Structural Transformation by Cohort

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Abstract

This paper documents the facts of which workers are reallocated across sectors during the process of structural transformation using repeated cross-sectional microdata covering 47 countries at all levels of development. The key finding is that structural transformation affects primarily the young. More than half of all structural transformation happens between cohorts, meaning that new cohorts choose different sectors than existing ones. Half of the within-cohort reallocation happens by age 30 and most by age 40. We develop and calibrate an overlapping generations model of structural transformation with sector-specific human capital investments that replicates these and other stylized facts. The model generates much slower transitional dynamics than the standard growth model even in the face of a large, one-time shock to TFP.

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1 Introduction

One of the key stylized facts of economic growth is that it involves structural transformation: the reallocation of economic activity in predictable ways among the sectors of the economy. Economic activity can be broadly measured in a number of ways, but here we focus on the reallocation of labor. Whereas most workers are employed in agriculture in the very poorest countries, growth is accompanied by expanding employment first in the manufacturing and then in the service sector.[1] A recent literature has suggested multiple possible mechanisms that could generate this predictable reallocation of workers as a consequence of growth (Kongsamut et al., 2001; Ngai and Pissarides, 2007).

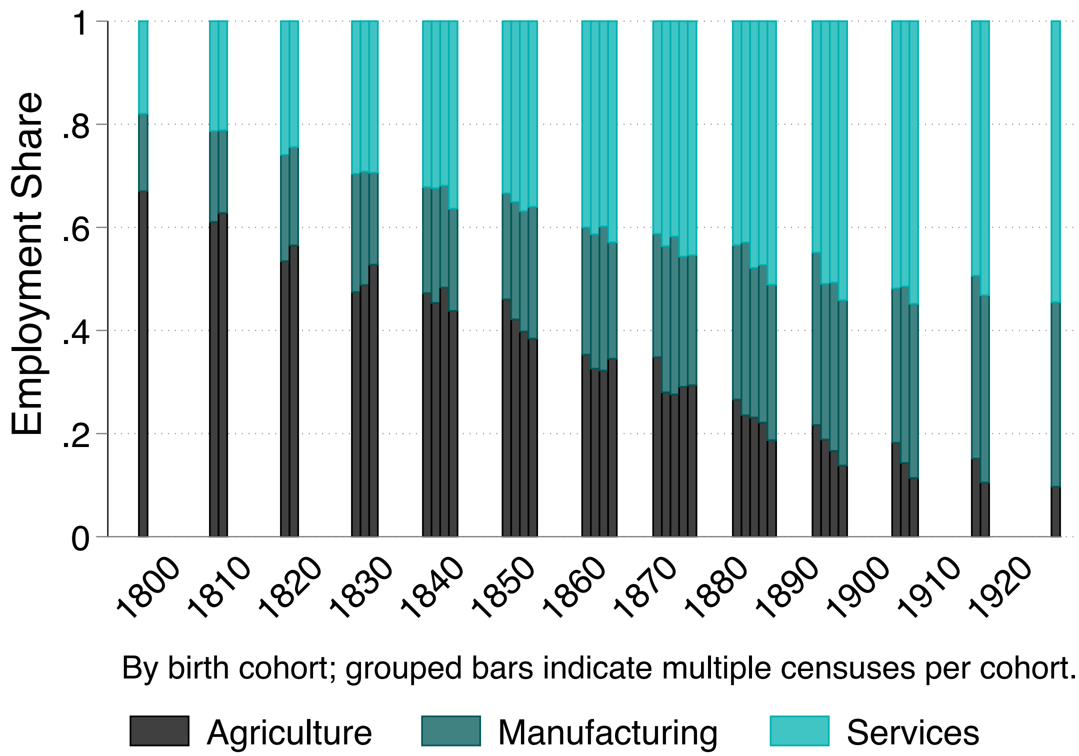
What is less well understood is how structural transformation affects workers. Typically, measures of structural transformation draw on aggregate statistics; for labor, they might give the fraction of the workforce in a given sector in a given year. While these statistics convey the broad changes, they are less useful for trying to figure out who actually switches sectors, and when. Our goal is to fill in this missing information.

To do so we draw on the census data available from IPUMS (Minnesota Population Center, 2014; Ruggles et al., 2010). IPUMS provides census microdata from a large number of countries and years. We restrict our attention to countries with repeated censuses so that we can observe structural transformation take place in the microdata; there are 47 such countries with the mean (median) country covered for 29 (25) years. The United States is covered for a particularly long period, from 1870 to 2015. More importantly, IPUMS has devoted a great deal of energy to harmonizing the responses to key variables across countries. Thus we have consistently measured workforces and sectors of employment, as well as covariates of interest such as gender, education, and so on. Our goal is to use this dataset to study the determinants of structural change at the worker level. To do so, we compare the sectoral allocation of workers of a given birth cohort between censuses and investigate the determinants of their sectoral reallocation.

