From Agriculture to Services: Development without Industrialization

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Abstract

Is an industrial revolution necessary for sustained long-run growth? This paper builds a unified growth model of the development process featuring structural change, endogenous fertility and misallocation through firm level distortions in order to explore the implications of bypassing manufacturing in today's developing countries. The model is able to replicate several stylized facts including: (i) current GDP per capita is significantly related to a country's peak manufacturing employment share, (ii) fertility is higher (lower) in countries which have a larger (smaller) services share of non-farm labor, (iii) countries with lower peak manufacturing employment shares have lower levels of education. Through the lens of the model, 14% of current GDP per capita gaps are explained by countries having lower peak manufacturing employment shares. Cross-country income inequality is projected to increase over time as countries which bypass industrialization land on balanced growth paths with lower productivity growth.

Keywords: structural change, trade, unified growth.
JEL Classification: O14, O15, O41, F16, J23, O33, E24

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1 Introduction

Over the past two centuries, the distributions of world income and population have exhibited substantial changes. These can be summarized in Figure 1: the parts of the world that have fallen behind in income per capita have also captured the largest share of population growth. Existing theories of unified growth, which model the transition from the Malthusian world in which income per capita is stagnant, to sustained economic growth generally feature an inevitable development path: all countries, eventually, should converge to a balanced growth path where income per capita is growing at a constant rate (Galor and Weil, 2000; Galor and Moav, 2002; Cervellati and Sunde, 2015). This prediction is increasingly at odds with the data. With the exception of a handful of countries, no developing country has managed to achieve sustained per capita income growth on the scale of that observed in advanced economies (Jones and Romer, 2010). Moreover, other changes in the macroeconomic aggregates of low-income countries make this prospect increasingly unlikely. In particular, developing countries today have larger shares of employment in the service sector and lower shares of employment in the manufacturing sector at all levels of GDP per capita, a phenomenon which has been termed "premature de-industrialization" in the literature (Rodrik, 2016). Although this fact has been known for almost a decade, we still have scarce evidence on (i) what causes countries to move out of industrial activities toward services and (ii) what are the implications of bypassing a manufacturing boom on long-term development. The latter point is especially salient given that very few advanced economies have achieved sustained growth without experiencing an industrialization boom at some point in their history (Kuznets, 1973; Chang, 2003; Murphy et al., 1989).

In this paper, I build a unified growth model which captures the transition from stagnation to growth with a key role played by the development of the manufacturing sector. In the model, a transition to sustained economic growth is possible only for specific parameter sets and, crucially, GDP per capita in levels is proportional to a country's peak manufacturing employment share, regardless of its current growth rate. Integrating structural transformation to the benchmark unified growth model of Galor and Weil (2000) adds several

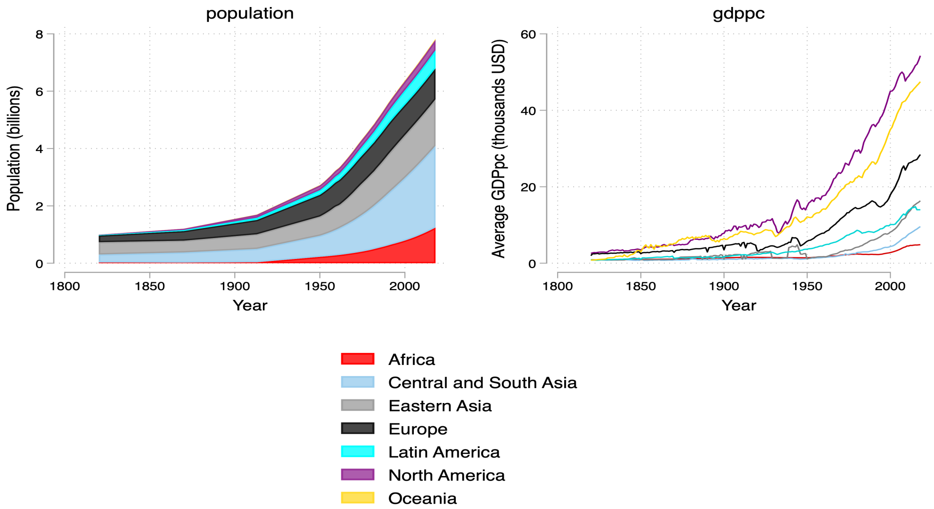


Figure 1: World distribution of income and population. Data is from Maddison (2020).

testable predictions which can be used to discipline the model's parameters, including the relationship between structural change within the non-agricultural sector (movement of labor from manufacturing to services and vice-versa) and total fertility rates, which, to the best of my knowledge, has not been previously documented in the data. More specifically, countries with higher shares of manufacturing employment within the non-farm sector have lower fertility, a relationship which holds at all levels of development and in almost all countries in the IPUMS microdata. The model is able to rationalize this given the well-known fact that productivity growth is lowest in the service sector (e.g. Buera and Kaboski, 2012a; Moro et al., 2017) and a lower growth rate relaxes the quantity-quality tradeoff by lowering the value of educational investment.[1] Using this framework, I explore the implications of a structural transformation process lacking manufacturing on long-term development possibilities and a

1. The assumption that returns to human capital are positively affected by the economy's growth rate is widespread in the quantity-quality tradeoff literature since the earliest contributions of Becker et al. (1990); Galor and Weil (2000); Parente and Prescott (2002) and others. This assumption reflects the well-known fact that aggregate productivity growth has an erosion effect on human capital, raising the return to educational investment (Nunn, 2014).

country's ability to achieve sustained growth. The baseline counterfactual exercise I run is exploring how the GDP per capita of the US today would differ if they had not had an industrialization boom, finding that reducing the peak employment share of manufacturing by 50% reduces current GPD per capita by 4.15%. These results are preliminary and conservative. In future iterations, the model will feature heterogeneity within the services sector, which, together with a complementarity of manufacturing with *high-skill* services (Cravino and Sotelo, 2019) implies that lowering the peak manufacturing share will bias the service sector towards *low-skill* activities, where the productivity growth rates are even lower (Vollrath, 2020). Further counterfactual exercises will explore the dynamic effects of international trade, which is a known factor influencing the premature exit from manufacturing activities in emerging economies (Sposi et al., 2021). Using IPUMS microdata from 95 countries, I construct regional trade shocks in the spirit of Autor et al. (2013) to study the effect of increasing international trade exposure on deindustrialization and, through the lens of the model, the full development process including the demographic transition and achieving sustained growth starting from a stagnant agrarian economy. These results are still not finished as I will first need to augment the model with distortions, capital accumulation and productivity investment to produce meaningful counterfactuals. For now, I present the empirical results, which show a pervasive negative effect of increasing trade exposure on manufacturing employment shares, across all low and middle income countries, and a positive effect on the employment shares of *low-skill* services.

This paper contributes to several strands of literature on structural change, trade, and development. Economists have taken an interest in questions related to structural transformation and, more generally, the movement of labor out of the rural-agricultural sector since at least the times of Kuznets (1966, 1973), Lewis (1954) and Rostow (1959). This line of research saw a revival with the contributions of Matsuyama (1992b,a); Kongsamut et al. (2001); Ngai and Pissarides (2007); Buera and Kaboski (2012a,b) and others who saw the potential for structural transformation to provide new insights when combined with growth theory. In the context of trade policy, Matsuyama (1992a), for instance, argued that international trade could reverse the relationship between agricultural productivity and industrialization, leading higher productivity agrarian economies to industrialize *later* due to specialization in agriculture induced by comparative advantage. This formalized the arguments of Prebisch (1959) that developing economies would be disadvantaged by international trade by specializing in the production of agricultural commodities which carry low income elasticities of demand due to *Engel's law*. Notwithstanding these early contributions, the literature is still unable to answer the question of whether a manufacturing boom is a *necessary* condition to achieve sustained development, with some recent contributions pointing in the direction of service led growth being a real possibility (Fan et al., 2023; Herrendorf et al., 2022; Juhász et al., 2023). This paper contributes to providing an answer to this important question by building a unified growth model featuring structural transformation and, in future iterations, distortions, endogenous factor accumulation and other characteristics that are salient explanatory variables in the cross-country income comparison literature (Hsieh and Klenow, 2009, 2007; Buera et al., 2011; Buera and Shin, 2013)

The rest of this paper is structured as follows: Section 2 presents cross-country evidence relating manufacturing booms and income gaps, the differences in structural change patterns between late and early starters and the relationship between structural change and fertility. Section 3 presents the baseline model environment. Section 4 presents the calibration strategy and counterfactual exercises. Section 5 empirically documents the relationship between trade exposure and the manufacturing sector, laying the groundwork for future counterfactual exercises. Section 6 concludes.

2 Stylized Facts

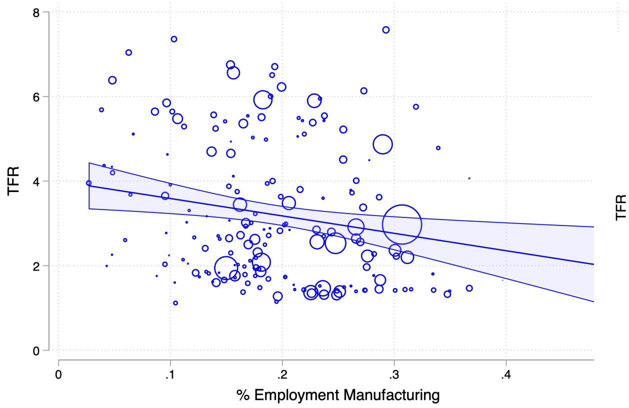
This section presents three stylized facts concerning structural change and the demographic transition. Data on modern sectoral employment shares in developing countries is from two sources: the Growningen Growth and Development Center Hamilton and de Vries (2023) and Gapminder, whereas the corresponding historical values for the US are from the 19th century censuses compiled and cleaned by Haines (2001) and FRED for the post 1940 period. I compare the recent evolution of the employment shares in developing countries to that of the US at the turn of the 20th century for two reasons: first, there is high quality and easily accessible data for the US which can be used to arrive at employment shares going as far back as 1880,[2] secondly, the US provides an example of an early industrializer which developed at considerable distance and high levels of tariff protection from the frontier economy at the time, Great Britain (Chang, 2003). If the import competition channel has played a role in shaping the structural change process historically and now in developing countries, differences should arise in the employment shares of the US as it was developing and those observed in today's developing countries.[3] Using this data, I document the following facts:

FACT 1: Countries with higher shares of manufacturing (services) employment in the non-farm sector have lower (higher) total fertility rates. Using IPUMS microdata this relationship is shown to be driven by differential fertility rates within countries: women working in the manufacturing sector have lower fertility rates than those in the - low productivity - services sector.

