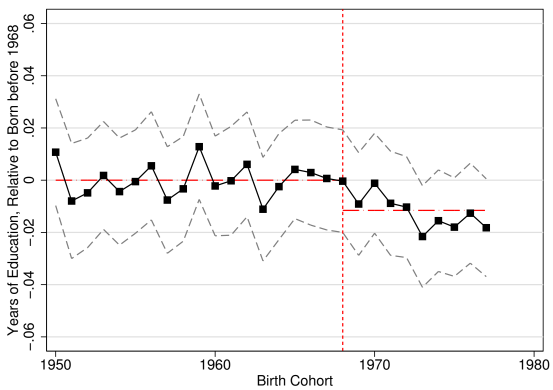
[30]When we omit the controls for children enrollment in 1972, schooling years show a pre-trend. For this reason, we keep the controls throughout our analysis.

Figure VI: INPRES School Construction

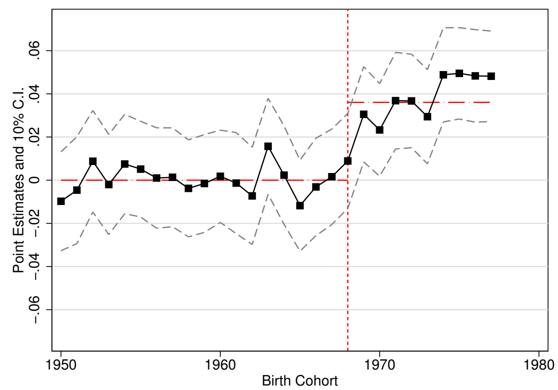
(a) Point Estimates for Education



(b) Point Estimates for Agriculture



(c) Point Estimates for non-Agriculture



Notes: data for agricultural employment and schooling are from the 1995 intercensal survey of Indonesia (SUPAS); data for treatment intensity are from Duflo (2001). Figure (a) shows the estimates of the cohort dummies from the first stage regression according to specification (13) when the left hand side variable is years of schooling. Figures (b) and (c) show the estimates for the reduce form results – from the same specification (13) – with either agricultural or non-agricultural employment as left-hand side variables. The red dotted vertical line separates the treatment from the control cohorts.

In order to improve power, following again Duflo (2001), we focus on the comparison of two cohorts: a treatment cohort of individuals that were between 2 and 6 years old at the time the program was implemented, and a control cohort of individuals that were between 12 and 17 years old. The specification remains the same as in (13), but with only one treatment cohort, and thus one coefficient of interest, the interaction between program intensity and treatment cohort.

The first stage gives a 5%-significant point estimate equal to 0.137 (0.037): one extra school per 1000 children increases schooling by ~ 0.14, just as in Duflo (2001). The reduced form gives a 5%-significant point estimates equal to -0.0086 (0.0043). In order to interpret the magnitude, we compute an IV where we instrument for years of schooling using the interaction between treatment intensity and treated cohort. One extra years of school significantly (at 5%) reduces agricultural employment by 6.27% (3.04%). This evidence shows that schooling increase impacted the relative returns from agricultural production for the affected cohorts.

6.2 Within-Country Variation Across Cohorts

Quasi-experimental variation is scarce. However, for all the countries in our sample, our data includes cohort-level information on average schooling attainment. We next use this data to provide suggestive evidence that the causal relationship documented for Indonesia holds true for all countries in our sample.

We would like to show a (causal) relationship between the cohort level human capital shifters $h_{c,j}$ and average schooling. As a first step, we use individual level information on educational attainment to compute the average schooling years for each cohort in our dataset. Since we observe cohorts in multiple cross-sections, we extract average schooling by cohort using, separately for each country, a procedure similar to the one used in DeLong et al. (2003) for the United States. We project the log of cohort-level average schooling years on a full set of cohort dummies, a cubic in age and cyclical year dummies as in Deaton (1997). The age cubic trend controls for late enrollment in school (i.e. after 25 years old) and, especially, for mortality and morbidity differences by education groups. The year dummies control for differences across survey waves in educational attainment reporting. The cohort dummies are the coefficient of interest. We transform them in levels, and define the schooling dummy for cohort c in country j to be $s_{c,j}$.