Figure 1 provides a simple graphical illustration of our approach. It shows the reallocation of labor between sectors using the decadal censuses between 1870 and 1950 in the United States. Each group of bars represents a particular birth cohort, ranging from 1800 to 1920. Multiple bars grouped together indicate that we observe that cohort working in multiple censuses. So, for example, there is only a single bar for the 1800 cohort (observed in 1870

[1] See for example Schultz (1953) and Echevarria (1997) for early references, or Herrendorf et al. (2014) for a recent overview. Herrendorf et al. (2014) shows that structural transformation is a predictable function of PPP GDP p.c.

Figure 1: Structural Transformation in the United States



but not working by 1880); two bars for the 1810 cohort (observed in 1870 and 1880 but not working by 1900) and so on. The y-axis shows the sectoral allocation across the three standard sectors of agriculture, manufacturing, and services.

There are two main lessons to be learned from this graph. First, by comparing bars within a cohort, we can see that there is some reallocation of labor over the life cycle. The largest changes tend to happen early in the life cycle, e.g., between the first two bars. In some cases, such as the 1830 cohort, this reallocation goes the wrong way: workers move out of manufacturing and into services as they age. Second, there are clear differences in the sectoral allocation of labor between cohorts, which can be seen in the relatively large differences in labor allocations between groups of bars.

We are not the first to document this pattern for a particular country; Kim and Topel (1995) noticed the same for Korea and Perez (2016) for Argentina. Our empirical contribution is to document these patterns for a large number of countries across a wide range of development. We introduce a simple accounting metric that decomposes overall structural transformation into the fraction that occurs within and between cohorts. We find that on average, 56 percent of structural transformation takes place between cohorts. Our metric also allows us to decompose the within portion and ask when over the life cycle workers reallocate across sectors. We find half of the within reallocation happens by age 30 and 80 percent happens by age 40. Thus, the findings for the U.S. in Figure 1 hold more broadly. We also document some variation in these patterns at different levels of development.

Our second contribution in this paper is to show that structural transformation by cohort has implications for growth dynamics. It is well-known since Christiano (1989) and King and Rebelo (1993) that a standard neoclassical growth model without frictions generates very rapid growth and faster convergence to a new steady state than is observed empirically. Previous authors have pointed out that incorporating structural transformation already slows down the convergence dynamics (Schultz, 1953; Gollin et al., 2004, 2007). Here, we show that growth is slowed even further by the fact that structural transformation only comes through the reallocation of young workers.[2]

To do so we build an overlapping generations model of sectoral choice and structural transformation. At the aggregate, differential technology growth by sector and a low elasticity of substitution in the utility function generates trends in relative prices of goods produced in different sectors as in Ngai and Pissarides (2007). This price signal filters into labor markets as trends in relative wages. Workers perfectly foresee the entire future path of wages. Different from the standard model, we assume that workers have idiosyncratic, sector-specific skills as in Lagakos and Waugh (2013). They also have to make a sector-specific investment before working in a sector as in Caselli and Coleman (2001). Because of these frictions, workers may not reallocate until wages are equalized across sectors as in most models of structural transformation. Instead, the model allows for an interplay between the rate of sectoral productivity growth, the speed of labor reallocation, and relative wages by sector.

We show that this model generates the key facts we have documented. The mechanics are as follows. Forward-looking workers choose the sector that maximizes the present discounted value of lifetime earnings when they enter the market. They remain in this sector unless relative wages change rapidly or they are hit by a sufficiently large negative productivity shock. The chances that a shock will be large enough to make re-investment and a sectoral switch profitable declines as they age and their remaining working life shrinks. Average wages in shrinking sectors is lower, and in growing sectors is higher, in order to induce

[2]See also Mankiw et al. (1992), Barro and Sala-i-Martin (1995), Chang and Hornstein (2015), and Buera and Fattal-Jaef (2016) for other mechanisms that can slow growth and transitional dynamics.

relative more or less workers into that sector.

We calibrate the model to replicate the key facts we have documented about how structural transformation happens between and within cohorts. In particular, we calibrate the sectoral investment costs and the size of the idiosyncratic wage shocks to replicate the fraction of sectoral reallocation that happens within versus between cohorts as well as the entire life-cycle profile of sectoral switching.

We then study the model's growth and transition dynamics, compared to the standard one-sector neoclassical growth model. The model delivers much slower growth patterns. A large shock to TFP in the neoclassical growth model induces a rapid transition. In our model a large shock to productivity in the growing sectors generates much slower growth. The key friction is that growth in our model requires structural transformation, and structural transformation requires a reallocation of workers across sectors, but workers have made a sunk cost in their existing sector. Wages in the growing sectors do rise and give some mostly younger workers incentives to switch sectors, but overall the slow reallocation of labor still acts as a brake on growth.