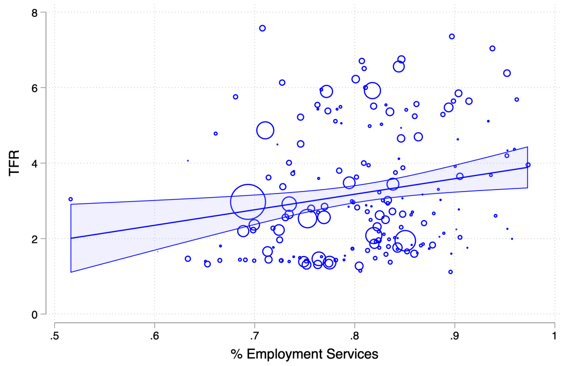
Figures 2 and 13 show that there is a strong relationship between the direction of the structural change process and the pace of a country along the demographic transition. Previous literature has documented how exit from the agricultural sector is associated with lower fertility due to a decrease in the value of child

2. One could go back as far as 1850 although the earlier censuses are generally considered less reliable.

3. This pattern generally holds if we replace the US with another advanced economy at the time of its transition out of agriculture, however, the comparison is often less clear as in the case of France, Germany, Italy and others significant political developments over the 19th century, as well as their significant proximity to Great Britain, may contaminate these comparisons.



(a) Manufacturing



(b) Services

Figure 2: Scatterplot of total fertility rates (TFR) against the share of manufacturing (left) and services (right) in non-agricultural labor. Each dot represents a country average over 1990-2018, size refers to population in the last observed year. Source: Gapminder.

labor, an increase in the returns to education, and the opportunity cost of parents' time (Ager et al., 2020). However, there is little work on the heterogeneity in fertility patterns within the non-farm sector. Heterogeneity within the non-agricultural sector is a strong predictor of a country's fertility rates as countries where the non-farm sector is primarily service based tend to have higher fertility rates. These relationships are statistically significant at the 5% level in the cross-sectional averages over 1990-2018, as well as in panel data regressions with country and year fixed effects as shown in Table 2 in Appendix B.

FACT 2: A country's peak manufacturing employment share is positively related to its current level of GDP per capita.

Figure 3 shows the relationship between peak manufacturing employment shares over the past two centuries and GDP per capita in 2018.[4] I take 2018 as the "current" gdp per capita to avoid any transitory effect of the Covid-19 pandemic and its fallout which could temporarily alter the distribution of GDP per capita

4. Gapminder provides data for the past 30 years for developing countries, where employment in manufacturing, in any case, did not peak prior to the 1990s.

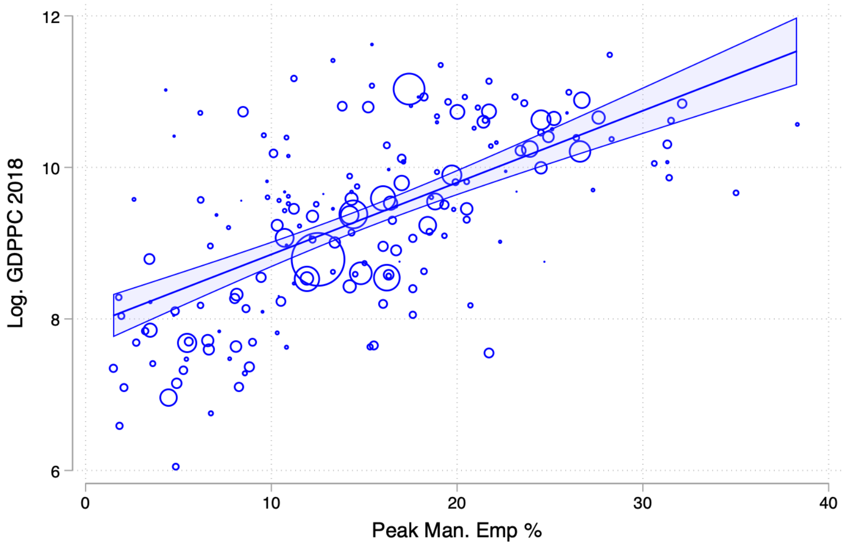


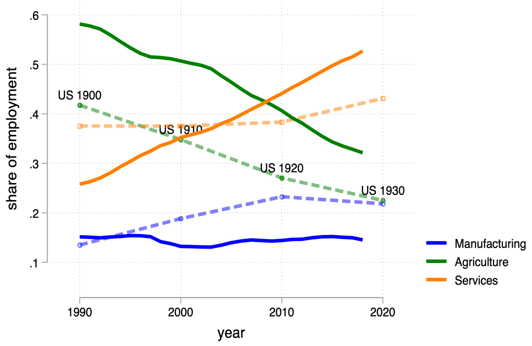
Figure 3: Weighted scatter plot of GDP per capita against the peak employment share of manufacturing in 195 coutries. The weights correspond to population in 2018. Data source: Gapminder.

in recent years.[5] This confirms the well-known fact that virtually all rich countries have experienced large manufacturing shares of employment, or industrial booms, at some point in their past.

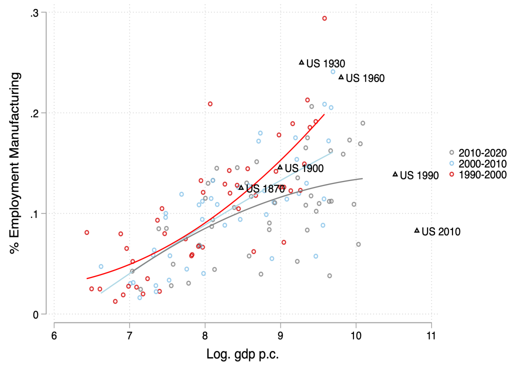
FACT 3: Developing countries over 1990-2018 have lower shares of manufacturing employment compared to the US at similar levels of GDP per capita.

Panel (b) of Figure 4 compares the evolution of sectoral employment shares in the developing countries covered by the GGDC to those of the US at the turn of the century, starting in 1900 when it had a similar level of the manufacturing employment share as that in developing countries in 1990. This exercise shows two striking differences. Firstly, the transition out of agricultural labor is much faster in today's developing countries than it was for the US: over a thirty year period when the US agricultural share declined by 18pp, the agricultural share in developing countries declined by almost 30pp. The same holds for the entry

5. This relationship is highly significant and not affected by choosing 2018 or another reference year.



(a) Over time



(b) Over development

Figure 4: Scatter plot of manufacturing employment shares over development by decade (right) and time series plot of the average of the three employment shares weighted by population compared to the corresponding values for the US one century before (dashed lines) in 45 low and middle income countries (left). Source: GGDC Economic Transformation Database and US Censuses of Population 1880-1930 and FRED.

into services, Figure 4 shows that virtually all labor exiting agriculture over 1990-2018 in developing countries has been absorbed by the service sector.

Panel (b) of Figure 4 plots this relationship over levels of GDP per capita instead of time. Virtually all countries in the period between 2010 and 2020 had lower (higher) levels of manufacturing (services) employment shares when compared to the US at a similar level of development.[6] We can also see that this relationship is relatively recent, in the period spanning 1990-2000 developing countries had, on average, similar levels of manufacturing employment shares, albeit higher services employment shares. Rodrik (2016) first discovered these patterns, although without making an explicit comparison with a (now) developed country at similar levels of GDP per capita. Sposi et al. (2021) showed that international trade throuhg an import competition mechanism is an important driver of the downward trend in the manufacturing employment share's relationship with GPD per capita. In Section B.2 I estimate the effect of increasing trade exposure on the sectoral employment shares finding that trade shocks

6. This statement is clear for levels of GDP per capita above 8000$, however there is no data from when the US was at a level of GDP below 8000$ it is difficult to make a comparative statement for the poorest developing countries.

have not only lowered manufacturing shares of employment, but also raised those of non-tradeable low-skill services.

3 Model

This section presents a general equilibrium model of structural change and the demographic transition. The baseline structure borrows from Galor and Weil (2000) and Lagerlöf (2006) to which I add sectoral and firm heterogeneity, correlated distortions and endogenous productivity investment. Necessary features of the model which we will require to study the role of manufacturing in the development process in a way which is consistent with Section 2 are: (i) multiple sectors, (ii) endogenous fertility choices, (iii) endogenous technological change, (iv) the ability to generate a "takeoff" from stagnation to growth as in other models which study long-run development outcomes (e.g. Galor and Weil, 2000; Cervellati and Sunde, 2015; Parente and Prescott, 2002) and (v) a source of frictions in the manufacturing sector.[7] While this may seem like a very exigent set of modeling features, the model presented below remains highly tractable, with many of its mechanisms being summarized in closed form relationships between key variables.