Table II: Decomposition of Labor Reallocation out of Agriculture

	(1)	(2)	(4)	(5)
	Agriculture Cohort Effects			
				(IV)
Schooling Cohort Effects	- 0.074	- 0.076	- 0.173	- 0.215
	(0.012)	(0.030)	(0.014)	(0.069)
County Fixed Effects	Y	Y	Y	Y
Cubic Trend	N	Y	Y	Y
Country-specific Trend	N	N	Y	Y
Observations	3,127	3,127	3,127	2,688

Notes: standard errors in parenthesis are clustered at the country level.

Our main empirical specification studies the relationship between the estimated cohort effects from specification (11), $\tilde{\mathbb{C}}_{c,j}$, and cohort schooling $s_{c,j}$

$$\tilde{\mathbb{C}}_{c,j} \quad = \quad \beta s_{c,j} + DX_{c,j} + \varepsilon_{c,j} \tag{14}$$

where β is the coefficient of interest, and $X_{c,j}$ is a set of controls. We first estimate specification (14) pooling all countries together. We have a total of 3,127 birth-cohorts for which we observe both $\tilde{\mathbb{C}}_{c,j}$ and $s_{c,j}$. The median and mean number of birth-cohorts by country is 65. The results are shown in Table (II). Standard errors are clustered at the country level. Column (1) shows the simplest specification that controls only for country fixed effects. Cohorts with more schooling have lower agricultural employment, as expected. This result however is fragile since it may be driven by time trends in both variables: as already discussed, younger cohorts have more schooling and also lower agricultural employment. Therefore, column (2) includes a cubic trend in cohorts' birth years, and column (3) – our benchmark specification – allows the cubic trend to differ by country. Our main result is that one additional year of school decreases the agricultural cohort effect by approximately 17% (not 17 percentage points). Due to the presence of the cubic trend, the estimated coefficient captures the fact that cohorts that are relatively more educated than the trends are also relatively less likely to work in agriculture.

In order to show the fit of the regression, we project – separately for each country – both $\tilde{\mathbb{C}}_{c,j}$ and $s_{c,j}$ on a constant and a cubic trend for cohorts' birth-years. In Figure (VIIa), we plot the residuals of the two projections against each other. The slope is, of course, negative, but most importantly the fit is strong: deviations from the schooling trend explain 29% of the variation across cohorts in deviations from the agricultural employment trend. Further, we run the benchmark specification (14) separately for each country in our sample. In Figure (VIIb), we plot the point estimates $\hat{\beta}_j$ as a function of the country real GDP per capita in 2010. The figure shows that in almost all countries the estimated relationship between schooling and cohort effects is negative and significant. It also shows that relationship is steeper in rich countries, suggesting that one extra year of school in rich countries may have a larger effect on the relative return to non-agricultural production.

We should be cautious in interpreting the results shown as causal. Direct reverse causality is not an issue since we measure agricultural employment after schooling is completed. Selection of higher skilled individuals into schooling and out of agriculture is also not an issue since we are studying cohort-level outcomes. However, two other relevant concerns remain. First of all, if parents decision to invest in children's education is forward looking, the estimated negative relationship may be driven by parents anticipating higher returns from children education.[31] Second, schooling may be a signal of other cohort-level characteristics, such as early-life human capital investment, rather than the main driver of higher relative return in non-agricultural production.

We can alleviate the first concern, but at the cost of making the second one possibly more severe, by instrumenting for schooling using exposure to the cyclical component of GDP during youth. The idea is simple: if children's education is a normal good, children that grew up during

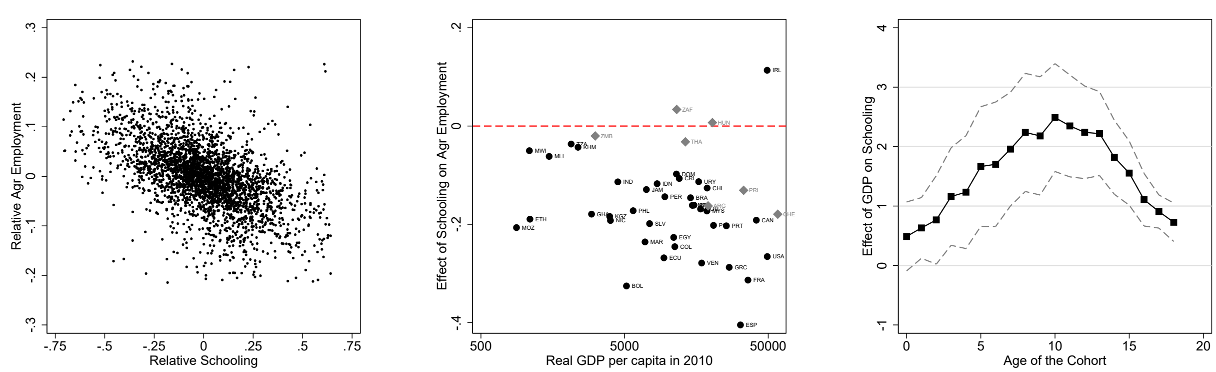
[31] Even though, recall that the cohort effects are estimated controlling for aggregate economic conditions.