In addition to the literature cited above, we are closely related to a few other papers that have recently explored the structural transformation using microeconomic data. Kim and Topel (1995) and Herrendorf and Schoellman (2017) explore the patterns of wages by sector for countries experiencing structural transformation. Duernecker and Herrendorf (2017) document a close linkage between structural change and occupational reallocation, while Barany and Siegel (2016) suggest that structural transformation may play a role in polarization and wage shifts in the United States.

The rest of the paper proceeds as follows. Section 2 describes the data and our empirical results. Section 3 contains the model, while section 4 describes the calibration and results. Section 5 concludes.

2 Data and Empirical Results

In this section we describe our data and the empirical results. Our particular focus is on documenting the stylized facts of worker reallocation across sectors that motivate our model in Section 3.

2.1 Data

Our data all come from Ruggles et al. (2010), which includes U.S. Census data from 1870–2015, and from Minnesota Population Center (2014), which includes samples from an additional 80 other countries worldwide.[3] Most samples were nationally representative censuses, so we use the term census for the rest of the paper. However some samples are more properly household or employment surveys, which makes little difference for our analysis. We restrict our attention to the 47 countries with multiple samples that collected information on the key variables for our analysis, which are age, employment status, and sector of employment.

The IPUMS team has devoted a great deal of energy to harmonizing variables and responses across countries and years. The most important for our purposes is that they have re-coded each country's original responses for the industry or sector question (e.g., the one describing the activity or product produced at the respondent's workplace) into a variable they call indgen, which is a slightly modified version of the ISIC 1-digit industry coding scheme. As they note, this coding process is non-trivial, in three main ways. First, for some countries the underlying codes are too coarse to be mapped into indgen at all; these countries are absent from our data. Second, in some countries not all of the original industry codes can be mapped into the indgen classification scheme. We exclude a few countries where more than 25 percent of the population could not be coded. Finally, there are inevitably some judgment calls when constructing such crosswalks. The main examples described by the IPUMS team involve categories which are small (repair work) or judgment calls that are not relevant for our work (distinguishing among the service industries when mapping an industry).

We maintain as few sample restrictions as possible so that the aggregate results implied by our microdata should match up with national accounts data. To that end, we focus on employed workers with valid responses to age and sector of employment. We aggregate indgen codes to the standard three sectors of agriculture, manufacturing, and services.[4] We construct birth cohort as the difference between age and census year. We then construct the fraction of workers born in cohort c in country i that works in sector j at time t, n_{ijct}. We

[3] Ruggles et al. (2010) actually has U.S. Census data as far back as 1850, but the 1850 and 1860 censuses did not collect employment information for slaves. Given that our goal is to compare employment statistics for a given cohort across years, this missing information would bias our analysis, so we choose to start our study in 1870.

[4] Agriculture includes agriculture, fishing, and forestry. Manufacturing includes mining, manufacturing, and construction. Services include utilities, trade, hotels and restaurants, FIRE, public administration and defense, education, health and social services, private household services, and other/miscellaneous services.

ignore reported industries for workers less than 22 years old because few workers work at these ages and the reported industries likely represent temporary or part-time work rather than real careers.

In the introduction we displayed these results graphically for the United States. In Appendix A we plot similar figures using three censuses from Malawi (a poor country) and four censuses from Brazil (a middle income country). Broadly, the same patterns apply as for the United States: small changes within a cohort, mostly early in life; larger changes between cohorts. But to study the common patterns among our sample of 47 countries, we need simple metrics that we can compare across countries and over time.

2.2 Accounting Results

To document our key patterns more broadly, we turn to a within-between accounting exercise. The standard accounting exercise would decompose sectoral employment n_{ijt} into the shares of various cohorts in the labor market ω_{ict} and the propensity for each cohort to work in sector j, n_{ijct}. Here rather than decompose the variance of levels, we decompose the variance of changes in sectoral employment between $t-1$ and t, $var(\Delta n_{ijt})$. The corresponding accounting equation is given by:

$$1 = \underbrace{\frac{cov\left(\sum_c \bar{\omega}_{ict}\Delta n_{ijct}, \Delta n_{jt}\right)}{var(\Delta n_{jt})}}_{\equiv \text{ within component}} + \underbrace{\frac{cov\left(\sum_c \bar{n}_{ijct}\Delta \omega_{ict}, \Delta n_{jt}\right)}{var(\Delta n_{jt})}}_{\equiv \text{ between component}} \tag{1}$$

where we use $\bar{\omega}_{ict}$ to denote the average share of cohort c between $t-1$ and t and Δ to denote the difference.