3.1 Households

Time is discrete and indexed by t. The world is populated by overlapping generations of identical households who live for two periods. Following Galor and Weil (2000), individuals receive education when young and, in adulthood, make decisions about fertility, consumption, labor supply, and their children's education. Preferences are defined over a composite consumption good C_t and the effective number of children is $n_t h_{t+1}$, where h_{t+1} denotes the human capital of each child. The household maximizes:

7. Condition (v) is necessary to account for the well known fact that the manufacturing sector is more or less distorted in different countries/time-periods Alfaro et al. (2023), therefore complicating the study of industrial policy in promoting cross-country convergence.

$$\max_{c_{at},c_{mt},c_{st},n_t,e_t} (1-\gamma)\ln(C_t) + \gamma \ln(n_t h_{t+1}) \tag{1}$$

subject to the following constraints:

$$\begin{aligned}
C_t &\geq \bar{c} \\
p_{at}c_{at} + c_{mt} + p_{st}c_{st} &\leq (1 - n_t(e_t + \tau))w_t, \\
h_{t+1} &= \frac{e_t + \rho\tau}{e_t + \rho\tau + g_t}, \\
1 &= \sum_{i \in \{a,m,s\}} \omega_i^{1/\sigma} \left(\frac{C_{it}}{C_t^{\varepsilon_i}} \right)^{\frac{\sigma-1}{\sigma}}
\end{aligned}$$

where p_{mt} is normalized to 1 and $\bar{c}$ represents a minimum consumption floor. Parameters satisfy $\gamma, \tau, \rho \in (0,1)$, and $\sigma \in (0,1)$, sectors are gross complements. By assuming households give the same level of education to all their children, a tradeoff between quantity and quality is generated in the spirit of Becker et al. (1990). Households who have many children face steep education costs as education takes time away from labor market supply and lowers effective income. The functional form of human capital accumulation is taken from Lagerlöf (2006) and satisfies the assumptions in Galor and Weil (2000), namely $\partial h/\partial e > 0$, $\partial h/\partial g < 0$ and $\partial h/\partial e \partial g > 0$. These assumptions ensure that technological growth has an erosion effect on current human capital by rendering existing knowledge obsolete, which raises the returns to educational investment. On the household side, the model differs from previous literature by adding non-homothetic preferences in the spirit of Comin et al. (2021). This preference structure is implicitly additive with constant price elasticity of substitution across goods, governed by σ, but different income elasticity of demand across goods. The parameter ε_i effectively generates an aggregate income varying weight, following the literature I assume that $\varepsilon_a < \varepsilon_m < \varepsilon_s$, that is agriculture has a lower income elasticity of demand than manufacturing and services.

3.2 Production

The economy consists of three sectors:[8] agriculture a, manufacturing m, and services s. To bring the model closer to policy, the manufacturing sector features heterogeneous firms with correlated distortions generating resource misallocation. Agriculture and services, on the other hand, operate in a frictionless world where their output can be generated using the following representative firm setup with CRS technology:

$$Y_{it} = K_{it}^{1-\nu}\left((h_t L_{it})^{\alpha}(XA_{it})^{1-\alpha}\right)^{\nu}, \quad \alpha, \nu \in (0,1) \tag{2}$$

where X is a fixed supply of land and A_{it} is the sector-specific level of technology, K is capital and L is labor. To abstract from capital *accumulation*, I assume a fixed world interest rate which determines the level of capital as a function of technology and other inputs to the production function, which implies that the effective production function is DRS in labor:

$$K^* = \left(\frac{1-\nu}{\bar{r}}\right)^{\frac{1}{\nu}}(h_t L_{it})^{\alpha}(XA_{it})^{1-\alpha} \quad \Longrightarrow \quad Y_{i,t} = \underbrace{\left(\frac{1-\nu}{\bar{r}}\right)^{\frac{1-\nu}{\nu}}}_{\Omega}(h_t L_{it})^{\alpha}(XA_{it})^{1-\alpha}$$

As there is a single labor market with homogeneous workers, in equilibrium we will have that the FOC for labor will equalize across the sectors yielding:

$$\frac{p_a}{p_s} = \left(\frac{A_s/L_s}{A_a/L_a}\right)^{1-\alpha} \tag{3}$$

8. Potentially this could be extended to distinguish between high and low productivity services.

Relative prices are pinned down by technology, with the only difference being that here they will also depend on the sectoral employment shares due to the fact that X is in fixed supply. Aside from this variation, necessary to generate the Malthusian relation between wages and population, the agriculture and services sectors of the economy are relatively standard and align very closely with benchmark models of structural transformation (e.g. Herrendorf et al., 2014). The manufacturing sector on the other hand, features heterogeneous firms with firm level distortions in the spirit of Hsieh and Klenow (2009), generating misallocation of productive resources in the economy. Each firm i in the manufacturing sector produces output according to:

$$y_i(z_i, l_i) = z_i(h_t l_i)^{\phi_1}(A_{m,t}X)^{\phi_2}$$

where $z_i \in \{z_{low}, ..., z_{high}\}$ is a discrete firm-specific productivity level, h_t is the labor-augmenting human capital common across sectors, $A_{m,t}$ is the manufacturing-specific technology, and X is the fixed supply of land and the manufacturing goods price p_m is normalized to one. Firms face idiosyncratic distortions τ_i that act as wedges on labor costs, such that they pay $(1+\tau_i)w_t l_i$ to hire l_i units of labor at the equilibrium wage w_t. Manufacturing firms make two decisions: each period firms chooses labor to maximize profits:

$$\pi(z_i) = \max_{l_i} \; z_i(h_t l_i)^{\phi_1}(A_{m,t}X)^{\phi_2} - (1+\tau_i)w_t l_i$$

and between periods firms can pay a fixed investment cost in order to increase the possibility of raising their TFP. The timing is such that these decisions are taken sequentially. In the absence of productivity enhancing investment, each period TFP can go up - increase one step on the ladder - with probability p and down with probability $1-p$, whereas if the firm pays a fixed investment cost κ this probability goes up to $p_i > p$. The value function of the manufacturing firm is therefore:

$$V(z) = \max_{\mathcal{I} \in \{0,1\}} \left\{ \pi(z) - \kappa \mathcal{I} + \beta \mathbb{E}_{z'|z,\mathcal{I}}[V(z')] \right\} \tag{4}$$

where $\mathcal{I} \in \{0, 1\}$ is the binary innovation decision, κ is the fixed cost of innovation, and $\pi(z)$ denotes current-period profits as a function of firm productivity z. The law of motion for productivity follows a discrete Markov process:

$$\Pr(z' = z_j \mid z = z_i, \mathcal{I} = 0) = P_{ij}, \qquad \Pr(z' = z_j \mid z = z_i, \mathcal{I} = 1) = P_{ij}^{\text{innov}}$$

where P and P^{innov} are the transition matrices for firms that, respectively, do not and do innovate, and P^{innov} governs the transitions when firms pay the innovation cost. These matrices feature zero entries whenever $abs(i - j) > 1$, i.e. a firm can only move up one step or down one step each period. Innovation increases the probability of moving to a higher productivity level. The innovation decision is added to the model to endogenize the growth of aggregate productivity in manufacturing A_m as will become clear in Section 3.3. Within a period, the first-order condition for labor yields:

$$l_i(z, w, \tau) = \left(\frac{\phi_1 z_i h_t^{\phi_1} (A_{m,t} X)^{\phi_2}}{(1 + \tau_i) w_t} \right)^{\frac{1}{1-\phi_1}}$$

Letting Φ_t and Ψ_t denote distortion-weighted productivity aggregates:

$$\Phi_t \equiv \int (1 + \tau_i)^{-\frac{1}{1-\phi_1}} z_i^{\frac{1}{1-\phi_1}} \, di, \quad \Psi_t \equiv \int (1 + \tau_i)^{-\frac{\phi_1}{1-\phi_1}} z_i^{\frac{1}{1-\phi_1}} \, di$$

Aggregate labor demand in manufacturing is:

$$L_{m,t} = \left(\frac{\phi_1 h_t^{\phi_1} (A_{m,t} X)^{\phi_2}}{w_t} \right)^{\frac{1}{1-\phi_1}} \Phi_t$$

Aggregate manufacturing output is:

$$Y_{m,t} = A_{m,t}^{\frac{\phi_2}{1-\phi_1}} X^{\frac{\phi_2}{1-\phi_1}} h_t^{\frac{\phi_1}{1-\phi_1}} L_{m,t}^{\phi_1} \cdot \left(\phi_1^{\frac{\phi_1}{1-\phi_1}} \Psi_t \Phi_t^{-\phi_1} \right)$$

Output in manufacturing is shaped not only by fundamentals but also by the extent of misallocation, summarized by the term $\Psi_t \Phi_t^{-\phi_1}$. In a frictionless benchmark where distortions τ_i vanish, this term collapses to a one, and all firms operate at the same marginal return to labor. With as long as some firms face positive wedges however, the manufacturing output will be less than its full potential by a factor of $\Psi_t \Phi_t^{-\phi_1} \in (0, 1)$. For analytical tractability we parameterize the output elasticities ϕ_1 and ϕ_2 such that manufacturing output scales with $(A_{m,t} X)^{1-\alpha}$. This requires setting:

$$\phi_2 = (1-\alpha)^2, \quad \phi_1 = \alpha$$

Under this condition, relative prices across sectors can be derived by equalizing marginal products of labor across sectors, yielding expressions that depend on sectoral employment shares, technology, and the misallocation term. Following these steps, relative prices of agriculture and services are:

$$\begin{aligned} p_a &= C \left(\frac{A_m}{A_a} \right)^{1-\alpha} \left(\frac{s_m}{s_a} \right)^{\alpha-1} \\ p_s &= C \left(\frac{A_m}{A_s} \right)^{1-\alpha} \left(\frac{s_m}{s_s} \right)^{\alpha-1} \end{aligned} \tag{5}$$

where:

$$C = \alpha^{\frac{\alpha}{1-\alpha}} \cdot \Psi \cdot \Phi^{-\alpha} \cdot h_t^{\frac{\alpha^2}{1-\alpha}}$$

is a market level constant. Dividing p_a by p_s yields an expression consistent with (3).

