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Structural Transformation and Spatial Convergence Across Countries

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Abstract

I document how the importance of structural transformation for spatial convergence of labor income varies across countries. I use microdata to show that in recent decades structural change accounts for a much larger share of income convergence in developing countries than in rich countries. Convergence in sectoral composition of employment accounts for most of the contribution of structural change. Using a quantitative general equilibrium model, I find that the increase in educational attainment has been a key determinant of income convergence in developing countries. The results of the model imply that unbalanced productivity growth in agriculture is mostly relevant for convergence in sectoral composition of employment, but not for income convergence.

Keywords: structural transformation, spatial convergence, productivity, human capital
JEL codes: E24, J24, O11, O18, R11

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1 Introduction

Economic development is typically uneven across space within countries. In both rich and poor economies there are significant disparities in average income between regions. For instance, in 2010 the richest state in India was almost 9 times richer that the poorest state. In the same year, the equivalent gap in the United States was larger than 2. More generally, in an average country the richest region can be nearly 5 times richer than the poorest one (see Gennaioli et al., 2014). These facts motivate both academic and policy interest in explaining the persistence or reduction of regional income gaps.

The first goal of this paper is to evaluate if structural transformation - the reallocation of workers from agricultural to non-agricultural activities - is an important contributor to spatial convergence of labor income within countries, and if that contribution varies with the level of development across countries. If changes in the sectoral composition of employment are quantitatively important for reductions in regional income gaps, especially in developing countries where poor places still have large fractions of their labor force in agriculture, then policies that aim to accelerate structural change could have a meaningful impact on reducing income inequality across space.

I start by documenting the relationship between structural change and spatial convergence of labor income using harmonized microdata for 9 countries, including poor and rich economies. In all cases, the period of time covered starts after 1970. The main empirical finding is that structural transformation accounts for a much larger fraction of income convergence in developing countries than in rich countries. This finding echoes the previously documented fact that structural change became less important for regional convergence in the United States as the economy grew in the 20th century (Caselli and Coleman II, 2001).

Furthermore, I show that most of the contribution by structural transformation in developing countries is due to convergence in sectoral composition of employment (reallocation out of agriculture), and to a lesser extent to convergence of labor income *between* sectors. In contrast, spatial convergence of labor income *within* sectors of the economy has been the main contributor to regional convergence in rich countries. Additionally, I show that recent improvements in educational attainment in developing countries can account for a meaningful fraction of regional convergence in sectoral employment.

Given the empirical findings, the second goal of the paper is to shed light on the quantitative importance of typical structural change drivers for spatial convergence of labor income in developing countries, especially the importance of increases in educational attainment. To do that, I build a multi-sector, multi-region general equilibrium model that accounts for worker selection and regional comparative advantage. In the model, individuals choose location and sector of employment based on their human capital and idiosyncratic preferences, and their choices are constrained by mobility costs across space.

Then, I calibrate the model to match moments of two different developing countries, Brazil and Indonesia, using detailed microdata. The quantitative results of the model imply that the recent boost in educational attainment has been an important contributor to income convergence in developing countries. However, selection of internal migrants according to human capital, as well as price changes in equilibrium, are key for the extent of spatial convergence that can be generated from human capital growth through education. Taking general equilibrium effects into account, the average contribution of increases in educational attainment to income convergence is close to 30 percent.

On the other hand, unbalanced and spatially uneven productivity growth in agricultural production has been key for spatial convergence in sectoral composition of employment, though the results of the model imply that it does not generate income convergence by itself. Consistent with previous findings in the literature, unbalanced productivity growth is important for the large decline in agricultural employment in developing countries. Moreover, the results imply that promoting internal migration can increase both spatial convergence and regional specialization if the average person, as opposed to high-skill individuals, can be induced to migrate from poor regions within developing countries.

This paper is related to the large literature on economic growth and structural transformation summarized by Herrendorf et al. (2014). In particular, to papers that study the spatial dimensions of structural change (Caselli and Coleman II, 2001; Michaels et al., 2012; Eckert and Peters, 2018). The paper makes a contribution to this literature by exploiting microdata to document new facts on the connection between spatial convergence and structural transformation among a group of countries with large variation in level of development. In particular, I show that in recent decades structural transformation has been an important contributor to spatial convergence of labor income in developing countries. The cross-country comparison in this paper, together with previous findings on U.S. regional convergence, suggest that the relevance of structural change in reducing regional inequality declines with economic development.[1]

In addition, the mechanisms emphasized in the quantitative model, particularly the role of changes in educational attainment, relates this paper to the literature exploring the connection between forms of human capital accumulation and structural transformation (Hobijn et al. 2018; Porzio et al. 2021). Furthermore, this paper is related to the macroeconomics literature that studies the link between sectoral or regional income gaps and worker selection in human capital (Young, 2013; Herrendorf and Schoellman, 2018). The paper contributes to these literatures by showing how various drivers of structural change in an economy, which change the overall supply or demand of workers in agriculture, can affect regional convergence in both labor income and sectoral composition of employment, and how this is influenced by worker selection and general equilibrium effects.

The rest of the paper is organized as follows. Section 2 describes the microdata used in the paper and presents the main findings regarding the contribution of structural transformation to spatial convergence of average labor income across a group of rich and poor countries. Section 3 presents a general equilibrium model with sectoral choices, internal migration, and worker selection. Section 4 describes how the model is taken to the data for multiple developing countries. Section 5 presents quantitative experiments using the calibrated model,

[1]More broadly, this paper is related to the literature on regional income convergence including work by Barro and Sala-i-Martin (1992), Bernard and Jones (1996), Gennaioli et al. (2014), and Giannone (2021).

Table 1: Countries, Time Period, and Categorization

Country	Years	Income Category
Canada	1991, 2011	
Israel	1972, 1995	High
United States	1990, 2010	
Brazil	1991, 2010	
Mexico	1990, 2010	Middle
Panama	1990, 2010	
India	1983, 2004	
Indonesia	1976, 1995	Low
Jamaica	1982, 2005	

Notes: Income categories based on quantiles of GDP per Capita (PPP - constant 2017 international $) from Word Bank data.

and Section 6 concludes the paper.

2 Empirical Evidence

This section presents the data and main empirical facts of the paper. I use harmonized microdata from IPUMS-International for the 9 countries used in the analysis. Most of the original data sources are national censuses. Based on Gross Domestic Product (GDP) per capita, the poorest country in this sample is India and the richest country is the United States. The group of countries includes some of the most populous economies in the world: Brazil, India, Indonesia, and the United States. For each country, I use two cross-sections that are roughly 20 years apart to focus on long-run patterns. In most cases the time period covered is between 1980 and 2010. The main variables that I use in the analysis are individual earnings, hours worked, industry of employment, and state of residence.

I define the variable wages as total labor earnings divided by hours worked. This is the variable used for average labor income throughout the paper. I restrict the sample to adult

(15-70 years old) male workers with non-negative earnings, excluding individuals who are classified as unpaid workers in the data. Women are excluded from the sample because men tend to be relatively more attached to the labor market and are more likely to move across space due to work-related reasons, especially in poor countries.