relatively more prosperous periods are likely to have spent more years in school. In practice, we merge our dataset with historical GDP data from Maddison (2003), which we filter using an HP filter. For each country and each birth-cohort, we then compute 19 variables, equal to the cyclical components of GDP per capita at birth, and at ages 1 to 18. We then use these variables to instrument for the cohort level schooling in the pooled specification (14), where we control for country-specific cubic trends. The first stage is strong, with an F-stat well above 10. Figure (VIIc) plots the point estimates of the effect of exposure to relatively high GDP on cohort schooling, for all ages from 0 to 18. Reassuringly, the effect is larger when we would expect to be so – i.e. at the children's ages when the parents need to decide whether to keep or not their children in school. Column (4) of Table (II) reports the two stages least square estimates for $\hat{\beta}_{IV}$. The estimated magnitude is similar, and slightly larger, than the one of the benchmark specification. In other words, birth-cohorts that have been exposed to relatively favorable economic conditions while growing up, spend more time in school and have – 15 or more years later – a lower chance of being employed in agriculture. Finally, notice that the number of observation declines slightly because we don't have available GDP data for all cohorts.

The results of this section must be interpreted as suggestive. Nonetheless, we find encouraging that the estimated magnitudes are inline with those for the case of Indonesia, where we use credible identification. In appendix (B), we show that running the benchmark specification using the school construction to instrument for school provides point estimates between - 0.10 and - 0.20, depending on how we treat the outliers.

Figure VII: Role of Schooling, Variation Across Cohorts

(a) Plot Across Cohorts (b) Estimates by Country (c) Effect of GDP on Schooling



Notes: the left figure plots, against each other, the residuals of projections of $\tilde{\mathbb{C}}_{c,j}$ and $s_{c,j}$ on a country-specific cubic trend. The center figure plots, as a function of Real GDP per capita, $\hat{\beta}_j$ of the regressions $\tilde{\mathbb{C}}_{c,j}$ on $s_{c,j}$ and a cubic trend. Coefficients that are significant at 5% are in black. The right figure plots the point estimates on the instruments of the first stage regression of cohort schooling on country specific cubic trend, country fixed effects, and dummies for GDP cycle at different cohort ages (the instruments). The dotted line represents the 95% confidence intervals.

6.3 Variation Across Countries and Time Periods

As a last exercise, we treat a country-year as a unit of observation and we study the relationship between the estimated cohort and year components and aggregate schooling growth.

Specifically, for each country-year we compute the change in the average schooling between that year and the next available cross-section. In practice, the change in average schooling is driven by the difference between the cohorts that exit our dataset because they become older than 59, and those that enter for the first time. Formally, consider a country j for which we observe a cross section at time t and one at time $t + k_{k,j}$. We compute yearly schooling change as

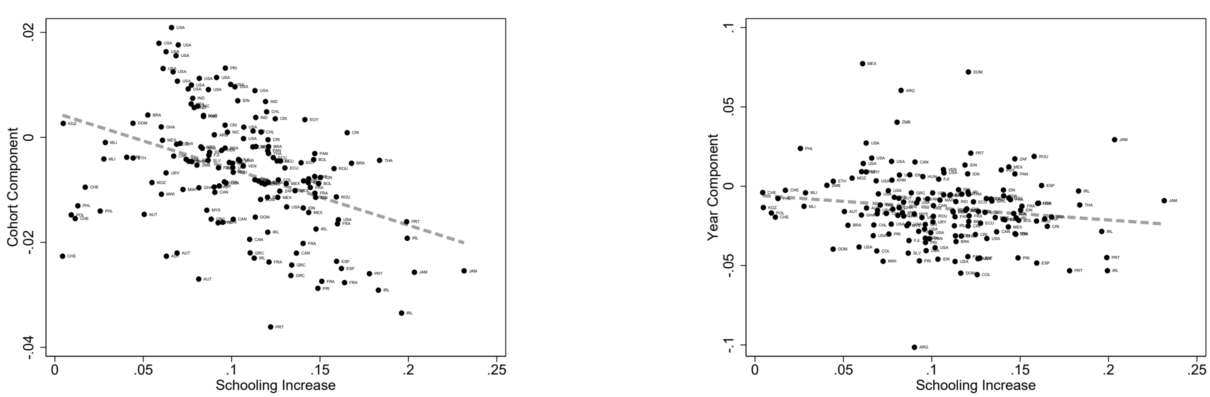
$$\Delta s_{j,t} \;\; = \;\; \frac{1}{k_{k,j}} \left(\sum_{c=t+k-N}^{t+k} n_{t,c,j} s_{c,j} - \sum_{c=t-N}^{t} n_{t,c,j} s_{c,j} \right)$$