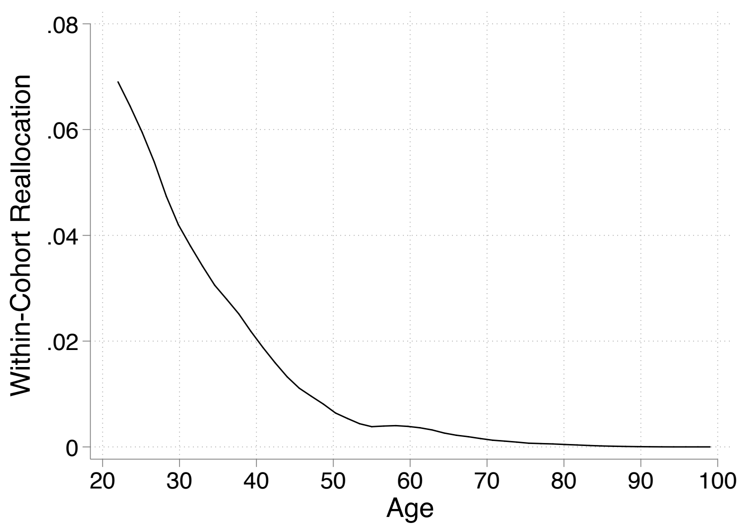
We implement this equation for all country-year pairs in our data. We have 177 samples from 47 countries, implying that we can study structural transformation across 130 country-year pairs that are an average of 10.2 years apart.[5] The results are given in Table 1. We start by looking at the simple average across all countries and sectors; in this case, 56 percent of structural transformation takes place between cohorts, and 44 percent within cohorts. This is the first point raised in the introduction: more than half of structural transformation is accomplished by reallocating new workers. We also look sector by sector, reporting results only for sectors that have at least a 1 percent change in employment share. Like Kim and Topel (1995), we find between-cohort reallocation is critical for the movement

[5] We discard a few samples that were spaced at annual frequency or that were too far from the next sample; the remaining range is 4 to 29 years.

Table 1: Accounting for Structural Transformation

	Total	By Sector		
		Agriculture	Manufacturing	Services
Share Between Cohorts	56%	83%	36%	53%

Figure 2: Within-Cohort Reallocation by Age



out of agriculture; it explains fully 83 percent of structural transformation for that sector. On the other hand, the relationship is somewhat weaker for manufacturing and services.

The second point we made in the introduction is that most of the sectoral reallocation within a cohort takes place early in life. To document this more formally, we exploit the fact that our accounting equation (1) is fully additive. This means that we can further decompose the within component and study the contribution of each cohort to overall reallocation at time t:

$$\underbrace{\frac{cov\left(\sum_c \bar{\omega}_{ict}\Delta n_{ijct}, \Delta n_{jt}\right)}{var(\Delta n_{jt})}}_{\equiv \text{ within component}} \equiv \sum_c \underbrace{\frac{cov\left(\bar{\omega}_{ict}\Delta n_{ijct}, \Delta n_{jt}\right)}{var(\Delta n_{jt})}}_{\equiv \text{ age } a=t-1-c \text{ contribution}} \tag{2}$$

There is of course a one-to-one mapping from cohort to age, conditional on year. Thus, this exercise is equivalent to asking what fraction of the within-cohort reallocation takes place at each age. Here, we index the results by age in the initial period $t-1$.

The results of this exercise (averaged across all countries) are given in Figure 2. The key

Table 2: Alternative Accounting for Structural Transformation

	Total	By Sector		
		Agriculture	Manufacturing	Services
Share Between Demographic Groups	10%	8%	14%	6%

takeaway is that within cohort reallocation is highest at young ages and falls off relatively quickly. Half of the total within cohort reallocation takes place by age 30 and more than 80 percent by age 40. Since within-sector reallocation already accounted for less than half of structural transformation, these figures imply that workers switching sectors after 30 or 40 play only a minor role in structural transformation.

The results of Table 1 and Figure 2 are the main findings that motivate our model of structural transformation at the worker level. In particular, they explain why we put a premium on forces that generate most sectoral labor reallocation between cohorts or at early ages within a cohort. Two additional results will help explain our approach.