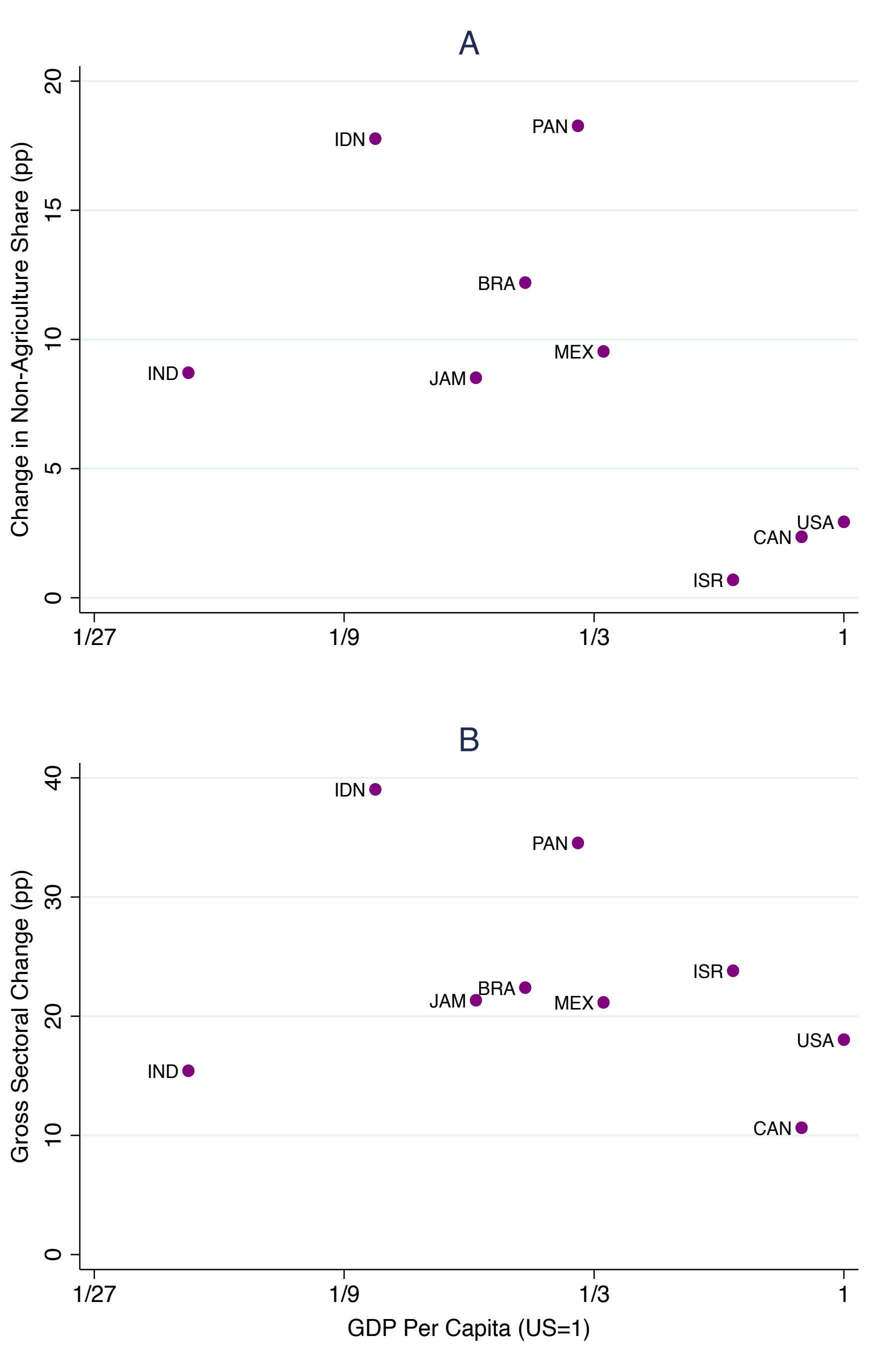
Importantly, income data for the poorest countries in the sample is only available for wage and salary jobs. This is important because self-employment accounts for a large fraction of the workforce in the poorest countries, especially in agriculture. That said, previous work has shown that focusing on wage and salary income does not seem to be a major concern for qualitative conclusions extracted from income comparisons across sectors (see Herrendorf and Schoellman, 2018.)

2.1 Structural transformation and spatial convergence

First, I show that every country in the sample made progress in the process of structural transformation during the period of time covered in the data. Panel A in Figure 1 presents the change in the fraction of employment in non-agriculture. This change is positive in every case, though it is larger in developing countries. That is because rich countries already had a relatively small fraction of employment in agriculture in the second half of the 20th century and labor reallocation is mostly happening from manufacturing industries to services. On average, low and middle income countries experienced an increase in the share of labor in non-agriculture of 12.5 percentage points over time, while the share of employment in services in rich countries increased by 8.6 percentage points.

Additionally, to look at another comparable measure of labor reallocation across countries, Panel B in Figure 1 presents the gross sectoral change in employment shares for three sectors: agriculture, manufacturing and services. To be clear, that measure is defined as the following sum: $|\Delta\text{Agr. Share}| + |\Delta\text{Man. Share}| + |\Delta\text{Ser. Share}|$. The gross sectoral change shows that in every country there is meaningful labor reallocation across sectors over time, though labor reallocation out of agriculture is the predominant force in poorer economies. Similar facts about structural transformation have been extensively documented

Figure 1: Structural Transformation



Notes: This figure presents the change in the fraction of employment in non-agriculture and the gross sectoral change in employment shares (sum of absolute value of the change in each sector). Changes are expressed in percentage points. Income refers to GDP per Capita (PPP - constant 2017 international $) from Word Bank data.

in the literature cited in the introduction.

Next, I document new facts on spatial convergence of labor income across countries. For each country, I define a group of convergent states based on two criteria: (i) they had an average income below the national mean in the first wave or cross-section; *and* (ii) the income gap relative to the national mean decreased between both cross-sections. In other words, the convergent group are relatively poor states that have closed the income gap with respect to the national average over time. Furthermore, to evaluate the role of structural change in low and middle income countries, I consider two sectors: agriculture (a) and non-agriculture (n). For high income countries, I split sectors into services and the rest of the economy based on the facts presented above, though I keep the notation simple by using a and n for economic sectors in all cases.

To measure convergence of regional income, as well as its decomposition into structural transformation and other channels, I use the same methodology as Caselli and Coleman II (2001), which works as follows. First, define the two groups or regions of states in each country as convergent (c) and rich (r) for simplicity of notation. Also, let w_t be the average wage in period t; N_{at} be the fraction of employment in agriculture in period t; ω_t be the sectoral wage gap, $\big(w_{at} - w_{nt}\big)/w_t$, such that w_{at} is the average wage in the agriculture and w_{nt} is the average wage in non-agriculture; and $\Delta x = x_t - x_{t-1}$ be the change over time for any variable x. Then, allowing variables to have a regional superscript when necessary and using $\bar{x}_t$ to denote the average value of variable x over time, we can define regional convergence of average labor income as:

$$
\begin{aligned}
\text{Convergence} \equiv \frac{w_t^c - w_t^r}{w_t} - \frac{w_{t-1}^c - w_{t-1}^r}{w_{t-1}} \\
= \underbrace{\bar{\omega}_t^c \Delta N_a^c - \bar{\omega}_t^r \Delta N_a^r}_{\text{Convergence in employment composition: labor reallocation}} \\
+ \underbrace{\Delta\omega\big(\bar{N}_{at}^c - \bar{N}_{at}^r\big)}_{\text{Convergence in wages } \textit{between} \text{ sectors}} \\
+ \text{Residual: convergence of wages } \textit{within} \text{ sectors}
\end{aligned}
\tag{1}
$$