where $s_{c,j}$ are estimated cohort schooling as previously described. We then plot across all country-year pairs, the cohort and year components that we estimated in Section (5), as a function of schooling change. The results are shown in Figures (VIIIa) and (VIIIb). Countries that experienced a faster increase in schooling have also experienced a large decrease in agricultural employment due to the cohort component.

Of course, it is hard to argue that cross-country differences in schooling growth are exogenous. Nonetheless, we find reassuring that schooling growth is strongly correlated with the change in supply of agricultural workers and only weakly so with the change in demand.

Figure VIII: Role of Schooling, Variation Across Country-Time Pairs

(a) Cohort Components (b) Year Components



Notes: both figures have average schooling changes $\Delta s_{j,t}$ on the x-axis; the left figure has cohort components, $\log \tilde{\chi}_{t,j}$, and the right figure has year components, $\log \tilde{\psi}_{t,j}$, on the y-axis.

7 The Aggregate (General Equilibrium) Effect of Schooling

We have established that the supply of agricultural workers decreased in almost all countries and that the increase in schooling likely played a central role in this process. We next turn to the third and last question and study how the changes in supply affected the aggregate rates of labor reallocation.

Combining Propositions 1 and 2 we can express the aggregate effect on labor reallocation of changes in the supply of agricultural workers as the product of the cohort component estimated in Section (5) and a general equilibrium multiplier

$$\underbrace{-\left(\frac{v}{1-\gamma}\right)(1+\Theta_S)\,\gamma\log g_h}_{\text{Aggregate Effect of Supply (Prop 1)}} = \underbrace{\frac{1-\tau\eta\eta_H}{1+\left(\frac{v}{1-\gamma}\right)(\alpha+\eta\eta_L)}}_{\text{GE Multiplier}} \times \underbrace{\log\tilde{\chi}}_{\text{Cohort Component (Prop 2)}} .$$

The equation shows that the aggregate effect of supply changes depends on three sets of parameters. The first set of parameters modulates the strength of general equilibrium in the goods market: i) the elasticity of the relative agricultural price η, which captures – in reduced form – how much the relative agricultural price is affected by within country changes; and ii) the relative elasticities to a change in the human capital stock and in agricultural labor, given by η_H and η_L. The second set of parameters modulates the strength of general equilibrium in the labor market: i) α is the role of the fixed factor in production, which pins down the decreasing returns in agriculture; and ii) $\frac{v}{1-\gamma}$ is the elasticity of agricultural labor supply to relative agricultural wage, as can be seen in equation (9). Finally, we need to calculate the elasticity of human capital stock to the cohort effect, which is given by τ: when τ is low, cohort effects are driven by taste for non-agricultural production, rather than change in relative productivity – or human capital – and as such the GE effects working through the human capital stock are muted.

The GE multiplier is likely to vary across countries. For example, due to the fact that they are in different stages of development, which would affect the role of land in agricultural production, hence α, or due to their size and openness to trade. It is beyond the scope of this work to measure the GE multiplier for each country in our sample. Instead, we provide a range of estimates relying on estimates from the literature, when available.

Partial Equilibrium. We first consider the aggregate effects in partial equilibrium – i.e when $\eta = \alpha = 0$. In this case, the GE multiplier is trivially equal to 1 and the cohort components give directly the aggregate effects. Using the results shown in Table (I), we conclude that – in partial equilibrium – the decrease in supply of agricultural workers could explain, on average, 40% of the total observed reallocation out of agriculture. We believe this to be a likely upper bound of the aggregate effect for most countries.