First, we explore how much of the between cohort effect is implicitly driven by the well-known trends in worker characteristics over time and across cohorts. In particular, we focus on labor force composition by gender, marital status, and education. We choose these characteristics because existing work has documented that they play a role in explaining structural transformation and wage patterns.[6]

To see how important they are in our sample of countries, we re-conduct our accounting exercise as in equation (1), except that instead of c denoting different cohorts c denotes different demographic cells, where each cell is an element of $gender \times marital \times education$. Since we classify marital status as simply married or not married and education into four bins, this produces a total 16 possible cells. Table 2 shows the corresponding accounting results. 10 percent of structural transformation happens between demographic cells, whereas 90 percent happens within a demographic cell. The fraction varies little across sectors. Hendricks (2010) has a similar fact for a more detailed educational categories.

This finding suggests to us that cohort is not simply a summary statistic for trends in education, female labor force participation, and so on. Much of the sectoral reallocation of labor happens across cohorts even within these cells. This fact motivates us to write down a model that focuses on common economic driving forces that affect all cohorts, e.g,

[6] See for example Caselli and Coleman (2001) on education and structural transformation out of agriculture, or Rendall (2010), Buera et al. (2013), and Ngai and Petrongolo (2016) on the complementarity between the rise in female labor force participation and the structural transformation into services.

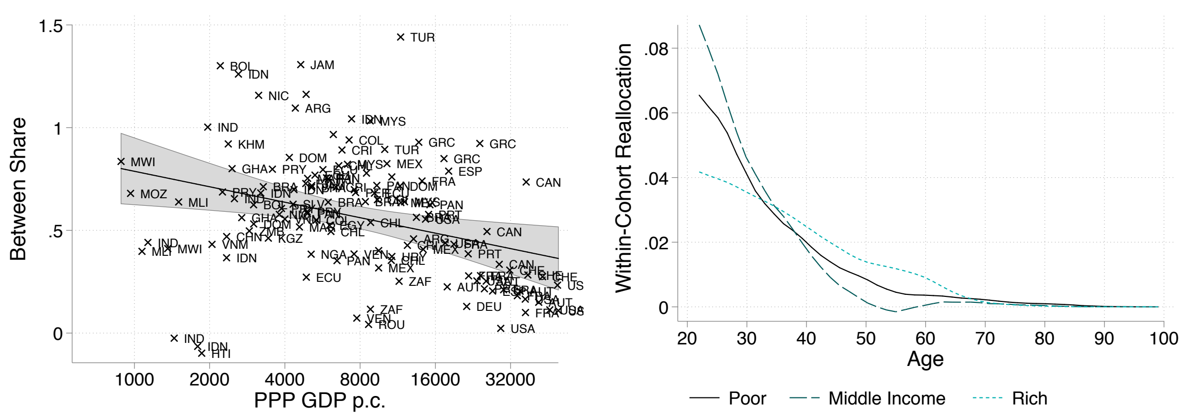
changing relative productivity by sector, and to abstract from country-specific institutions such as the education system or incentives for women to work.

Finally, it is important to note that our results vary predictably with development. We show this in two ways in Figure 3. First, in Figure 3a we plot the between share against PPP GDP p.c. from Feenstra et al. (2015). There is substantial heterogeneity in the between share, which in the extremes accounts for less than none or more than all of structural transformation. However, there is a noticeable downward trend, indicated by the regression line and corresponding 95 percent confidence interval.[7] This regression line indicates that around 75 percent of structural transformation happens between cohorts in poor countries but only around 40 percent happens between cohorts in rich countries. Figure 3b plots the life-cycle profile of within-cohort reallocation separately for countries in the bottom quartile (poorest), middle two quartiles (middle income) and top quartile (richest). There are pronounced differences, particularly for the richest countries: much more of the within cohort reallocation takes place late in the life cycle.

Figure 3: GDP p.c. and Structural Transformation

(a) Between Share

(b) Within-Cohort Reallocation by Age



We have investigated other cuts of the data, but find that consistently the strongest pattern is with development. For example, there is no consistent relationship with growth or the overall rate of structural transformation (see Figure A3 in the Appendix). We also investigate alternative ways of dividing the economy into sectors. Our main patterns of interest hold unless we focus on a two-sector (agriculture versus non-agriculture) analysis, in which case there are very few rich countries undergoing structural transformation anyway (see

[7] Standard errors clustered at the country level.

Figures A4 and A5). Given that our patterns appear robust, we now turn to a model that helps explain and interpret them.

3 Model of Structural Transformation by Cohort

The goal of our model is twofold. First, we want to show that the patterns of worker reallocation between cohorts can be understood using a simple model where workers have to make a sector-specific investment before working in a sector.[8] Second, we want to explore how the resulting model can produce slower growth dynamics than what is found in Christiano (1989) and King and Rebelo (1993).

The basic framework is an overlapping generations model with three sectors and structural transformation generated through relative price effects as in Ngai and Pissarides (2007). We modify the model to add cohorts, sector-specific human capital, and sector-specific skill investments so that workers face a more complicated labor supply choice than in the standard structural transformation model.