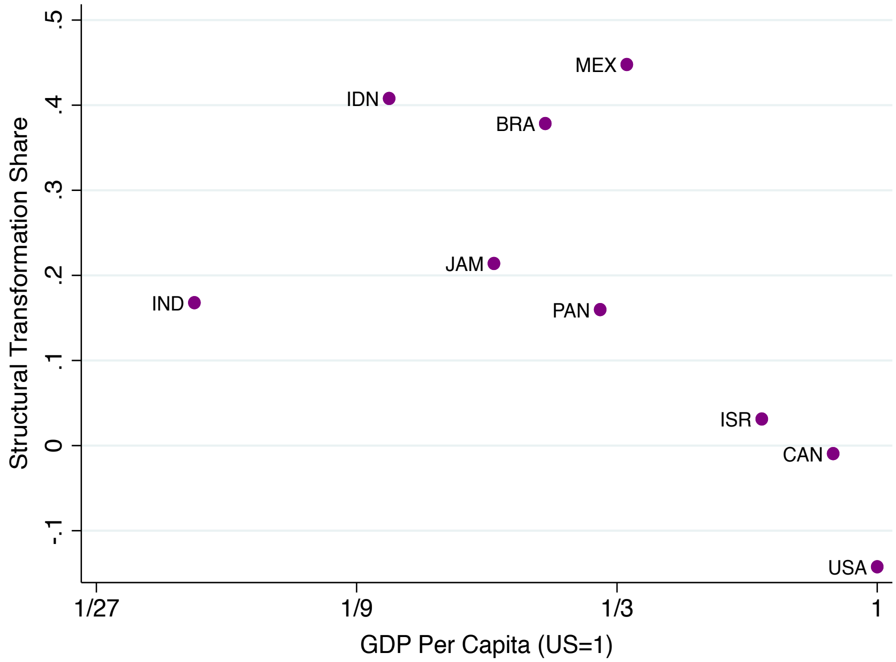
The convergence decomposition in equation (1) has three components: labor reallocation across sectors, wage convergence between sectors, and wage convergence within sectors. The labor reallocation channel in the second line captures spatial convergence in sectoral composition of employment. That is, fixing the sectoral wage gap to its average over time, if the fall in agricultural employment is larger in the convergent region than in the rich region, then there is a positive contribution to income convergence given that average wages are higher in non-agriculture. Thus, uneven labor reallocation out of agriculture across space contributes to regional convergence within countries.

Next, the third line in equation (1) captures convergence in average wages *between* sectors in the economy. That is, if agricultural employment is higher in the convergent region during a given period of time, a reduction in the sectoral wage gap represents a positive contribution to income convergence given that the region with the largest employment share in agriculture benefits the most from relative income gains in that sector.

The first two channels in the decomposition of regional convergence represent the contribution of structural transformation as they involve movement of labor between sectors, as well as convergence of agricultural wages to non-agricultural wages in the economy. The third component in the decomposition includes residual forces that lead to regional convergence of average wages within each sector, such as changes in spatial frictions.

Based on the definitions in previous paragraphs, Figure 2 presents a novel finding in this paper. It shows that structural transformation accounts for a larger share of income convergence in developing countries than in rich countries. It also implies that almost all convergence in rich countries is accounted for by within-sector convergence of wages across space. One plausible explanation for these results is that rich countries are far advanced in the process of structural transformation, so most of the observed convergence is due to other forces that generate factor price equalization among regions. Moreover, the wage gap between services and non-services in rich countries is not as large, or even positive, as the wage gap between non-agriculture and agriculture in developing countries. The latter partly explains the negative contribution of structural change to income convergence in the United

Figure 2: Spatial Convergence and Structural Transformation



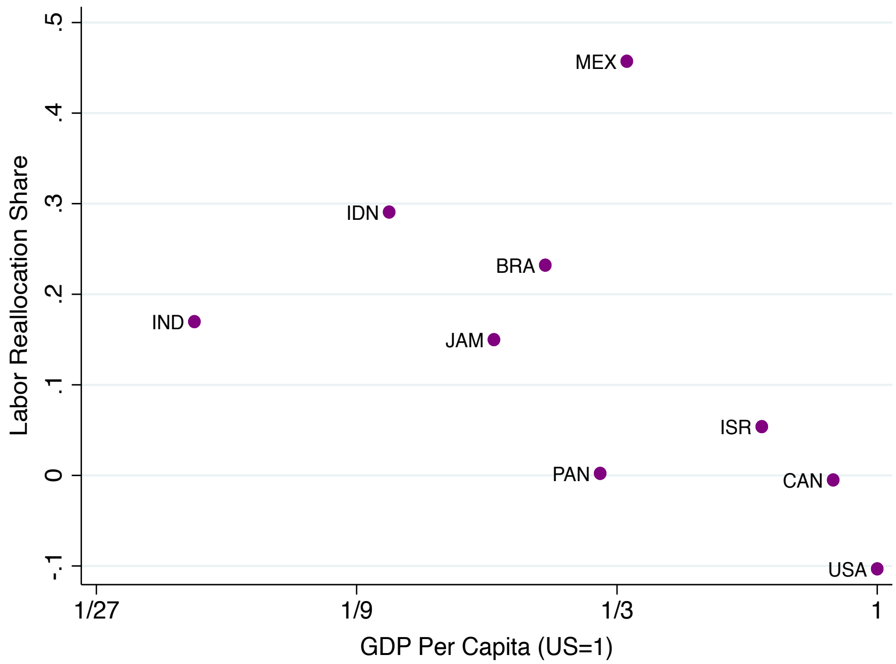
Notes: This figure presents the fraction of regional convergence accounted by structural transformation in each country. Income refers to GDP per Capita (PPP - constant 2017 international $) from Word Bank data.

States.

Therefore, these facts suggest that structural transformation is more important for spatial convergence of labor income in earlier stages of development when labor reallocation out of agriculture accounts for most of the change in sectoral composition of employment. These results are consistent with the findings by Caselli and Coleman II (2001), who show that structural change accounted for a large fraction of regional convergence in the United States during the first half of the 20th century. That contribution declined in the second half of the century as the U.S. economy kept growing.

To isolate the importance of labor reallocation between sectors, Figure 3 shows how much of the observed convergence in average labor income is accounted for by convergence in the sectoral composition of employment. To reiterate, the labor reallocation channel captures the possibility that regions within countries are converging in the fraction of workers employed in non-agriculture, which is the sector with higher wages. The results presented in the figure

Figure 3: Spatial Convergence and Labor Reallocation



Notes: This figure presents the fraction of regional convergence accounted by labor reallocation in each country. Income refers to GDP per Capita (PPP - constant 2017 international $) from Word Bank data.

show that the labor reallocation channel accounts for a larger share of income convergence in most developing countries.

Table 2 summarizes the empirical findings by income group. First, the second column presents average convergence in regional labor income within each income group. In low and middle income countries, there was a decline in the regional income gap of approximately 15 percentage points during the time period covered. In rich countries, the regional income gap fell by 11 percentage points over a similar period of time. According to the third column in the table, structural transformation accounted for 26 and 33 percent of income convergence in low and middle income countries, respectively.

In contrast, structural transformation had a negative contribution to income convergence in rich countries. This means that, on average, structural transformation by itself would have generated divergence of labor income between the groups of states in rich countries. That is in part because in those countries labor is mostly reallocating from manufacturing to the

Table 2: Spatial Convergence Decomposition

		Contribution of	
Income Group	Convergence	Structural Transformation	Labor Reallocation
Low	15.2	26.3	20.3
Middle	14.7	32.9	23.1
High	10.6	-4.0	-1.8

Notes: This table presents average regional convergence by income group, and the percentage accounted by structural transformation and labor reallocation. Income categories are based on quantiles of GDP per Capita (PPP - constant 2017 international $) from Word Bank data.

service sector where average wages are not much higher, or even lower, than in other sectors of the economy.