3.3 Population and Technology Dynamics

Each period, population evolves according to fertility decisions:

$$L_{t+1} = n_t L_t. \tag{6}$$

Technological progress in each sector is endogenous and depends on the size of the population up to a sector specific threshold $\bar{a}_i$:

$$A_{i,t+1} = (1 + (e_t + \rho\tau)a_{it})\, A_{it}, \quad \text{where } a_{it} = \min\{\theta L_t, \bar{a}_i\}. \tag{7}$$

Technological progress is exogenously lower in the service sector, with $\bar{a}_s < \bar{a}_a$ and manufacturing productivity growth reaches its full potential only when all firms are investing in innovation, that is, there is an externality whereby firm innovation not only raises individual TFP but also the growth rate of aggregate productivity A_m:

$$\bar{a}_m = \bar{a}_m^{max} \sum_z \mu(z)\mathcal{I}(z)$$

Where $\mathcal{I}(z)$ is the innovation policy, μ is the stationary distribution over z and $\bar{a}_s < \bar{a}_m^{max} \leq \bar{a}_a$.

3.4 Equilibrium

A competitive equilibrium in period t consists of household decisions $\{c_{it}, n_t, e_t\}$, firm decisions $\{L_{it}, l_{it}, k_{it}, \mathcal{I}(z)\}$, prices $\{w_t, p_{mt}, p_{st}\}$, technologies $\{A_{it}\}$ and a distribution of firms over productivity levels $\mu(z)$; such that, given prices, the innovation cost κ and a distortion schedule $\tau(z)$:

- **Labor market clears:**

$$L_t = \sum_{i \in \{a,m,s\}} L_{it}. \quad L_m = \sum_z l(z, w, \tau(z))\mu(z)$$

- **Goods markets clear:**

$$Y_{it} = c_{it}, \quad \text{for all } i \in \{a, m, s\}. Y_{mt} = \sum_z y(z)\mu(z)$$

- **Households optimize:** The household solves 1.
- **Aggregate Distribution**:

$$\mu = \mu \cdot \left[(I - \mathcal{I})P + \mathcal{I}P^{\text{innov}} \right]$$

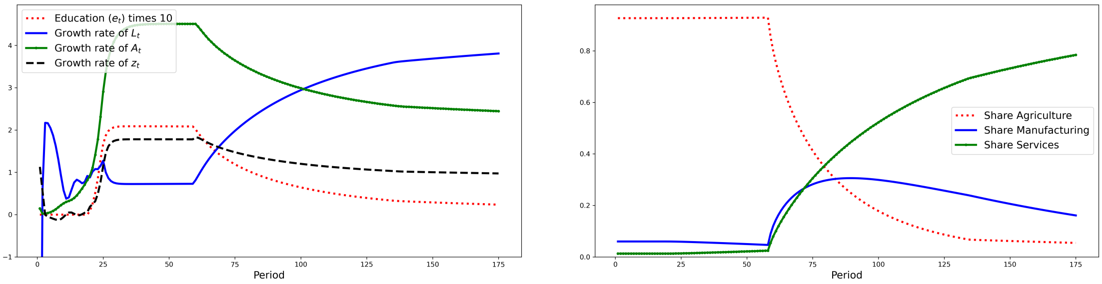
As in Buera et al. (2020) the economy approaches a BGP when as $s_s \to 1$.

3.5 Characterization

As in standard structural change models (Herrendorf et al., 2014), wages equalize across the sectors since a competitive labor market implies firms face an infinite labor supply elasticity. The capital labor ratios also will equalize and take the following form:

$$\frac{k_i}{l_i} = \frac{w_t}{\bar{r}} \cdot \frac{1 - \nu}{\nu \alpha}, \tag{8}$$

Following Lagerlöf (2006) and Galor and Weil (2000) we can derive closed form expressions for the optimal fertility and education choices. Define $\tilde{z} = \bar{c}/(1 - \gamma)$ as the income level which allows the household to cover its subsistence requirement by allocating its preferred time share γ to child rearing. The optimal fertility decision is then:



(a) Growth process **(b)** Shares

Figure 5: Model simulation starting from an arbitrary set of initial parameters.

$$n_t(\tau + e_t) = \begin{cases} \gamma, & \text{if } w_t \geq \tilde{z}, \\ 1 - \frac{\bar{c}}{w_t}, & \text{if } w_t \in (\bar{c}, \tilde{z}), \\ 0, & \text{if } w_t \leq \bar{c}. \end{cases} \tag{9}$$

If income is sufficiently low, the subsistence constraint is binding and the household can only afford to dedicate $1 - \frac{\bar{c}}{w_t}$ of its time to child rearing, the time it has left over after earning enough to consume $\bar{c}$. The optimality condition for education is slightly more involved, however, we can show that:

Proposition 1. *The household education choice satisfies:*

$$e^* = \max\{0, \sqrt{g_t(1-\rho)\tau} - \rho\tau\} \tag{10}$$

Proof. See Appendix A □

The optimal condition for e shows that education investment is a positive function of the aggregate growth rate in this model. There are several reasons why this is a reasonable prediction, one of which is that technological change is often found to erode the stock of human capital, thereby raising the return to education (Nunn, 2014).

Using the Marshallian demand system from 1, the dynamics of population and technology 6, 7, the decisionf for education and fertility 10, 9 and the pricing equations 5 we have a system of 11 equations for 11 endogenous variables, $\{c_{it}, p_{it}, e_t, n_t, A_{i,t+1}, L_{t+1}, h_{t+1}\}_{i\in\{a,m,s\}}$ which we can solve each period and simulate forward starting from arbitrary initial values. The model generates the following qualitative patterns: (1) an initial Malthusian pseudo-steady state where income per capita and population are fluctuating, (2) a post-Malthusian phase where income per capita and population are growing, (3) a sustained growth regime where fertility declines and income per catita grows at a quasi constant rate and (4) a growth slowdown as the economy transitions to the lowest productivity sector (services) with a corresponding rise in fertility. Unlike other unified growth models where development is "inevitable", i.e. given sufficient amount of time the economy reaches a balanced growth path with sustained income per capita growth (Cervellati and Sunde, 2015; Galor and Weil, 2000), in this model the heterogeneity in sector growth rates introduces an additional layer of complexity which makes development a non-trivial outcome of this process. In particular, whether the economy successfully exits the Malthusian trap will be substantially affected by its structural change process. More specifically:

Proposition 2 (Escape from Stagnation and the Onset of Development)**.** *The necessary and sufficient condition to achieve sustained growth in income per capita is that:*

$$e^* > 0 \iff g_t > \frac{\rho^2\tau}{1-\rho} \quad \textit{where} \quad g_t = \sum_i s_{it} g_{it} \tag{11}$$

Proof. See Appendix A □

In order to escape the Malthusian trap positive investment in education is necessary, which only occurs when the growth rate of the economy crosses a well defined threshold. As the technological constraints on growth are different across sectors, reflected in the assumption that $\bar{a}_a > \bar{a}_m > \bar{a}_s$, the potential growth rate of service sector productivity is lower than that of manufacturing and agriculture (e.g. Vollrath, 2020; Moro et al., 2017), whether the economy is able to takeoff at all is dependent on its structural change process. A service-bias of

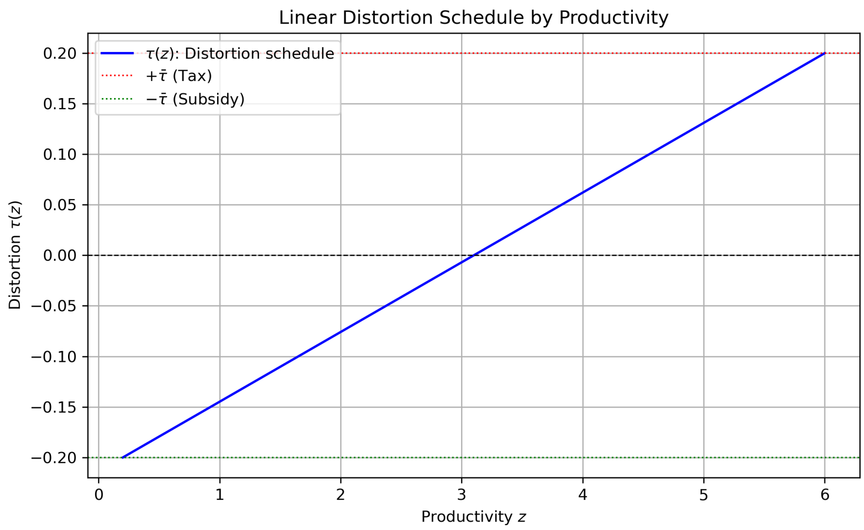
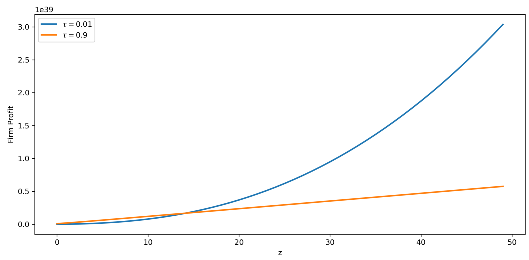


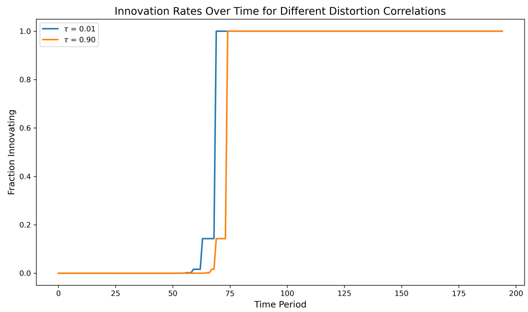
Figure 6: Distortion schedule example, the highest productivity firm pays a tax of 20% of its wage bill, whereas the lowest productivity firm gets a subsidy of 20%.

the structural change process implies a lower probability of takeoff, as it requires stronger parameter restrictions, in particular a small time cost per child and a small baseline human capital level. Moreover, larger, and more productivity correlated, distortions will also lower $\bar{a}_m$ making the manufacturing sector endogenously less productive. Hence, as whether the economy ultimately achieves a takeoff into sustained growth depends on the growth of economy wide aggregate productivity, calculated as in 2, correlated distortions can delay the timing of the economy's takeoff into sustained growth as it reaches its peak growth frontier $\bar{a}_m^{\max}$ only when all firms are innovating. This will eventually occur as long as the investment cost remains fixed as aggregate productivity A_m is growing over time, albeit at a lower rate if at least some firms are not innovating. For the purpose of this exercise, consider a distortion schedule which is a simple linear mapping between distortions τ and z with upper and lower bounds $\bar{\tau}$, meaning that the lowest productivity firm z_{low} receives a subsidy of $\bar{\tau}$ whereas the highest productivity firm z_{high} pays a tax of $\bar{\tau}$. We can see this in Figure 6.