At each date t a new cohort of workers enters the labor market. Workers are initially of age $t-c=0$ and work until they are A years old, at which point they die, exit the model, and are replaced by a new cohort of the same size.

Workers maximize the present discounted value of consumption:

$$\max \sum_{t=c}^{c+A} \beta^t U(c_{at}, c_{mt}, c_{st})$$

where the utility aggregator for the three consumption goods is given by:

$$U(c_{at}, c_{mt}, c_{st}) = \left(\lambda_a c_{at}^{1-1/\varepsilon} + \lambda_m c_{mt}^{1-1/\varepsilon} + \lambda_s c_{st}^{1-1/\varepsilon}\right)^{\varepsilon/(\varepsilon-1)}.$$

The λ are preference weights on different goods and obey the usual restriction $\lambda_a+\lambda_m+\lambda_s=1$. ε is the elasticity of substition among goods from sectors; Ngai and Pissarides (2007) show that $\varepsilon<1$ generates structural transformation consistent with the data.

Our model of labor markets breaks from the standard structural transformation model and adds skills as in Lagakos and Waugh (2013) and sector-specific investments as in Caselli and Coleman (2001). Workers observe and take as given the wage per unit of human capital in

[8]Within-cohort reallocation is work in progress.

each sector w_{jt}. Each worker has idiosyncratic human capital draws for the sectors given by h_{jt}, which are independent draws from a Fréchet distribution with dispersion parameter θ as in Lagakos and Waugh (2013). θ controls the dispersion of human capital in each sector, with smaller θ implying more dispersion. However, before workers can enter a sector they need to pay a sector-specific investment ξ. These assumptions yield the lifetime budget constraint:

$$\begin{aligned}
&\sum_{t=c}^{c+A} \left[p_{at}c_{at} + p_{mt}c_{mt} + p_{st}c_{st}\right] \\
&\quad = \sum_{t=c}^{c+A} \left[w_{at}h_{at}d_{at} + w_{mt}h_{mt}d_{mt} + w_{st}h_{st}d_{st}\right] - \xi \left[\max_t(d_{at}) + \max_t(d_{mt}) + \max_t(d_{st})\right].
\end{aligned} \tag{3}$$

$d_{jt} \in \{0, 1\}$ is an indicator for whether the worker works in sector j and obeys the standard restriction $d_{at} + d_{mt} + d_{st} = 1$. The left-hand side is the standard cost of purchasing consumption. The first term on the right-hand side is the standard lifetime income. The second term on the right-hand side is the total cost of acquiring skills for sector(s) of employment.

The firms in our model are straightforward. Each sector admits a representative firm that hires labor L_{jt} and produces output using a linear production function with sector-specific productivity A_{jt},

$$Y_{jt} = A_{jt}L_{jt} \tag{4}$$

Markets are assumed to be competitive, so the firm takes as given the price for sector j goods p_{jt} and the wage for labor which will in equilibrium be given by $w_{jt} = p_{jt}A_{jt}$.

3.1 Model Properties

We now describe some of the qualitative properties of the model. The first useful feature is that the model admits a two-step solution: first, workers choose the sector that maximizes lifetime income; second, they decide how to allocate that lifetime income to the consumption goods. We start wtih the sectoral choice. In the standard model of structural transformation, wages are equated across sectors and labor is indifferent among the sectors. That is not the case here. Nonetheless, as Lagakos and Waugh (2013) show, the Fréchet distribution leads to a very simple expression for labor allocations. In the absence of shocks, workers make a single sectoral choice at the start of their life, taking into account the future path of wages. It turns out that the share of workers in cohort c who choose sector j, n_{jc} is given by

$$n_{jc} = \frac{\left(\sum_{t=c}^{c+A} p_{jt} A_{jt}\right)^{\theta}}{\sum_j \left(\sum_{t=c}^{c+A} p_{jt} A_{jt}\right)^{\theta}} \tag{5}$$

This expression has an intuitive intepretation. $\left(\sum_{t=c}^{c+A} p_{jt} A_{jt}\right)$ is the present discounted value of future wages from working in a particular sector j. The fraction of workers choosing sector j increases as the present discounted value of future wages increase, relative to the present discounted value of future wages in all possible sectors. θ appears because it governs the amount of dispersion in sector-specific human capital. Workers maximize earnings, which is the product of the wage rate and human capital. All else equal, larger values of θ imply less dispersion in sector-specific human capital and hence increase the relative importance of wage rates in determining sectoral labor choice.