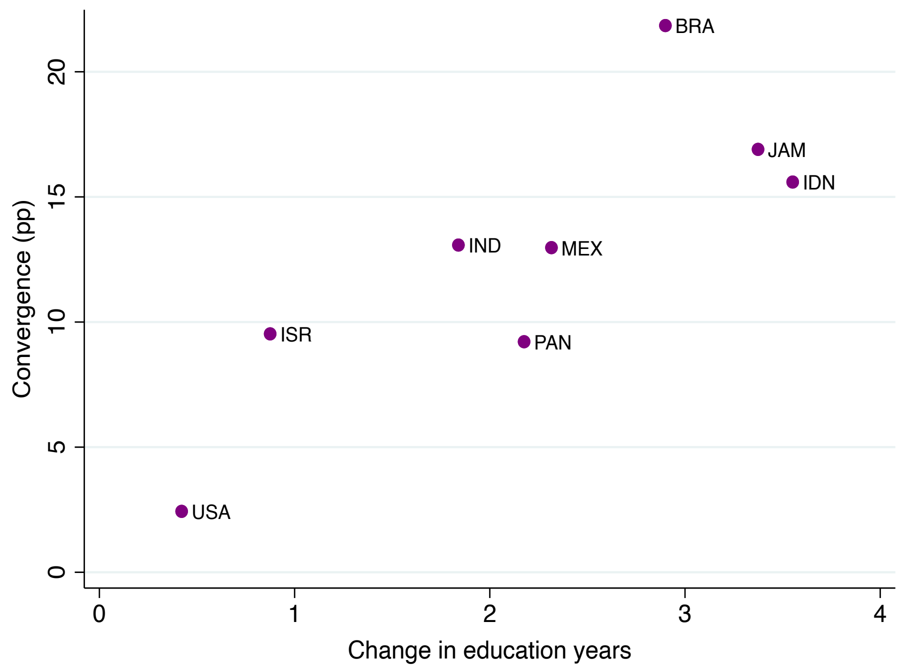
Lastly, the results presented in the fourth column of Table 2 imply that the labor reallocation channel accounts for most of the contribution of structural transformation to income convergence in developing countries: around 70 percent or higher. Thus, these findings suggest that structural change, especially labor reallocation out of agriculture, could be key to reduce regional inequality in those countries. The results can have important policy implications given the large disparities in average income across regions in many developing countries.

2.2 Education and spatial convergence

Next, to motivate the quantitative importance that human capital growth can have for regional convergence, Figure 4 presents the change in educational attainment over time in each country and the amount of regional convergence in labor income as defined above.[2] The figure shows a positive relationship between improvements in educational attainment and income convergence, which reinforces the idea that human capital accumulation through educational attainment is important to reduce income inequality across space within countries.

[2]Education changes are estimated based on the selected sample of workers in the analysis. Canada is excluded from this exercise because there are significant comparability issues of the educational attainment variable between the samples considered. See IPUMS International for more details.

Figure 4: Spatial Convergence and Education



Notes: This figure presents the change in educational attainment over time and convergence of labor income between the groups of states defined in the main text.

I complement the previous simple correlation by evaluating how much of the observed convergence in agricultural employment between regions can be accounted for by changes in educational attainment. To do that, first note that the change in the share of agricultural employment in any region over time, $\Delta N_a = N_{a,t} - N_{a,t-1}$, can be decomposed as:

$$\Delta N_a = \underbrace{\sum_e (\Delta N_{ae}) N_{e,t-1}}_{\text{within education group}} + \underbrace{\sum_e (\Delta N_e) N_{ae,t-1}}_{\text{education distribution}} + \underbrace{\sum_e \Delta N_{ae} \Delta N_e}_{\text{covariance}} \qquad (2)$$

where N_{ae} is the agricultural employment share of workers with education level e and N_e is the fraction of workers with education level e. The first term in the right hand side of the equation represents the contribution of changes in agricultural employment within each education group while fixing the distribution of education. The second term represents the contribution of changes in the distribution of educational attainment while fixing the employment shares; for instance, if the fraction of workers with low education falls over time

Table 3: Decomposition of Convergence in Agricultural Employment

Income Group	Total Convergence	Within Education	Education Distribution	Covariance
Low	13.25	11.28	3.44	-1.47
Middle	9.05	4.81	6.17	-1.93

Notes: Numbers represent percentage points. The sum of Columns 3 to 5 is equal to the value in Column 2.

and this education group had a relatively high probability of working in agriculture, then that term would contribute to an overall decline in agricultural employment.

Next, define convergence in agricultural employment between rich and convergent regions within each country as: $\Delta N_a^r - \Delta N_a^c$. This measure of convergence is positive if the decline in agricultural employment over time is larger in convergent regions. Then, I can decompose convergence in agricultural employment into each of the three components in equation (2). I do this for middle and low income countries where the aggregate decline in agricultural employment has been meaningful during the period considered. This analysis uses three education categories: less than 6 years of education (no primary school completed); less than 12 years but at least 6 years of education (primary school completed but not secondary); and 12 or more years of education.

The results presented in Table 3 show that there has been spatial convergence in agricultural employment in both groups of countries. The main difference is that the decline in agricultural employment within education groups is the most important contributor in low income economies, while improvement in educational attainment is the most important contributor in middle income countries. Despite the differences, these results highlight that changes in the distribution of educational attainment, mainly the decline in the size of low-education groups who tend to work in agriculture, has been quantitatively important for spatial convergence of agricultural employment in developing countries. It accounts for 68 percent of the observed convergence in middle income countries and 26 percent of the convergence in low income countries.

Building on the documented facts, the next section introduces a general equilibrium model that features internal migration, sectoral choices, and individual selection according to human capital. The main objective is to use a quantitative framework to assess and compare the relevance of typical structural transformation drivers, which affect the demand or supply of labor in agriculture, for spatial convergence in developing countries.

3 Model

The environment in the model is as follows. There are two regions indexed by j, a convergent (c) and a rich (r) region in reference to the previous section, and two sectors indexed by s, agriculture (a) and non-agriculture (n). Both consumption goods can be produced in each region and traded across space without costs. The economy is populated by a unit mass of individuals and a fraction μ_o of the population has geographic origin $o \in \{c, r\}$. The model builds on elements from macro-development papers on sectoral income gaps and human capital (Young, 2013; Herrendorf and Schoellman, 2018), and quantitative spatial equilibrium frameworks (Ahlfeldt et al., 2015; Rivera-Padilla, 2021).

3.1 Preferences and endowments

Every individual i living in region $j \in \{c, r\}$ has non-homothetic preferences over both consumption goods given by

$$U_{ixj} = b_{isj} \left(\frac{C_{inj}}{1-\alpha} \right)^{1-\alpha} \left(\frac{C_{iaj} - \overline{a}}{\alpha} \right)^{\alpha}, \tag{3}$$

where C_{isj} is individual consumption of goods from sector $s \in \{a, n\}$ and b_{isj} are idiosyncratic preferences for sector-location combination sj. The latter captures the possibility of preferring a sector and region based on individual factors other than income. Additionally, parameter $\alpha \in (0, 1)$ governs the long-run expenditure on agricultural goods and $\bar{a} \geq 0$ represents a subsistence level of food consumption.

Individuals are endowed with education years $e_i \in \{0, 1, .., \bar{e}\}$ and their supply of human capital in labor markets is given by $h(e) = \exp(e)$. This type of specification for individual human capital is commonly used in the macro-development literature (see e.g., Bils and Klenow, 2000). The mass of individuals from origin o who are endowed with education e is exogenous and denoted by ζ_{eo}. However, the distribution of education in each region and sector is endogenous as it depends on location and sectoral choices as described below.