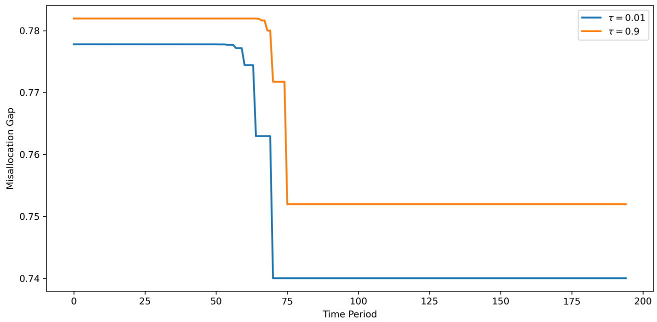
This distortion schedule achieves the intended goal of making innovation less appealing, as increasing z entails a higher distortion, while preserving tractability. We can now plot along the transition path the evolution of misallocation and innovation rates for different distortion schedules $\tau(z)$, which will help gain intuition over how correlated distortions can affect the takeoff into sustained growth.



(a) Firm profits



(b) Firm innovation rates



(c) Misallocation output gap

Figure 7: Firm-level outcomes: (a) profits, (b) innovation rates, (c) misallocation

Figure 7 shows that as the economy transitions to sustained growth, the misallocation gap $\Psi_t \Phi_t^{-\phi_1}$ goes down, owing to the fact that a growing aggregate productivity makes investment an attractive prospect even with correlated distortions. This implies that, as the firm innovation rate goes up, the productivity distribution becomes more concentrated at higher levels of z lowering aggregate labor misallocation.

4 Model Calibration

This Section uses data on employment shares and GDP per capita growth from the US over 1800-2020 to calibrate the model. In all counterfactual exercises I will measure misallocation from correlated distortions in relative terms compared to the US. I hence take the US as the benchmark, non distorted economy, with $\bar{\tau} = 0$, and κ sufficiently low that it is always optimal to invest in productivity, implying that the model effectively collapses to a production structure with three representative firms having DRS technology.

I calibrate the model parameters using the Generalized Method of Moments (GMM), targeting the evolution of employment shares in agriculture, manufacturing, and services over the period 1850–2010, as well as GDP per capita and population growth factors over 1800-2010.[9] The GMM objective function is as follows:

$$\begin{aligned}
\mathcal{L}(\theta) = \sum_{t \in T_{\text{moments}}} & \left[\left(s_{a,t}^{\text{sim}} - s_{a,t}^{\text{data}} \right)^2 + \left(s_{m,t}^{\text{sim}} - s_{m,t}^{\text{data}} \right)^2 + \left(s_{s,t}^{\text{sim}} - s_{s,t}^{\text{data}} \right)^2 \right] \\
& + \left(\frac{g_{\text{sim}}^{\text{final}} - g_{\text{data}}^{\text{final}}}{g_{\text{data}}^{\text{final}}} \right)^2 + \left(\frac{g_{\text{sim}}^{\text{mid}} - g_{\text{data}}^{\text{mid}}}{g_{\text{data}}^{\text{mid}}} \right)^2 \\
& + \left(\frac{P_{\text{sim}}^{\text{final}} - P_{\text{data}}^{\text{final}}}{P_{\text{data}}^{\text{final}}} \right)^2 + \left(\frac{P_{\text{sim}}^{\text{mid}} - P_{\text{data}}^{\text{mid}}}{P_{\text{data}}^{\text{mid}}} \right)^2
\end{aligned} \tag{12}$$

Where the "mid" moments for gdp and population correspond to the 1800-1900 population and gdp per capita growth factors, being 4.8 and 13 respectively. These moments are especially important as they help calibrate the timing of the transition.

9. the choice of 1800 as an initial year is due to data constraints, whereas the choice of 2010 as a final year is arbitrary.

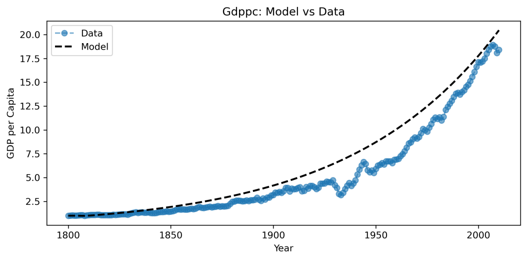
Parameter	Value	Description and Source
		Fixed Parameters
T	216	Time horizon in model periods (assumed)
α	0.6	DRS to labor in production (Restuccia and Rogerson, 2008)
σ	0.5	Substitution elasticity in utility (Buera and Kaboski, 2009)
ϵ_m	1.0	Income elasticity of manufacturing (normalization)
$r^{\star}$	0.02	World interest rate (normalization)
ν	0.5	Capital share in production (standard value)
ω_m	8.0	Utility weight on manufacturing (normalization)
		Estimated Parameters (GMM)
$\bar{c}$	3.6245	Subsistence consumption threshold
τ	0.2263	Time cost of children
θ	0.00016	Effect of population growth on technology
ω_a	0.8553	Utility weight on agriculture
ω_s	19.5410	Utility weight on services
X	59.9367	Stock of land
γ	0.7713	Utility weight on children (implied)
ρ	0.2364	Baseline human capital formation (implied)
$\bar{a}_s$	1.4381	Maximum productivity growth in services
$\bar{a}_m$	2.5548	Maximum productivity growth in manufacturing
$\bar{a}_a$	2.9853	Maximum productivity growth in agriculture
ϵ_s	1.0243	Income elasticity of services
ϵ_a	0.0552	Income elasticity of agriculture

Table 1: Model Parameters: Calibrated and Fixed

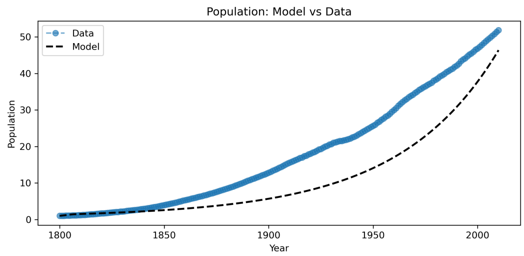
The model includes a total of 20 parameters, of which 7 are fixed based on values commonly used in the literature or normalized for identification. The remaining 13 parameters are internally calibrated to make the models moments as close as possible to the data. As there are 13 parameters and 52 moments, the system is overidentified. The estimation uses simulated employment shares from the model evaluated at a set of 16 time points, corresponding to years 1850, 1860, . . . , 2010 which are then compared to their data counterparts.[10] The GMM

10. Moments using model generated sequences of population and gdp per capita are first converted to yearly series assuming a model period of 20 years (Boldrin and Jones, 2002) and converting using the CAGR formula: $gX_t = 100\left(\left(1+\frac{X_{t+1}-X_t}{X_t}\right)^{\frac{1}{20}}-1\right)$

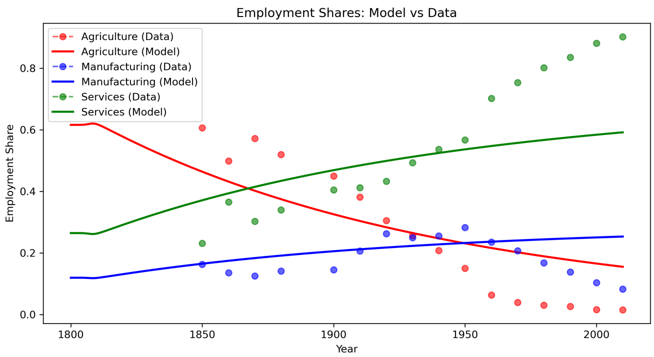
optimization then searches over the parameter space to minimize 4 assigning equal weights to all moments. We can see in Figure 5 that the model is able to match the data with a remarkable degree of accuracy. The estimated parameters capture key features of structural transformation and economic growth. The low elasticity of agriculture ($\epsilon_a = 0.0552$) and high elasticity of services ($\epsilon_s = 1.0243$) are consistent Buera et al. (2020) and crucial to generate the desired evolution of employment shares over income.



(a) GDPPC



(b) Population



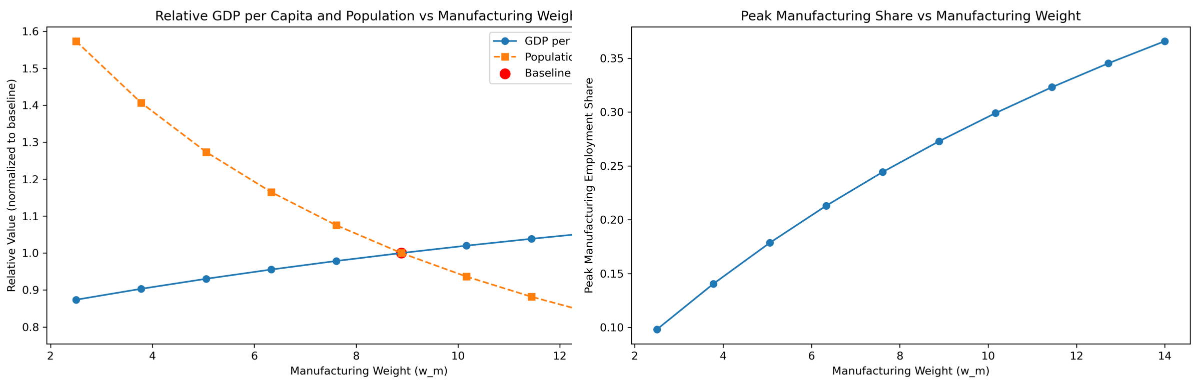
(c) Misallocation output gap

Figure 8: Model vs data: (a) gdp per capita, (b) population, (c) employment shares.