Because there is idiosyncratic human capital, we have to solve for the allocation of labor to each sector, which is different than the share of workers in each sector. Once again, the Fréchet gives a simple expression for this:

$$L_{jc} = \Gamma\left(\frac{\theta - 1}{\theta}\right) n_{jc}^{(\theta-1)/\theta} \tag{6}$$

where n_{jc} is the share of workers as given above and $\Gamma()$ refers to the Gamma function. Again, there is a clear intuition for this expression. The labor supply of a sector is proportional the share of workers who choose it raised to an exponent that is less than one. The exponent captures the idea that as more workers move into a sector average human capital falls, and hence labor supply does not expand as rapidly as the number of workers. The strength of this effect depends again on θ. If θ is alrge then productivities are not very dispersed and the marginal entrant has a human capital level similar to the sectoral average. Thus, sectoral labor supply in this case is close to the number of workers who choose the sector.

Total labor supply to sector j is simply the sum over the relevant set of cohorts:

$$L_{jt} = \sum_{c=t-A}^{t} L_{jc} \tag{7}$$

Now we turn to consumption allocations. In equilibrium workers will have different income levels. Nonetheless they have identical, homothetic preferences, so when faced with common prices at time t they all make the same consumption choices. Thus, consumption follows the same patterns as in Ngai and Pissarides (2007):

$$\frac{c_{jt}}{c_{j't}} = \left(\frac{\lambda_j}{\lambda_{j'}} \frac{p_{j't}}{p_{jt}}\right)^{\varepsilon} \tag{8}$$

Consumption of sector j output is increasing in its utility weight and decreasing in its price, with the curvature of relative consumption with respect to relative price controlled by the elasticity of substitution ε.

If we impose the market clearing condition $c_{jt} = Y_{jt}$ and equations (5), (6), (7), and (8), we have a complete system of equations that defines prices and allocations in the model. In general, this system of equations is tedious to work with, so we move to a simplifying example to build intuition.

3.2 Simplified Model: Two-Period OLG

4 Calibration and Results

[to be added]

5 Conclusion

[to be added]

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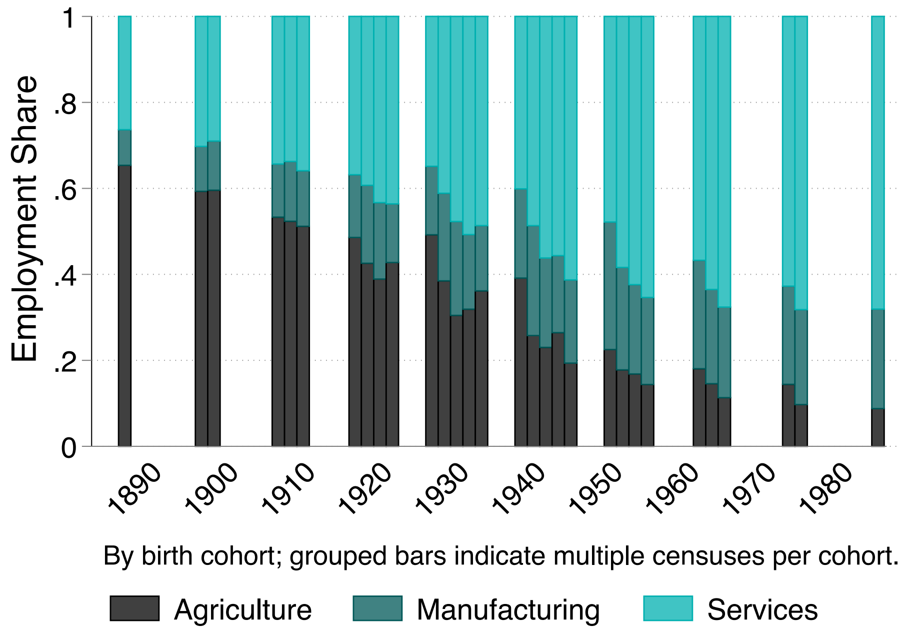
Figure A1: Structural Transformation in Brazil