Furthermore, an individual born in location o has the possibility to migrate between regions subject to migration costs given by $\tau_e = \bar{\tau}\exp(-\delta e) < 1$, with $\bar{\tau} > 0$. This specification of migrations costs is useful to capture selection of internal migrants in terms of education. In particular, it allows for the possibility that highly educated individuals face lower migration costs if δ is positive. For instance, highly educated individuals might find it easier to acquire information in other locations or might face less discrimination as internal migrants. That said, I do not impose any restriction on the value δ in the estimation of the model. Parameter $\bar{\tau}$ captures common migration costs that are broadly defined such as inconvenience of relocating or loss of local networks.

3.2 Production

There is a competitive market in both sectors of the economy. The non-agricultural good is produced in both regions using efficiency units of labor according to

$$Y_{nj} = A_{nj} \sum_{e} h(e)^{\gamma_n} N_{nj}(e), \quad j \in \{c, r\}, \tag{4}$$

where $N_{nj}(e)$ is the demand for workers of type e in sector n and region j. Parameter $\gamma_n > 0$ governs the value of human capital in non-agricultural production and A_{nj} governs exogenous labor productivity in that sector and region.

On the other hand, production of agricultural goods in each region uses efficiency units of labor such that

$$Y_{aj} = A_{aj} \Big[\sum_{e} h(e)^{\gamma_a} N_{aj}(e) \Big]^{\eta}, \quad j \in \{c, r\}, \tag{5}$$

where $\eta \in (0,1)$ is a parameter that governs decreasing returns to scale in agricultural production, parameter A_{aj} captures regional labor productivity in that sector, and $\gamma_a > 0$ governs the value of human capital in agriculture. I assume that farming profits are paid to a local landlord who only makes consumption choices in their region.[3]

3.3 Equilibrium

In a competitive equilibrium, we can define a wage rate per efficiency unit of labor in each sector and region as

$$\omega_{nj} = A_{nj} \quad \text{and} \quad \omega_{aj} = P_a A_{aj} \eta \Big[\sum_e h(e)^{\gamma_a} N_{aj}(e) \Big]^{\eta-1}, \qquad j \in \{c, r\}, \tag{6}$$

which means that individual labor earnings can be expressed as $W_{sj}(e) = \omega_{sj} \exp(\gamma_s e)$. This implies that if $\gamma_n > \gamma_a$, then the return to education is higher in the non-agricultural sector for given values of wages. Note that the demand for effective labor in agriculture has a negative slope because $\eta < 1$, which is important for general equilibrium effects of changes in the supply of labor in that sector. Additionally, note that spatial convergence of average labor earnings within and between sectors can be due to convergence in wages per efficiency unit and/or convergence in average human capital.

Furthermore, given their endowment of education, individuals who choose to live in location j maximize utility by choosing a consumption bundle subject to their budget constraint: $C_{inj} + P_a C_{iaj} = W_{sj}(e_i)$, where the non-agricultural good is used as the numeraire, and P_a is the price on agricultural goods in the economy. Note that in this notation I have used the fact that, in equilibrium, the price of the agricultural good does not vary across regions because there are no trade costs in the model.

Then, utility maximization results in the following individual demands for agricultural

[3] I assume that local landlords have homothetic preferences (no subsistence consumption) over both consumption goods with the same preference weight α. This means that total subsistence consumption only depends on the mass of workers who are making location and sectoral choices, and not on the relative size of landlords which is arbitrary in this case.

and non-agricultural goods:

$$C_{iaj} = \frac{\alpha}{P_a}\Big(W_{sj}(e_i) - P_a\bar{a}\Big) + \bar{a},$$
$$C_{inj} = (1-\alpha)\Big(W_{sj}(e_i) - P_a\bar{a}\Big). \tag{7}$$

A key implication of having non-homothetic preferences with $\bar{a} > 0$ is that the budget share of agricultural goods decreases with individual income. Therefore, as income grows in the economy, the budget share of agricultural goods converges to α with a corresponding decline in the share of employment in agriculture (see Kongsamut et al., 2001).

Additionally, the indirect utility of individuals with education e and origin $o \in \{c, r\}$ is given by

$$V_{isj|eo} = b_{isj}\,\underbrace{\left(W_{sj}(e_i) - P_a\bar{a}\right)\,P_a^{-\alpha}\left(1 - \tau_e \mathcal{I}_{[j\neq o]}\right)}_{\tilde{V}_{sj|eo}}, \quad j \in \{c, r\}, \quad s\{n, a\}, \tag{8}$$

where $\mathcal{I}_{[j\neq o]}$ is equal to one if the individual migrates and zero otherwise. I follow the literature by assuming that idiosyncratic preferences are independent and identically distributed, and drawn from a Fréchet distribution, $F(b) = \exp\big(-b^{-\theta}\big)$, where the shape parameter $\theta > 0$ governs the variation in idiosyncratic preferences. Then, the fraction of individuals living in each region and sector can be expressed as

$$\pi_{sj} = \sum_{e,o} \underbrace{\frac{\left(\tilde{V}_{sj|eo}\right)^{\theta}}{\sum_{xk}\left(\tilde{V}_{xk|eo}\right)^{\theta}}}_{\pi_{sj|eo}}\,\zeta_{eo}\mu_o, \quad j \in \{c, r\}, \quad s \in \{n, a\}. \tag{9}$$

Equations (8) and (9) imply that individuals choose the combination of region and sector that gives them the highest real income net of migration costs. Note that $\pi_{sj|eo}$ is the probability of choosing sector s and region j conditional on education and origin.

In equilibrium, total labor demand (for all individual types) in each sector and region must be equal to labor supply, that is,

$$\sum_e N_{sj}(e) = \pi_{sj}, \quad j \in \{c, r\}, \quad s\{n, a\}, \tag{10}$$

and local farming profits are defined as: $\Pi_{aj} = P_a Y_{aj} - \sum_e W_{aj}(e) N_{aj}(e)$.

Lastly, total demand for each consumption good must be equal to total supply in the economy, such that,

$$\sum_j C_{aj} = \sum_j Y_{aj}, \quad \text{and} \quad \sum_j C_{nj} = \sum_j Y_{nj}, \tag{11}$$

where C_{sj} is total consumption of goods from sector s in region j. This means that if one region has relative specialization in agriculture and the other region has relative specialization in non-agriculture, then the former region will export some of its agricultural goods in exchange for non-agricultural goods. Comparative advantage among regions depends on differences in sectoral productivities (A_{sj}) and on the distribution of educational attainment in each origin (ζ_{eo}).

Then, a *competitive equilibrium* is a set of prices, $\{P_a, \omega_{sj}\}$, $s \in \{n, a\}$ and $j \in \{c, r\}$; farming profits, Π_{aj}, $j \in \{c, r\}$; location-sector choices, π_{sj}, $s \in \{n, a\}$ and $j \in \{c, r\}$; individual bundles of consumption goods, $\{C_{iaj}, C_{inj}\}$, $j \in \{c, r\}$; landlord consumption choices in each region $j \in \{c, r\}$; and labor demand in each region, $N_{sj}(e)$, $s \in \{n, a\}$ and $j \in \{c, r\}$, for every worker type e, such that: (i) given prices, individual location choices and consumption bundles maximize utility; (ii) given prices, firms maximize profits in each sector; and (iii) market clearing conditions hold.

3.4 Human capital and selection

A key feature of the model is the role of human capital as a determinant of sectoral and migration choices. Selection according to education is crucial for the quantitative results presented below, so it is valuable to characterize it in the model. To do that, for exposition purposes, is is useful to assume that there are no subsistence consumption requirements or, alternatively, that they are very small. In such case, the next proposition describes selection in the model:

PROPOSITION 1: *Assume that $\bar{a} \approx 0$. In equilibrium, sectoral and location choices are such that,*

i) if $\gamma_n > \gamma_a$, then for a given $j \in \{c, r\}$: $\partial\left(\frac{\pi_{nj|eo}}{\pi_{aj|eo}}\right)\Big/\partial e > 0$.

ii) if $\delta > 0$, then for a given $s \in \{n, a\}$: $\partial\left(\frac{\pi_{sj|eo}}{\pi_{so|eo}}\right)\Big/\partial e > 0$.