The calibration fits the GDP per capita and population sequences exceptionally well while slightly falling short in the employment shares targeting. This can be improved with better optimization algorithms.

5 Counterfactuals

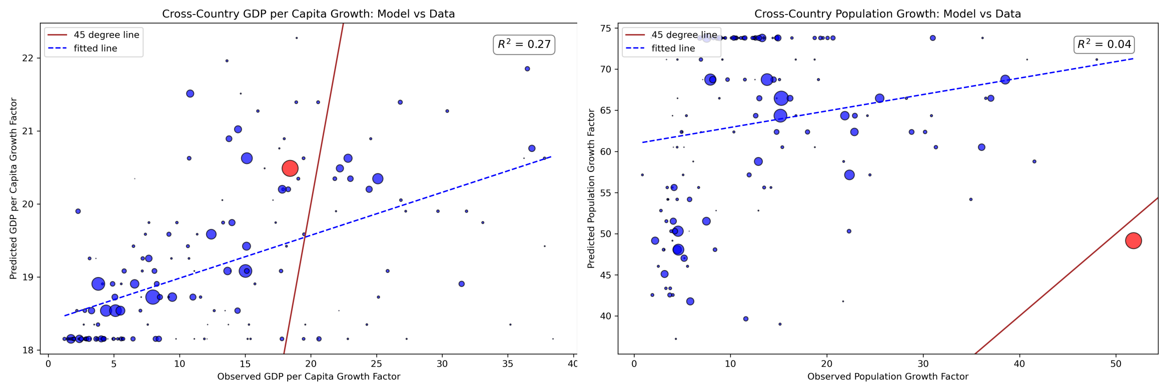
With the calibrated model in hand, the main counterfactual exercise I perform is to simulate the model for different utility weights of manufacturing consumption ω_m, which alters the peak employment share of the manufacturing sector and see the effects this has on GDP per capita at the end of the simulation window. This should recreate the pattern in Figure 3, where we can see that peak manufacturing shares are significantly correlated with current GDP per capita. The counterfactual results are presented in Figure 9 and qualitatively replicate this patter: a lower ω_m decrease the US' peak manufacturing share over the development trajectory and lowers its current GDP per capita. The mechanism which achieves this in the model is straightforward and intuitive: lowering the employment share of manufacturing lowers the average growth rate of the economy as less labor flows into the highest productivity sector, which in turn discourages education investments.



(a) GDPPC and Population **(b)** Peak Manufacturing Employment %

Figure 9: Calibrated model simulations for different values of ω_m.

This is true even for mild productivity growth differentials which arise in the calibration to the US where the service sector peak productivity growth is 1.5%, only one percentage point lower than the growth in manufacturing. The results are also quantitatively significant: halving the peak employment share of manufacturing reduces GDP per capita in 2010 by 10%. Counterfactual paths of population are even more striking as, due to lower aggregate productivity growth, parents chose quantity over quality as the incentive to invest in education is lowered. This results in a 60% larger population in 2010, underscoring how small changes in growth rates, when compounded over a number of years along a balanced growth path can have large implications. With the calibrated model in hand, I turn to the main question of this paper which is to what extent different peak employment shares in manufacturing can explain variation in GDP per capita gaps today. In the benchmark counterfactual exercise, I simulate model economies with many different values of ω_m and associate each country in the world with the model economy which achieves its peak employment share of manufacturing. This is a common type of counterfactual exercise in the macro-development literature (e.g. Ruggieri et al., 2024, 2023), where by varying a parameter in a model calibrated to a developed economy to replicate a specific feature of a developing country can yield insights into how much that feature can explain differential outcomes in cross-country settings. The results are presented in Figure 10.



(a) GDPPC growth factor

(b) Population growth factor

Figure 10: Calibrated model simulations for different values of ω_m. Each dot is a country with the size of the dot corresponding to its population in 2018. The y-axis shows the model economy growth factor whereas the x-axis shows the growth factor in the data.

Both population and GDP per capita growth factors are significantly related to their model counterparts, with model implied growth factors explaining 27% and 4% of the variation in growth factors in the data respectively. The model is also able to match education gaps across countries even though this is non-targeted. We can see in Figure 11, where I plot a country/year observation

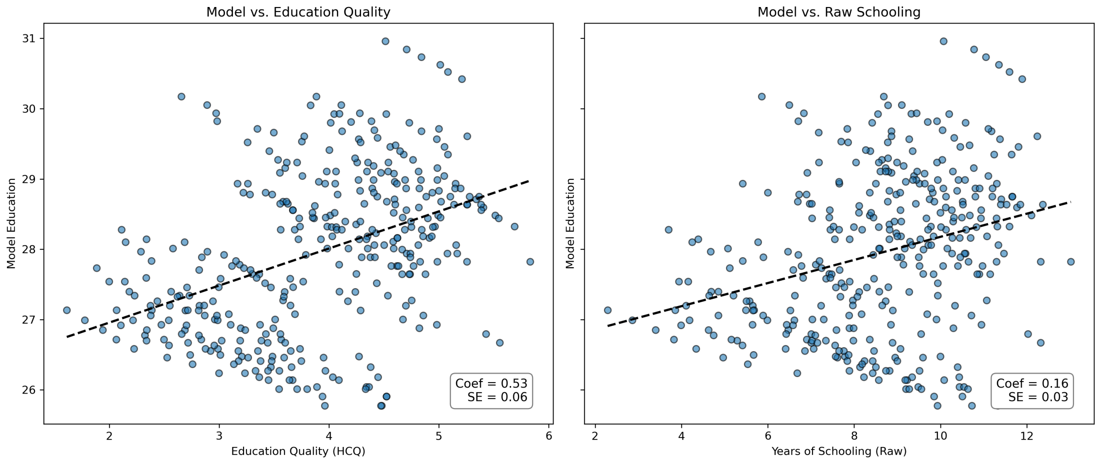


Figure 11: Each dot is a model at the country/year level, y axis shows the Barro Lee (2013) human capital quality index (left) and years of schooling (right) against the model's endogenous education decision.

of educational attainment, against the education choices implied by the model for that country/year observation. The data on educational attainment is from Barro and Lee (2013), who provide basic information on years of schooling and human capital quality indices based on test scores. The relationship between the data and the model implied education metrics is positive and statistically significant. The final exercise I do is to simulate the distribution of income and population in a world in which countries differ from the US only on their initial conditions and the peak employment share of manufacturing they reach. This essentially involves iterating forward along the model simulation for each country starting from its initial level in 1800 for these two variables. The results are shown in Figure 12, where we can see that changes in the growth factor due to differential levels of industrial attainment contribute to a large part of the rise in world income inequality over the past two centuries. Around 14% of cross-country income gaps today can be explained by whether countries transitioning out of agriculture saw employment go to manufacturing before the rise of the service sector. Due to the general equilibrium feedback mechanism linking aggregate productivity growth with education choices and education choices with sectoral productivity growth, the effect of lower manufacturing shares is present even *after* countries have deindustrialized. This is because by raising

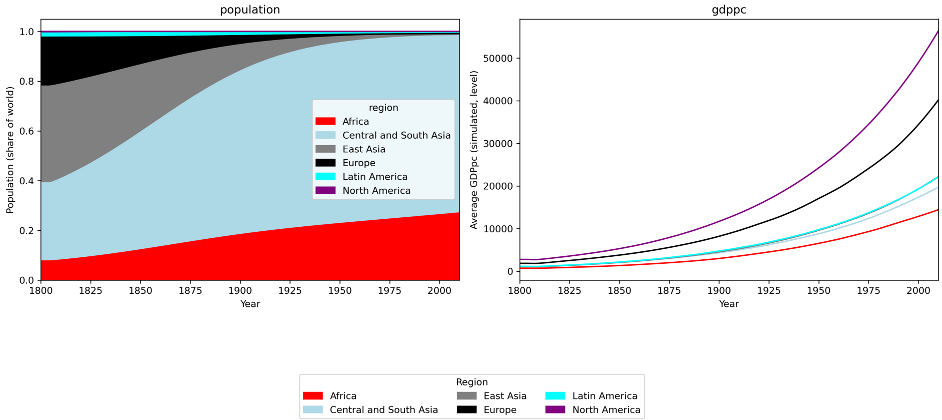


Figure 12: Path of income and population in 175 countries. A country's model implied path is determined by assigning it the model economy which achieves its peak-manufacturing employment share by chanding w_m with all other parameters anchored to the US calibration.

education levels, the service sector in countries which had large manufacturing booms is more productive and grows faster, giving rise to transition paths with persistently different growth rates.

6 Conclusion

This paper develops a unified growth model featuring structural change, endogenous fertility, and firm-level distortions to study the long-run consequences of bypassing industrialization. Calibrated to the historical US experience, the model replicates key stylized facts about the relationship between manufacturing employment and development outcomes. Counterfactual simulations reveal that a country's peak manufacturing employment share is a strong predictor of its current GDP per capita and population, with lower industrialization leading to slower productivity growth, lower education investment, and higher fertility. These mechanisms explain up to 14% of today's cross-country income differences. Future work will extend the counterfactual analysis to assess how trade openness and correlated distortions influence countries' ability to industrialize and converge, shedding light on the role of international trade and policy in shaping the global distribution of income.

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A Proofs

Proof of Proposition 1. We show that the optimal education decision e_t solves the same condition in both regimes of the model.