A Appendix: Additional Empirical Results

Figure A2: Structural Transformation in Ghana

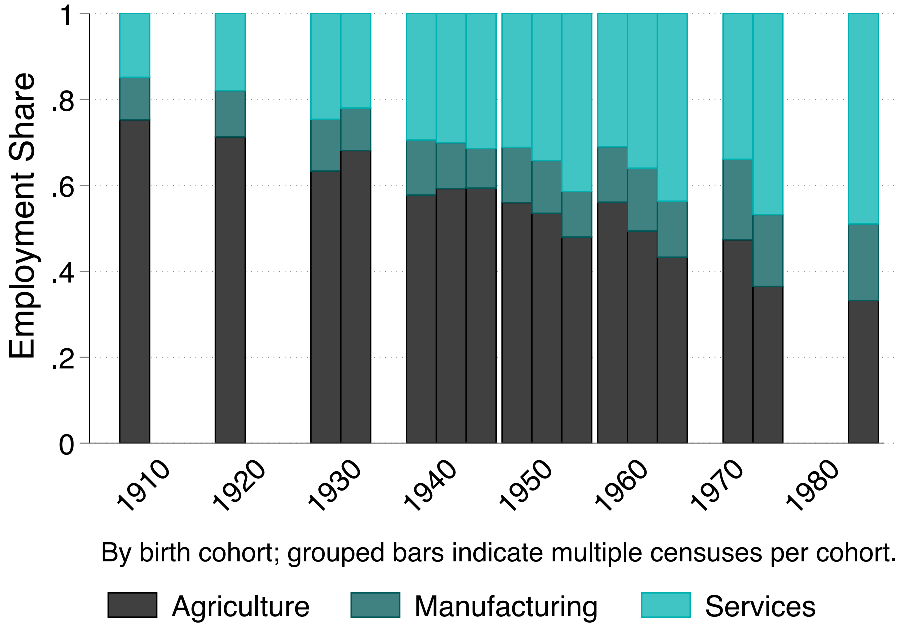


Figure A3: Between-Cohort Reallocation and Growth

(a) Growth

(b) Rate of Structural Transformation

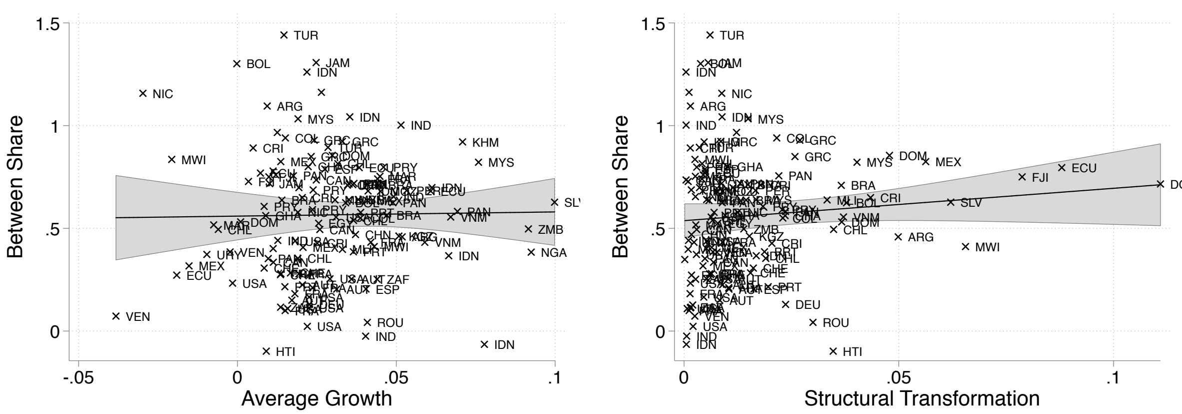


Figure A4: Between-Cohort Reallocation and Development

(a) Two Sectors (b) Fifteen Sectors

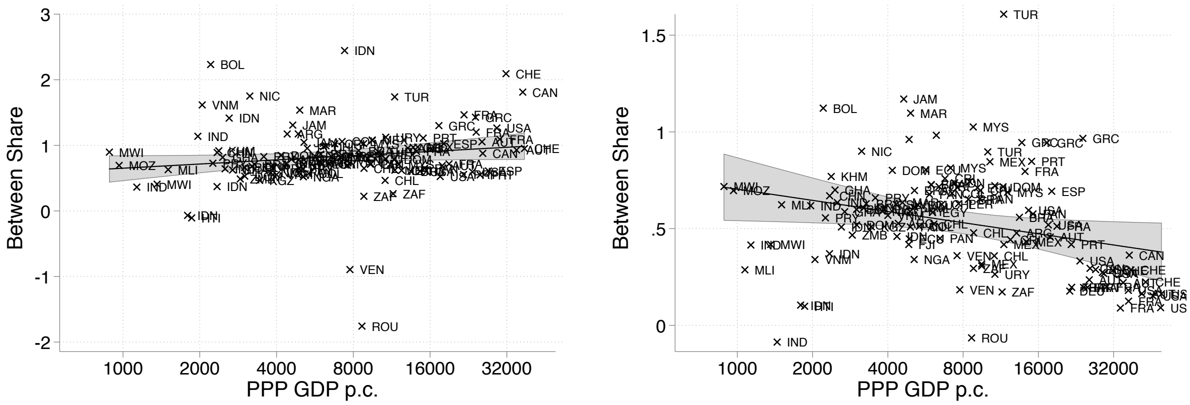


Figure A5: Within-Cohort Reallocation by Age and PPP GDP p.c. Levels

(a) Two Sectors (b) Fifteen Sectors