See the proof in Appendix A. Part (i) of the proposition implies that, for a given location choice, individuals with high education are more likely to work in non-agriculture if the returns to education are higher in non-agrilcutural production ($\gamma_n > \gamma_a$). On the other hand, Part (ii) of the proposition implies that, for a given sectoral choice, individuals with high education are more likely migrate from their origin if migration costs decline with education ($\delta > 0$). Therefore, the model features selection of heterogeneous workers into sectors and regions such that the difference in γ_s determines the strength of selection in sectoral choices, while the sign and size of δ determines the selection of internal migrants in terms of human capital.

4 Calibration

This section calibrates the model for two developing countries: Brazil and Indonesia. Both of these countries have relatively rich data that is useful to take the model to the data. I assume that region c in the model are convergent states as defined in Section 2.1 and region r are other relatively richer states. The general idea is to calibrate the model for an initial period in each country denoted by 0: 1991 for Brazil and 1976 for Indonesia based on the samples of data used in the paper. Then, given the observed changes over time in population (μ_o) and educational attainment (ζ_{eo}) by origin, I use sectoral productivity (A^t_{js}) growth in each region to match the relevant changes between the initial period and a terminal period denoted by T: 2010 for Brazil and 1995 for Indonesia.

The main objective is to use the quantitative model to evaluate and compare the importance of different structural change forces for spatial convergence in both labor income and sectoral composition of employment. First, I analyze the importance of improvements in educational attainment, which represent a negative labor supply shock in agriculture as explained below. Second, I evaluate the effects of a negative labor demand shock in agriculture coming from unbalanced productivity growth in that sector. Finally, I consider the effects of inducing higher migration to rich regions. The latter exercise is motivated by the related literature linking labor mobility fictions to structural change in an economy.

I follow the literature in setting the preference weight for agricultural goods α equal to 0.005, which implies a long-run consumption share of agricultural goods equal to 0.5 percent (Restuccia et al. 2008; Donovan, 2020). The fraction of population from origin μ_o, as well as the distribution of education years by origin ζ_{eo}, $\forall e$, are set using the region of birth in each period of the data. Additionally, the value of θ, which governs the variance of idiosyncratic preference shocks for sector and location pairs, is set equal to 2.5 based on the range of values in the literature (see Monte et al., 2018 and Tombe and Zhu, 2019).

Moreover, I calibrate the value of η, which governs decreasing returns in agriculture, assuming that $1 - \eta$ captures the income share of land in that sector. Then, using country-level data from the ERS-USDA on International Agricultural Productivity, I set η equal to 0.90 for Brazil and 0.70 for Indonesia based on the period of time covered for each country. The value for Brazil is closer to what the literature estimates for rich countries while the value for Indonesia is close to what previous work has found for poor economies (see Herrendorf et al., 2015 and Gollin and Udry, 2021).

4.1 Method of moments

The rest of the parameters are calibrated by matching model-simulated moments with their data counterparts in each country. To do that, the values of productivity parameters in the rich region in the initial period are normalized so that $A^0_{ar} = A^0_{nr} = 1$. Then, there are 11 remaining parameters that are calibrated to match 11 moments in the data. The chosen moments reflect the facts related to structural transformation and spatial convergence of labor income that are common among developing countries studied in this paper. Those targets are the following: average education years by sector in the initial period; difference in average education years between regions in the initial period; the fraction of individuals who leave their state of birth in the initial period (a migration rate); fraction of agricultural employment by region in each period; the regional gap in average labor earnings in both periods; and growth in real value added per worker between periods.

It is valuable to describe the connection between particular parameters in the model and targeted moments in the data. First, sectoral productivities in the convergent region in the initial period (A^0_{sc}), $s \in \{n, a\}$, are used to match the gap in average labor income between regions and the fraction of agricultural employment in that region. Then, given the regional gap in sectoral productivities, subsistence parameter $\bar{a}$ is used to target the agricultural employment share in the rich region.

Additionally, the value of common migration costs $\bar{\tau}$ directly governs labor mobility between regions; whereas parameter δ controls the selection of migrants according to education: a positive value means that migration costs decline with education. The difference in education levels between regions in the data (given the distribution of education by origin) is informative about the extent of that selection in the model. Furthermore, the value of γ_s for $s \in \{n, a\}$, governs the value of human capital in production, so it is used to target education years by sector.

Lastly, the four remaining sectoral productivities in the terminal period (A^T_{sj}) are used to target the change in the income gap between regions and the decline in agricultural employment in each region (given the changes in μ_o and ζ_{eo} over time), as well as growth in real value added per worker between the initial and terminal year. The latter is estimated for both countries based on the Growth and Development Time-Series Data (GGDC, Timmer et al., 2015) and expressed as terminal value divided by initial value.[4]

[4]I use a Fisher price index to estimate growth of real value added per worker in the model.

Table 4: Calibration Parameters

Parameter	Value Brazil	Value Indonesia	Related Target
$\bar{a}$	0.40	0.57	Agriculture employment share, region r period 0
A_{ac}^0	1.21	0.92	Agriculture employment share, region c period 0
A_{nc}^0	0.81	0.70	Regional gap in earnings, period 0
γ_n	0.17	0.10	Avg. education years in non-agriculture, period 0
γ_a	0.06	0.01	Avg. education years in agriculture, period 0
$\bar{\tau}$	0.55	0.86	Share of migrants, period 0
δx10	0.05	0.38	Difference education years btw regions, period 0
A_{ac}^T	2.05	1.34	Agriculture employment share, region c period T
A_{ar}^T	1.60	1.61	Agriculture employment share, region r period T
A_{nc}^T	0.59	0.95	Regional gap in earnings, period T
A_{nr}^T	0.64	1.17	Growth in value added per worker

The estimates of parameters are presented in Table 4. The results imply that productivity growth in agricultural production (A_{aj}^t) is much larger than productivity growth in non-agriculture (A_{nj}^t) in both countries. This is in line with established theories of structural transformation that emphasize unbalanced sectoral productivity growth in the economy (see Ngai and Pissarides, 2007). In the case of Brazil, the joint calibration implies that productivity per efficiency unit of labor in non-agriculture had to decline over time after the increase in educational attainment is taken into account. That is because growth in real value added per worker was much lower in Brazil than in Indonesia during their respective periods of time.

The calibrated value of migration costs for individuals without education are much larger in Indonesia than in Brazil (see value of $\bar{\tau}$), though they decline faster with education (see value of δ). The latter means that selection of migrants in terms of education is stronger in

Table 5: Calibration Targets

Target	Data=Model Brazil	Data=Model Indonesia
Agriculture employment share, region r period 0	0.14	0.27
Agriculture employment share, region c period 0	0.37	0.44
Regional gap in earnings, period 0	1.70	1.57
Avg. education years in non-agriculture, period 0	6.10	5.90
Avg. education years in agriculture, period 0	2.20	1.90
Share of migrants, period 0	0.14	0.07
Difference in education years btw regions, period 0	1.80	1.30
Agriculture employment share, region c period T	0.20	0.21
Agriculture employment share, region r period T	0.09	0.17
Regional gap in earnings, period T	1.37	1.35
Growth in value added per worker	1.15	1.75

Indonesia. As expected, in both countries the value of education in non-agriculture has to be much larger than in agriculture ($\gamma_n > \gamma_a$) in order to match the differences in educational attainment of workers between sectors.