Regime I: When $w_t \geq \tilde{z}$, the subsistence constraint is slack, and the household chooses fertility and education jointly. Substituting the optimal fertility rule $n_t = \gamma/(\tau + e_t)$ into utility, the problem reduces to:

$$\max_{e_t} \ln \left(\frac{\gamma}{\tau + e_t} \cdot \frac{e_t + \rho\tau}{e_t + \rho\tau + g_t} \right).$$

Taking the first-order condition yields:

$$-\frac{1}{\tau + e_t} + \frac{1}{e_t + \rho\tau} - \frac{1}{e_t + \rho\tau + g_t} = 0,$$

which after algebraic manipulation gives:

$$e_t = \sqrt{g_t \tau (1 - \rho)} - \rho\tau.$$

Regime II: When $w_t \in (\bar{c}, \tilde{z})$, the subsistence constraint binds. The household no longer chooses n_t freely, but education is still a choice variable. In this case, the constraint determines fertility:

$$n_t = \frac{1 - \bar{c}/w_t}{\tau + e_t},$$

and utility becomes:

$$u(e_t) = \text{const} + \gamma \ln \left(\frac{1 - \bar{c}/w_t}{\tau + e_t} \cdot \frac{e_t + \rho\tau}{e_t + \rho\tau + g_t} \right).$$

This again reduces to:

$$\max_{e_t} \ln \left(\frac{1}{\tau + e_t} \cdot \frac{e_t + \rho\tau}{e_t + \rho\tau + g_t} \right),$$

as the multiplicative constants do not affect the first-order condition. Taking the derivative gives the same FOC as in Regime I:

$$-\frac{1}{\tau+e_t}+\frac{1}{e_t+\rho\tau}-\frac{1}{e_t+\rho\tau+g_t}=0.$$

Solving as before, we find:

$$e_t=\sqrt{g_t\tau(1-\rho)}-\rho\tau.$$

Since education must be non-negative, we conclude that in both regimes, the household chooses:

$$e_t^*=\max\left\{0,\sqrt{g_t\tau(1-\rho)}-\rho\tau\right\}.$$

□

Proof of Proposition 2. Let $R_t = w_t(1-n_t(e_t+\tau))$ denote effective income per capita, where the wage is determined by

$$w_t=\alpha\left(\frac{1-\beta}{\bar{r}}\right)^{\frac{1-\beta}{\beta}} h_t^{\alpha}\left(\frac{A_{mt}X}{L_{mt}}\right)^{1-\alpha},$$

and human capital evolves as

$$h_{t+1}=\frac{e_t+\rho\tau}{e_t+\rho\tau+g_t},\quad \text{with}\quad g_t=\sum_{i\in\{a,m,s\}} s_{it}g_{i,t},\quad g_{i,t}=(e_t+\rho\tau)a_{i,t},$$

and $a_{i,t}=\min\{\theta L_t,\bar{a}_i\}$. Households choose fertility according to

$$n_t(e_t+\tau)=\begin{cases}\gamma, & \text{if } w_t\geq\tilde{z}=\bar{c}/(1-\gamma),\\ 1-\bar{c}/w_t, & \text{if } w_t\in(\bar{c},\tilde{z}),\\ 0, & \text{if } w_t\leq\bar{c}.\end{cases}$$

Then the economy evolves in one of the following regimes:

- **Regime I (Modern Growth Regime)**: If $w_t \geq \tilde{z}$, then $n_t(e_t + \tau) = \gamma$ and $R_t = w_t(1-\gamma)$. Effective income per capita grows as long as the growth rate of technology in the manufacturing sector exceeds the growth of manufacturing labor.

- **Regime II (Subsistence-Constrained Regime)**: If $w_t \in (\bar{c}, \tilde{z})$, then $1 - n_t(e_t + \tau) = \bar{c}/w_t$ and $R_t = \bar{c}$. Effective income per capita is constant.

- **Regime III (Collapse Regime)**: If $w_t \leq \bar{c}$, then $n_t = 0$ and $L_{t+1} = 0$. Population collapses unless this regime is avoided. We assume parameters (e.g., large X) are such that $w_t > \bar{c}$ always.

Now we need to prove that a transition from Regime II to Regime I can happen if and only if the household choses a positive education level e. In Regime II, the wage evolves according to:

$$w_t = \alpha \left(\frac{1-\beta}{\bar{r}} \right)^{\frac{1-\beta}{\beta}} h_t^{\alpha} \left(\frac{A_{mt} X}{L_{mt}} \right)^{1-\alpha},$$

and the corresponding growth rate is:

$$\frac{\Delta w_t}{w_t} = \alpha \cdot \frac{\Delta h_t}{h_t} + (1-\alpha) \left(\frac{\Delta A_{mt}}{A_{mt}} - \frac{\Delta L_{mt}}{L_{mt}} \right).$$

We examine each component:

1. Human capital growth. The law of motion implies:

$$h_t = \frac{e_{t-1} + \rho\tau}{e_{t-1} + \rho\tau + g_{t-1}}, \quad h_{t+1} = \frac{e_t + \rho\tau}{e_t + \rho\tau + g_t}.$$

Hence,

$$\frac{\Delta h_t}{h_t} = \left(\frac{e_t + \rho\tau}{e_t + \rho\tau + g_t} \cdot \frac{e_{t-1} + \rho\tau + g_{t-1}}{e_{t-1} + \rho\tau} \right) - 1.$$

This is strictly positive for $e_t > e_{t-1}$, and weakly increasing in e_t.

2. Technology growth. The sectoral technology grows at:

$$\frac{\Delta A_{mt}}{A_{mt}} = g_{m,t} = (e_t + \rho\tau) \cdot a_{m,t}, \quad \text{with } a_{m,t} = \min\{\theta L_t, \bar{a}_m\}.$$

This is strictly increasing in e_t.

3. Labor growth. The fertility rule gives:

$$n_t = \frac{1 - \bar{c}/w_t}{e_t + \tau} \Rightarrow \frac{\Delta L_t}{L_t} = n_t - 1 = \frac{1 - \bar{c}/w_t}{e_t + \tau} - 1.$$

Thus, labor growth is decreasing in e_t, which increases wage growth.

Define the function:

$$\Gamma(e_t, w_t) := (e_t + \rho\tau)a_{m,t} - \left(\frac{1 - \bar{c}/w_t}{e_t + \tau} - 1\right),$$

so that:

$$\frac{\Delta w_t}{w_t} = \alpha \cdot \frac{\Delta h_t}{h_t} + (1 - \alpha) \cdot \Gamma(e_t, w_t).$$

Now evaluate $\Gamma(0, w_t)$:

$$\Gamma(0, w_t) = \rho\tau a_{m,t} - \left(\frac{1 - \bar{c}/w_t}{\tau} - 1\right),$$

and multiply both sides by τ and rearrange:

$$\Gamma(0, w_t) > 0 \quad \Leftrightarrow \quad \rho\tau^2 a_{m,t} + \tau > 1 - \frac{\bar{c}}{w_t}.$$

Thus, if the parameter condition $\rho\tau^2 a_{m,t} + \tau < 1$ holds, and $w_t > \bar{c}$, then:

$$\Gamma(0, w_t) > 0 \Rightarrow \Gamma(e_t, w_t) > \Gamma(0, w_t) > 0, \quad \text{for all } e_t > 0.$$

Moreover, since $\frac{\Delta h_t}{h_t} \geq 0$ for $e_t > 0$, it follows that:

$$\frac{\Delta w_t}{w_t} > 0.$$

Hence, wages grow over time as long as $e_t > 0$, and by continuity, will eventually satisfy $w_t \geq \tilde{z}$, completing the transition to Regime I. $\square$

B Empirical Analysis

B.1 Fertility and Structural Change.

In this section I provide further evidence on the cross country relationship between fertility and structural change. In Figure 2 I show that fertility rates are, on average, strongly related to a country's composition within its manufacturing sector. This relationship also holds if we disaggregate the data at the country/year level. We can see this by running the following regression:

$$tfr_{c,t} = \alpha_c + \delta_t + \beta \left(\frac{\%Man._{c,t}}{1 - \%Agr._{c,t}} \right) + \Gamma' X_{c,t} + \varepsilon_{c,t}$$

Where X is a vector of controls including log of gdp per capita and the agricultural share of employment. Table 2 shows that the manufacturing share of the non-farm labor force is a strong negative predictor of a country's total fertility rates even when controlling for gdp per capita, the agricultural employment share and country and year fixed effects.

The estimated effect of the manufacturing employment share on total fertility is not only statistically significant, but also economically meaningful. When controlling for log of gdp per capita, the agricultural employment share, country and year fixed effects, a 1pp increase in the manufacturing employment share of non-farm labor is associated with a reduction of total fertility of 0.45 or 14% of the sample average. To understand whether the relationship between manufacturing and total fertility rates is driven by unobserved variation within

Table 2: OLS Regressions

	(1)	(2)	(3)	(4)	(5)
% Man./ (1-% Agr.)	-2.522*	-3.352***	-3.352***	-4.204***	-4.025***
	(-2.03)	(-4.22)	(-4.22)	(-4.80)	(-4.59)
Log GDP p.c.		-0.790***	-0.790***	-0.763***	0.399***
		(-5.60)	(-5.60)	(-5.35)	(3.91)
% Agr.		1.708*	1.708*	1.695*	1.759**
		(2.45)	(2.45)	(2.41)	(2.72)
N	5249	5249	5249	5249	5249
R2	0.0161	0.644	0.644	0.666	0.964
Country FE	no	no	no	no	yes
Year FE	no	no	no	yes	yes

t statistics in parentheses
Dependent variable is total fertility rate. Standard errors are clustered at the country level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

countries and years, we can use microdata from IPUMS to quantify the fertility differentials across the sectors of the economy within a country for multiple samples/years. The total sample includes 46 million women aged between 15 and 45 from 89 low and middle income countries, which comprises all samples available through IPUMS between the years of 1970 and 2020 from low and middle income countries. When a woman is not working, I assign her the sector of the husband. When a woman is unmarried and does not work or when both the husband and the woman have no reported sector, I am forced to drop them, which leaves me with a sample of over 40 million women in 89 different low and middle income countries. Using this dataset, I regress the woman's total fertility rate on a wide array of controls to remove selection driven by age, rural-urban status, country, time period and their educational attainment. I then estimate the residuals from model 13 and average them by sector.[11]

$$nchild_{i,c,t} = \alpha_{a,c,t} + \delta_{e,c,t} + \gamma_{n,c,t} + \xi_{u,c,t} + \varepsilon_{i,c,t} \tag{13}$$

11. This is equivalent to showing the sector fixed effect in a model with no constant so that the reference category is the sample average.