Small Open Economy. Next, consider the case that we have labeled small open economy – i.e. when the labor market is in general equilibrium, but the goods market is in partial equilibrium – $\alpha > 0$ and $\eta = 0$. In order to compute the aggregate effect, we need to pin down the values of $\left(\frac{v}{1-\gamma}\right)$ and α. First, notice that the GE multiplier is decreasing in both parameters: a high $\left(\frac{v}{1-\gamma}\right)$

implies that a small movement in the wage leads to a large reallocation of labor, and a high α implies that a small movement in labor leads to a large change in relative wage. If $\left(\frac{v}{1-\gamma}\right)\alpha$ is very large, the GE multiplier can be close to zero. How can then a large cohort component coexist with small aggregate effects? The cohort component captures the differences across cohorts in returns from non-agricultural production, but, as younger birth-cohorts become more biased towards non-agriculture, the older ones are being pulled back into agriculture, where they face an increasing comparative advantage. When the GE multiplier is small, this indirect effect is strong.

We have shown in Section (5), that data on wage variance provides an upper bound for $\left(\frac{v}{1-\gamma}\right)$ ranging from 1 to 3 across countries, and averaging 1.5. Next, we focus on α, which is the land income share in agriculture. Herrendorf et al. (2015) gives us an estimate for α for the United States: it finds $\alpha_{US} = 0.07$. Land, however, may have a higher income share in lower income countries, where agricultural production is less capital-intensive. For example, in ongoing work, Gollin and Udry (2017) estimates production function for micro plots in Uganda and Ghana and find land shares in the range 0.40-0.50. Combining the estimates for the two parameters, gives a GE multiplier for the small open economy ranging between 0.4 and 0.9. We conclude that, in small open economies, the decrease in supply of agricultural workers could explain between 16% and 36% of the observed labor reallocation.

General Equilibrium. Finally, we consider the case when both the labor and the goods markets are in general equilibrium. In this case, we would need to pin down four parameters: η, η_H, η_L, and τ. The literature on structural change, has argued that, in closed economies, $\eta\eta_L > 1$ and, if we assume homothetic demand, also $\eta\eta_H > 1$ – see, for example, Ngai and Pissarides (2007). Under this parametric assumption, and further letting $\tau = 1$, the decrease in supply of agricultural labor would pull labor *into* agriculture, since the GE multiplier would turn negative. In fact, this result is not particularly surprising. When $\tau = 1$, the decrease in the supply of agricultural workers increases the relative productivity of non-agricultural production. If the elasticity of substitution between agricultural and non-agricultural goods is below one, which in our setting maps into $\eta\eta_L > 1$ and $\eta\eta_H > 1$, then the agricultural price would increase so much as to make relative revenue labor productivity *increase* in agriculture.

Allowing for $\tau < 1$ and considering non-homothetic demand can turn, depending on the magnitudes of parameters, the GE multiplier positive and large. If $\tau = 0$, the change in relative return from non-agricultural production is purely driven by a change in preferences or in the cost of working in non-agriculture, and not by a change in relative productivity. As a result, the argument of the previous paragraph would not apply and the GE multiplier would turn positive. At the same time, the increase in human capital – as long as $\tau > 0$ – generates an income effect. If demand is non-homothetic, the income effect would lead to an increase in the demand for non-agricultural goods. The parameter η_H captures both the income effect and the relative productivity effect of human capital. If the former dominates, then $\eta_H < 0$, thus turning the GE multiplier positive, and possibly even bigger than one.

8 Conclusion

This paper explored the hypothesis that the steep increase in schooling observed during the 20^{th} century might have contributed to the process of structural transformation, by equipping the new generations of workers with skills more useful to be employed out of agriculture.

We used theory and evidence to bring support to the hypothesis. We developed a methodology to infer changes in the relative supply of agricultural labor from micro level data on agricultural employment by cohort. We concluded that, as a result of changing characteristics of the labor force, the supply of agricultural workers decreased steeply. We then showed, exploiting different sources of variation, that schooling seems to have played a key role in transforming the labor force. Finally, we studied the aggregate implications. With fixed prices, the documented supply shift, could explain as much as 40% of global labor reallocation out of agriculture. However, when both labor and goods market are in equilibrium, the net effects are ambiguous, and likely to vary across countries.

We think that it is premature to conclusively argue that the increase in schooling led to large labor reallocation out of agriculture. More work is still needed to pin down the general equilibrium effects in all countries. Nonetheless, we believe that this paper has highlighted that changes in the supply of agricultural labor, and the role of schooling in causing them, should be major players in any theory of structural transformation.

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