Table 5 shows that the model can match the main features of the data, namely the differentiated decline in agricultural employment across space, the patterns of selection in education among sectors and regions, and the convergence of average labor income between regions. Note that based on the period of time considered for each country, Indonesia is a poorer economy with higher employment shares in agriculture, lower education levels, and a smaller migration rate. Also, as a reminder, the distribution of education in each origin (ζ_{eo}) is changing exogenously as part of the calibration, so the model is taking into account the large increase in educational attainment in both countries.

As additional validation of the model, the estimated value of $\bar{a}$ for Indonesia in the initial period represents 36 percent of average income. This is consistent with the 33 percent reported by Lagakos and Waugh (2013) for poor countries. In the case of Brazil, the calibrated value of $\bar{a}$ represents 14 percent of average labor income, which is somewhat lower than the 22 percent value estimated by Alvarez (2020) for that country. In addition, the fraction of agricultural production in total value added is equal to 7.6 percent for Brazil and 21.9 percent for Indonesia taking the average across periods in the model. In comparison, based on the GGDC, agriculture accounted for 6.4 percent of total value added in Brazil between 1991 and 2010, and for 21.5 percent in Indonesia between 1976 and 1995. Therefore, the model matches well the relative size of agricultural production in both economies.

5 Quantitative Experiments

This section uses the calibrated model to evaluate the quantitative importance of typical forces behind structural transformation for spatial convergence in developing countries. In the counterfactual experiments presented below, spatial convergence of average labor income is defined as in Equation (1) in Section 2.1, and convergence of agricultural employment is defined as $\Delta_t(\pi_{ar} - \pi_{ac})$, where π_{aj} is the agricultural employment share in region $j \in \{r, c\}$.

5.1 Increase in educational attainment

First, I isolate the effects of human capital growth through increases in educational attainment. This represents a negative supply shock in agricultural employment given that human capital is more valuable in non-agricultural production. For this experiment, I start from the initial period economy and only change the distribution of education by origin to the terminal period values (i.e. from ζ_{eo}^{0} to $\zeta_{eo}^{T}, \forall e$), holding all other parameters constant to their initial values.

To analyze the quantitative importance of educational attainment, Table 6 starts by presenting the counterfactual changes in partial equilibrium where all prices in the economy are held fixed (to the initial period values). For Brazil, the increase in education quantity ac-

Table 6: Education Improvements in Partial Equilibrium

Brazil	Baseline	Fixed Prices	Fixed P_a
Convergence of regional income (pp)	21.12	9.01	8.77
Convergence of agriculture employment (pp)	12.02	8.82	7.93
Δ Agricultural employment share (pp)	-11.54	-10.57	-9.31
Indonesia			
Convergence of regional income (pp)	15.04	-0.18	0.36
Convergence of agriculture employment (pp)	12.97	7.92	3.91
Δ Agricultural employment share (pp)	-16.87	-17.82	-11.62

Notes: This table presents the results from changing the distribution of educational attainment to terminal period values, holding all other parameters constant to their value in the initial period. Two cases are considered for partial equilibrium: one where all prices are held constant and one where only the price of agricultural goods is held constant.

counts for 43 and 73 percent of convergence in regional income and agricultural employment, respectively. That is because more individuals choose to work in non-agriculture where education has more value and measured labor productivity is higher, which leads to convergence in labor income given that the change in labor allocation is larger in the convergent region.

In the case of Indonesia, education improvements account for 61 percent of convergence in agricultural employment, though there is no convergence in labor income. The key difference is that migrants in Indonesia are highly selected in terms of education ($\bar{\tau}_{IDN} > \bar{\tau}_{BRA}$ and $\delta_{IDN} > \delta_{BRA}$), which means that highly educated individuals move in larger proportions to the rich region generating a minor divergence in labor income.

These partial equilibrium results highlight that, while education improvements can account for spatial convergence in sectoral composition of employment and the large decline in agricultural employment in the economy, the direct effects on spatial convergence of labor income depend significantly on the strength of selection of internal migrants according to human capital. If highly educated individuals have a relatively high probability of migrating from poor regions, as is the case in Indonesia, then there is potential for a "brain drain" effect that hinders the convergence of labor income as education increases in the economy.

The assumption of keeping all prices fixed can be relaxed by considering a situation that resembles a small open economy such that only the price of agricultural goods is held fixed (to the initial value). This case is presented in the last column of Table 6. The results for Brazil are similar to the previous case, though a little weaker for all outcomes. For Indonesia, there is now a minor amount of income convergence across regions, but the employment effects are weaker. Part of the differences in the results can be explained by the fact that decreasing returns to labor in agriculture are stronger in Indonesia, which makes labor demand, and thus agricultural wages, more responsive to supply shocks.

Next, the results in Table 7 present the counterfactual changes from increases in educational attainment in general equilibrium where all prices can adjust to clear markets. Now, for the case of Brazil, the increase in educational attainment accounts for 39 and 26 percent of convergence in regional income and agricultural employment, respectively. For the case of Indonesia, changes in the distribution of education account for 22 percent of convergence in regional income, but they generate divergence in sectoral employment.

To understand the previous results consider the following. In these experiments there is a large fall in labor supply for agricultural production because the population is more educated, which puts upward pressure on local agricultural wages due to decreasing returns in farming. Moreover, the measured productivity gains from higher education are biased towards non-agricultural production. Thus, the relative price of agricultural goods must increase so that more labor is pulled back to agriculture and enough food is produced in the economy. These effects are partly offset by the positive income effects of an overall increase in measured labor productivity. As a result, in general equilibrium, the increase in educational attainment accounts for 18.7 and 8.5 percent of the observed decline in agricultural employment in the economy.

The previous results are consistent with the findings by Porzio et al. (2021) regarding the

Table 7: Education Improvements in General Equilibrium

	Brazil		Indonesia	
Variable	Baseline	Counterfactual	Baseline	Counterfactual
Convergence of regional income (pp)	21.12	8.34	15.04	3.36
Convergence of agriculture employment (pp)	12.02	3.12	12.97	-1.63
Δ Agricultural employment share (pp)	-11.54	-2.16	-16.87	-1.44

Notes: This table presents the results from changing the distribution of educational attainment to terminal period values, holding all other parameters constant to their value in the initial period.

contribution of human capital accumulation for structural transformation. These quantitative results of the model are also consistent with the decomposition presented in Section 2.2 on the importance of changes in the distribution of education for convergence in sectoral employment in low and middle income countries.

In both countries, the general equilibrium effects from a decline in the overall supply of agricultural workers largely offset the convergence in sectoral employment. In the case of Indonesia, the effects are so strong that there is actual divergence in the composition of sectoral employment, completely reversing the partial equilibrium effects described above. However, in general equilibrium, both countries experience income convergence. These quantitative results imply that equilibrium effects, both from prices and selection of heterogeneous workers into sectors and regions, are crucial for the effects of human capital growth on spatial convergence.

5.2 Growth in agricultural productivity

In the following experiments, I isolate the effects from unbalanced and spatially uneven sectoral productivity growth by starting in the initial period and changing the values of agricultural productivity according to their calibrated values in the terminal period (A^t_{aj}), holding all other parameters constant including the distribution of education. This experiment generates a large decline in the relative price of agricultural goods in the model, and

Table 8: Productivity Growth in Agriculture

	Brazil		Indonesia	
Variable	Baseline	Counterfactual	Baseline	Counterfactual
Convergence of regional income (pp)	21.12	-1.41	15.04	-3.81
Convergence of agriculture employment (pp)	12.02	7.63	12.97	11.47
Δ Agricultural employment share (pp)	-11.54	-10.52	-16.87	-15.88

Notes: This table presents the results from changing the values of regional agricultural productivity (A_{aj}) to the terminal period values, holding all other parameters constant to their value in the initial period.

represents a negative shock to the demand for agricultural workers in the economy given that there is subsistence consumption requirements ($\bar{a} > 0$).