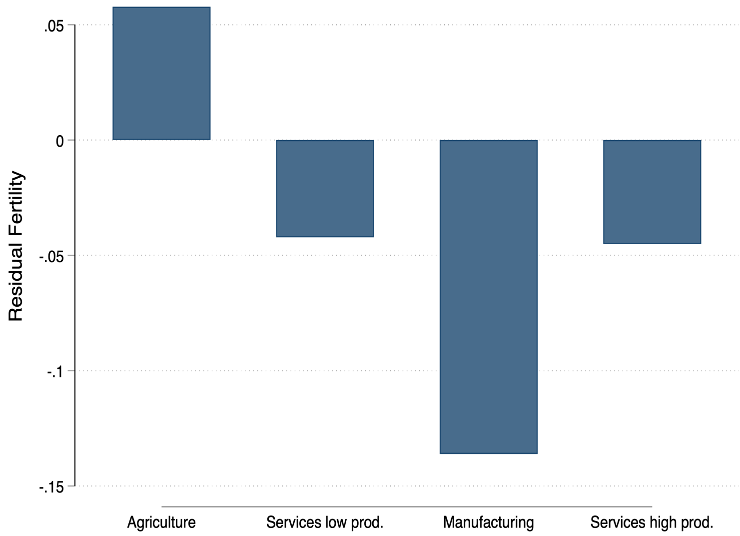


Figure 13: Average residuals by income group and sector from a regression of total fertility on contry-year fixed effects, urban dummy and age fixed effects. The data comprises samples of women between 15 and 45 from 89 low and middle income countries. Where women do not work or have missing sector information, I assign them to the husband's sector. Source: IPUMS International Survey Data.

Where i, c, t, a, e, n, u refer to individual, country, year, age, education level (detailed classification), employment status and urban status respectively. The regression shown in equation 13 includes 4027 fixed effects, cotrolling for time and country varying variables which could affect fertility. This exercise shows that there are strong differences in average fertility rates across the sectors of the economy. Not surprisingly, women working in agriculture have the highest residual fertility rates. However, consistently with the cross country data in Figure 2 there is heterogeneity within the non-farm sector with manufacturing women having the lowest residual fertility rates. Considering the sample average fertility rate of 2.1, this is approximately a 5% difference.

B.2 Estimating Trade shocks

This section builds on the descriptive evidence presented in Section 2 by using IPUMS microdata to run shift-share regressions of employment shares in different sectors against a local trade shock. The data encompasses 95 countries, each generally available for at least least three different samples between the years from 1990 to 2010, when the largest trade liberalizations took place. These samples are nationally respresentative and contain from 1 to 10 % of the population.

The empirical methodology used is very similar to that in Autor et al. (2013), where the shares of employment in trade affected sectors will provide variation in the incidence of trade at the sub-national level. Identification assumptions rely on the exogeneity of nation-wide trade patterns to the evolution of regional outcomes. This type of exercise has previously been possible only with detailed administrative data, as mapping workers to a product code classification system such as SITC4 or HS4 requires precise information on the sector in which the worker was active which goes beyond the standard 2-digit classification available in harmonized survey data (e.g. Autor et al., 2013, 2014; Dix-Carneiro and Kovak, 2017). By building a crosswalk linking textual descriptions of industries present in the IPUMS International data,[12] to SITC4 codes, I am able to accomplish this without requiring administrative data containing 4-digit industry classifiers. This has one main advantage being that I can explore the relationship between trade shocks and regional outcomes at the *global* level, which would not be possible unless one had admin data from *all* of the 95 countries which provide survey data through IPUMS International. The drawback is that IPUMS international generally provides samples comprising between 1% and 10% of the population. If one had access to the full universe, it would be possible to disaggregate regions at the level of commuting zones as done in Autor et al. (2013) and Dix-Carneiro and Kovak (2017), thereby gaining additional degrees of freedom. Using the IPUMS data I am restricted to analyzing this relationship using level 1 consistently defined administrative regions.

Table 3: Industry Descriptions and Corresponding SITC4 Codes

Sample	Industry Description	SITC4 Code
Ghana 2000	Agriculture and animal farming combined	0111, 0112, 0113,...
Ghana 2010	Agriculture and hunting	0111, 0112, 0113,...
Ethiopia 1984	Agriculture and livestock production	0111, 0112, 0113,...

12. This is IPUMS variable IND, which has varying codes by country/year sample.

Table 3 illustrates one of the main contributions of the paper: the construction of a crosswalk mapping textual industry descriptions to SITC4 codes. In the raw (non-harmonized) IPUMS data industries are reported in much greater detail than the harmonized variables, with considerable breakdown in the tradeable goods sector. The challenge is that these industry descriptions vary not only by country but also by sample. While the core classification may remain fixed, e.g. one category for "plants" and "animals" as in Table 3, the textual description of this category can still vary across samples within the same country. Using the ChatGPT API I map over 10 thousand text based industry classifications to SITC4 codes. This crosswalk is consistent across API calls.[13] Using this crosswalk, I construct regional trade shocks as follows:

$$\text{shock}_{i,c,t} = \sum_j s_{i,c,t-1,j}(M_{c,1990-2000,j} - M_{c,1980-1990,j})$$

Where $s_{i,c,t-1,j}$ is the share of employment in industry j and region i of country c at time $t-1$ and $M_{c,1990-1980,j}$ is the average value of imports between 1990 and 1980 of products corresponding to industry j arriving in country c between 1980 and 1990. This methodology is similar to that in Autor et al. (2013) but varies from that used by Autor et al. (2014) and Dix-Carneiro and Kovak (2017) in that they use variation in tariff changes at the industry level as a shifter instead of the amount of traded goods. This is preferable as tariff changes are a more relevant measure of trade protection than imports which also reflect local demand and supply shocks in the country of origin (Kovak, 2013). However, the global scope of this analysis means that constructing variation in tariff changes at the industry level would in practice be extremely cumbersome.[14] I then run the following regression model:

$$y_{i,c,t} = \alpha_i + \delta_t + \beta \ln(\text{shock}_{i,c,t-1}) + \epsilon_{i,c,t}$$

Where y is a regional outcome variable, α and δ are country and time fixed effects and ϵ is a classical error term. Guided by the stylized facts I consider

13. Creating the crosswalk several times shows similar results.
14. I am exploring data sources to find a way to automate this.

five outcome variables: employment shares in all three sectors plus fertility. I further divide employment in the services sector by the high-productivity FIRE services and group the rest in the low-productivity category.[15]

Table 4: OLS Regressions

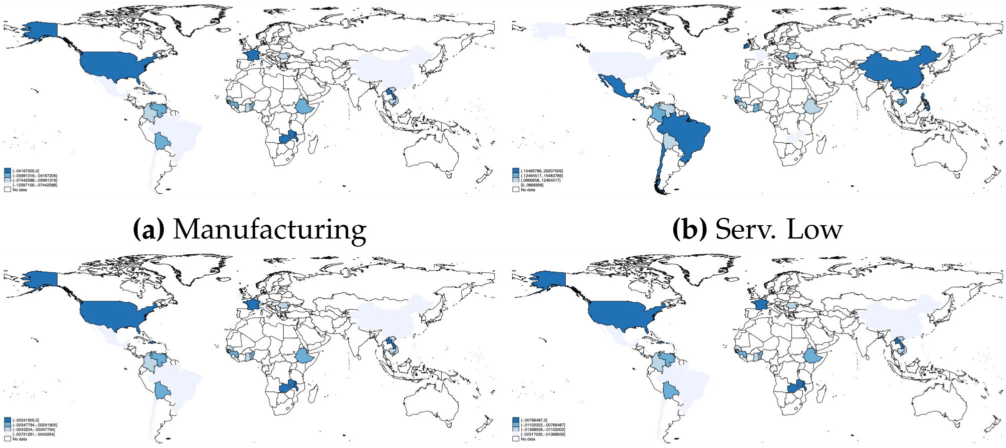
	(1) Manufacturing	(2) Serv. High	(3) Serv. Low	(4) Agriculture	(5) Fertility
(mean) ln_shock	-0.0128*	-0.000743	0.0266**	-0.0140***	-0.00235
	(-2.22)	(-0.91)	(3.03)	(-3.42)	(-0.10)
N	566	566	566	566	566
R2	0.856	0.895	0.732	0.871	0.715
Country FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results are consistent with the stylized fact and quantitatively important. Doubling trade exposure decreases the share of employment in manufacturing by 1 pp, decreases the share in high productivity services by 0.4pp and increases the share in low productivity services - generally retail services - by 1.9pp and average total fertility by 0.1. To get a sense of these results, the average employment share of manufacturing in this sample is around 14%, meaning that doubling trade exposure can lead to a 7% decline. There is also a small, but statistically significant negative effect of increasing trade exposure on the agricultural employement share of 0.5pp, this effect is small as the average employment share in the agricultural sector in this sample is above 30%, far larger than the share in high productivity services and manufacturing.

These results are, however, estimated in a model which pools together all regions from all countries. Using the subnational variation in outcomes and trade shocks, we can also estimate these relationships separately for each country to allow for heterogeneity in the effect of trade shocks. This is what I do next in Figure 14.

15. FIRE comprises finance, insurance real estate, health care and education.



(a) Manufacturing **(b)** Serv. Low

(c) FIRE **(d)** Fertility

Figure 14: Country level impact of trade shocks on regional outcomes.

The results show that there is a substantial amount of heterogeneity in the effect of trade shocks across countries. For instance, in Brazil the effect of trade on manufacturing is close to zero and insignificant while in China it is negative, significant and larger than the overall effect in Table **??**; whereas the effect on high productivity services is negative and statistically significant in both countries. Even within regions, such as in Sub-Saharan Africa, we see large amounts of heterogeneity. Although the sign of the coefficients generally is always consistent with those in the pooled regression models in Table **??**, the magnitudes can vary substantially across countries.