The results in Table 8 show that productivity growth in agriculture is key for the overall fall in agricultural employment, as shown in previous literature. Moreover, unbalanced productivity growth in isolation can account for 63 and 88 percent of the observed convergence in agricultural employment in Brazil and Indonesia, respectively. However, in this experiment there is divergence of regional labor income in both countries. That is because more workers with relatively low education reallocate to non-agricultural production reducing measured productivity in that sector, plus agricultural wages decrease due to the lower demand for labor in that sector. Both of these forces generate regional divergence in average labor income when the only change in the economy is growth in exogenous agricultural productivity.

5.3 Increase in internal migration

Lastly, I evaluate the effects of increasing migration to the rich region in each economy. To be specific, I take the fully calibrated economies for both countries and induce higher migration to the rich region in the terminal period by halving the value of $\bar{\tau}$ for individuals who start such period in the convergent region. This experiment looks at the effects of having higher migration to rich places given the growth in sectoral productivity and the increase in educational attainment in the economy. Note that reducing the value of $\bar{\tau}$ generates

Table 9: Increasing Migration to Rich Region

Variable	Brazil Baseline	Brazil Counterfactual	Indonesia Baseline	Indonesia Counterfactual
Convergence of regional income (pp)	21.12	25.12	15.04	18.31
Convergence of agriculture employment (pp)	12.02	10.55	12.97	8.88
Δ Agricultural employment share (pp)	-11.54	-11.39	-16.87	-17.05

Notes: This table presents the results of generating higher migration to the rich region in the terminal period by decreasing common migration costs ($\bar{\tau}$) by one-half for individuals who start that period in the convergent region.

inclusive migration in the sense that individuals with low education benefit the most from such reduction. This is because δ is positive in both countries, which means that migration costs are lower for individuals with high education.

The results presented in Table 9 show that promoting migration leads to lower convergence of agricultural employment in both countries; that is, higher migration increases regional specialization by allowing workers to sort across space according to individual comparative advantage based on human capital. Moreover, increasing migration also generates higher convergence in labor income among regions, despite the fact that individuals with high education face lower migration costs in both countries. To understand the latter, it is important to note that measured productivity in non-agricultural production in the rich region declines (relative to the terminal baseline value) as migrants with relatively lower human capital move to that place. The situation would be different if, instead, migration costs decrease in a way that favors highly educated individuals.

Summing up, the quantitative results of the model imply that human capital growth through education has been an important determinant of income convergence in both developing countries. Thus, the results provide stronger support for the evidence on educational attainment and spatial convergence presented in Section 2.2. That said, equilibrium effects in the economy, namely the increase in price and wages in the agricultural sector, attenuate the impact of increasing education on spatial convergence. Moreover, the degree of selection of internal migrants according to education is key for the direct effects of human capital growth on spatial convergence in both labor income and sectoral composition of employment.

Furthermore, unbalanced productivity growth in agriculture is mostly important for convergence in sectoral employment, but it does not generate income convergence by itself. A key observation for the latter result is that, without improvements in individual human capital, productivity growth in agriculture releases relatively unskilled labor from that sector. Finally, according to the results presented above, inducing inclusive migration to richer regions has the potential to increase both regional specialization and spatial convergence of labor income in developing countries.

6 Conclusions

This paper documents the relationship between structural transformation and spatial convergence of labor income using microdata for countries at different stages of development. I find that in recent decades structural change accounts for approximately 30 percent of income convergence in developing countries. I also find that labor reallocation out of agriculture accounts for more than two-thirds of the contribution of structural change. In contrast, regional convergence in rich countries is mostly explained by convergence of average wages within sectors of the economy. For developing countries, the empirical findings support the idea that policies with potential to accelerate structural change can reduce spatial inequality.

I also document that recent changes in the distribution of educational attainment can account for a meaningful fraction of the observed convergence in agricultural employment within developing countries. This reinforces the notion that human capital growth is not only important for the aggregate process of structural transformation, as documented in the literature, but also for reductions in spatial inequality through changes in the sectoral composition of employment.

Additionally, using a general equilibrium model, I find that the increase in educational attainment in developing countries can explain a considerable fraction of the observed convergence in regional labor income. Selection in human capital and price changes in equilibrium are relevant for the effects of education on spatial convergence. The quantitative results of the model also imply that unbalanced productivity growth in agriculture is mostly relevant for labor reallocation, but might not reduce income inequality across space by itself.

Multiple interesting puzzles remain based on the findings of this paper. First, given the observed variation in the importance of structural change for spatial convergence among developing countries, it could be valuable to know more about what conditions in a country increase the impact of structural change on spatial inequality. Second, convergence in wages within sectors has been the main contributor to regional convergence in recent decades, especially in rich countries. Can this be explained by a significant reduction in labor mobility barriers across space? What are other possible drivers of convergence in labor income within sectors and, most importantly, how do they vary across countries? Are any of those drivers subject to policy manipulation? Providing an answer to these questions can be an interesting avenue for future research.

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A Proof of Proposition 1

Assuming that $\bar{a} \approx 0$, so that individual preferences are homothetic, sectoral and location choices in equations(8) and (9) imply that:

$$
\begin{aligned}
\frac{\pi_{nj|eo}}{\pi_{aj|eo}} &\approx \left[\frac{W_{nj}(e)}{W_{aj}(e)}\right]^{\theta} \\
&= \left[\frac{\omega_{nj}\exp(\gamma_n e)}{\omega_{aj}\exp(\gamma_a e)}\right]^{\theta}
\end{aligned}
$$

which represents the probability of choosing the non-agricultural sector relative to the agricultural sector given a location choice $j \in \{c, r\}$. Then, it follows that:

$$
\partial\left(\frac{\pi_{nj|eo}}{\pi_{aj|eo}}\right)^{\frac{1}{\theta}} \Big/ \partial e = \frac{W_{aj}(e)\gamma_n W_{nj}(e) - W_{nj}(e)\gamma_a W_{aj}(e)}{\left(W_{aj}(e)\right)^2},
$$

which is positive if and only if the numerator is also positive, that is:

$$
\begin{aligned}
& W_{aj}(e)\gamma_n W_{nj}(e) > W_{nj}(e)\gamma_a W_{aj}(e) \\
\Leftrightarrow \quad & \gamma_n > \gamma_a.
\end{aligned}
$$

Additionally, under the same assumption, sectoral and location choices imply:

$$
\begin{aligned}
\frac{\pi_{sj|eo}}{\pi_{so|eo}} &\approx \left[\frac{W_{sj}(e)(1-\tau_e)}{W_{so}(e)}\right]^{\theta} \\
&= \left[\frac{\omega_{sj}\big(1-\bar{\tau}\exp(-\delta e)\big)}{\omega_{so}}\right]^{\theta}
\end{aligned}
$$

which represents the probability of migrating from origin o relative to staying in that location given a sectoral choice $s \in \{n, a\}$. Then, it follows that:

$$\partial \left(\frac{\pi_{sj|eo}}{\pi_{so|eo}} \right)^{\frac{1}{\theta}} \bigg/ \partial e = \frac{\omega_{sj} \delta \tau_e}{\omega_{so}},$$

which is positive if and only if the numerator is also positive. The latter is true if $\delta > 0$.