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Essays on Manufacturing and Growth

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Essays on Manufacturing and Growth

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Abstract

The first chapter of this dissertation studies the role of human capital in generating economic convergence through its impact on manufacturing productivity growth and allocation of labor across sectors of the economy. I confirm and extend existing results showing that productivity in manufacturing – unlike its economy-wide counterpart – has exhibited convergence; that is, countries further behind the technology frontier tend to catch up to those on the frontier. I then show that the convergence in manufacturing is (a) somewhat accelerated by countries' tertiary education levels and (b) faster in high-tech industries. Perhaps surprisingly, this is not driven by tertiary education's direct impact on the rate of catching up in any of the high-tech industries. Instead, tertiary education has a composition effect: it increases the share of labor allocated to the fast-converging high-tech sector. Since low-income countries usually have low shares of college-educated workers, these findings help explain "premature deindustrialization" in those countries, a process where, despite the potential of manufacturing to generate economic convergence, it is the sectors with fewer growth prospects (e.g, services) that are expanding. It also helps explain why previous studies tended to find negligible effects of tertiary education on growth.

The second chapter of this dissertation investigates the link between these labor inflows and foreign direct investment (FDI). Using a decomposition for labor productivity change with sectoral level data for Latin American and Asia countries between the years 1970 and 2011, I find that FDI has an important role in explaining this misallocation of workers across sectors. Furthermore, results indicate that this misallocation is driven mainly by a growth in the service sector.

Dedication

In the loving memory of my mother, Angela, whose absence left a permanent gap in my life, wherever you are, this is for you!

In the loving memory of my grandparents, Alonso and Hugo, who incentivized me to study and achieve my dreams

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Chapter 1

Human Capital, Manufacturing and Technological Intensity: A Cross-Country Analysis

1.1 Introduction

Two of the central questions that fueled the rise of the literature on economic growth since the late 1980s were the issue of economic convergence: do developing countries grow faster than rich ones? and the role of human capital in economic growth: do countries with more educated populations grow faster? Early research, particularly Baumol (1986) and Mankiw et al. (1992) suggested that the answer to both questions was a yes. This line of research was in line with prevailing theories of growth. However, subsequent research overturned many of the early conclusions. First, absolute convergence was not a fact; economies appeared to converge at a slow pace of 2% per year and only after controlling for many steady-state determinants. Second, the role of human capital was not very robust across studies and econometric specifications. For instance, Bils and Klenow (2000) find that the channel from schooling to growth is too weak to explain plausibly more than one-third of the observed relation between schooling and growth. In the same direction, Pritchett (2001) shows no association between increases in the labor force's human capital and the output growth rate per worker. In the opposite direction, Glaeser et al. (2004) and Cohen and Soto (2007) find that human capital is a primary source of economic growth. Recently, however, the resurgence of economic growth in developing countries led researchers to revisit some of the older questions using new approaches. Empirical studies focusing on a more disaggregated analysis of the growth process and theoretical work on the interaction of human capital and structural shifts across sectors led to some new results: within manufacturing, convergence does seem to be occurring at a pretty robust rate, and the role of structural transformation and allocation of resources, mainly labor, across sectors seems to play a crucial role in the process of development. This paper contributes to this literature by revisiting the process of productivity convergence within manufacturing and further investigating its determinants by disaggregating industries according to the technological intensity and establishing the connection between human capital and the process of catching up. Specifically, I estimate the convergence rate of labor productivity in manufacturing at the 2-digit ISIC level in a large sample of countries between 1965 and 2015. I confirm that the findings reported in the literature hold in a larger and more extended sample. There is rapid convergence at rates of up to 5.73% per year.

Most importantly, there is evidence of unconditional convergence with convergence rates up to approximately 2.11 %. Turning to investigate the causes of this phenomenon, I establish that education levels, especially the tertiary education achievement levels, play a role by fostering the catch-up rate. None of the other standard growth regressors, such as trade openness and different measures of institutional quality, have a similarly robust positive effect on convergence. I then allow the convergence rate to differ for highly technologically intensive industries versus those with low and medium technological intensity. Here, again confirming and extending some recent results (Erten and Schwank, 2021), I find that high-technology-intensive industries exhibit a faster convergence rate than low-technologically-intensive industries. These two findings, that education speeds up convergence within manufacturing and that technologically intensive industries converge faster, naturally lead to a hypothesis that education, especially at the tertiary level, disproportionately affects growth in high-tech industries. It accelerates the rate of technological adoption, which boosts growth in the high-tech manufacturing industries. However, this hypothesis is rejected by the data as education does not appear to affect any industries disproportionately. Hence, the effect of education on manufacturing convergence must work differently. I investigate this by estimating the effect of education on labor allocation across industries with different technological intensities. Indeed, I find that a higher level of tertiary education correlates with a higher share of labor in high-tech industries. In addition, I conclude that the faster rate of convergence exhibited by countries with more educated workers is mainly due to their ability to expand the fast-growing high-tech industries. Hence, it suggests that the faster rate of convergence of developed nations has less to do with the ability of those workers to speed up the high-tech industries' growth. These results suggest that the rate of growth in the high-tech industries may be determined primarily outside of the countries – by the nature of the technologies, the R&D investments by the technology leaders, or other global factors. However, the overall rate of growth of labor productivity in manufacturing is determined by the country's human capital.

It is tempting to reconcile these two findings, that education only slightly speeds up convergence within manufacturing and that technologically intensive industries converge faster, by one of the following arguments. Education may have a positive but small effect on the rate of catch-up growth in all industries. Alternatively, perhaps education has a more significant impact on high-tech industries. However, since most countries have a low share of those industries (and college-educated workers), this effect has a negligible effect on overall manufacturing growth. The latter explanation is perhaps more appealing because of the many theoretical channels by which higher skills and education connect to technology adoption and innovation, both hallmarks of high-tech industries. However, neither of these hypotheses finds support in the data. Education, even at the tertiary level, does not disproportionally affect high-tech industries, meaning that education's effect on manufacturing convergence must work differently. I investigate this by estimating the effect of education on labor allocation across sectors. Indeed, I find that a higher level of tertiary education correlates with a higher share of labor in high-tech industries. I conclude that the faster manufacturing convergence rate exhibited by countries with more educated workers is mainly due to their ability to expand the fast-growing high-tech sectors. This fact suggests that the faster rate of convergence of developed nations has less to do with the ability of those workers to speed up the growth within any of the sectors themselves, even the high-tech sector. Results instead suggest that the rate of growth in the high-tech sectors may be determined mainly outside of the countries either by the nature of the technologies, the R&D investments by the technology leaders, or other global factors. However, the overall rate of growth of labor productivity in manufacturing is determined by the country's human capital. This level of human capital enables manufacturing to expand into the high-tech sectors, explaining why the literature has rarely found significant effects of tertiary education on growth. To the extent that this kind of human capital only affects the ability to expand a sector of the economy but does not necessarily boost economy-wide growth, its impact will be small in countries with a low share of workers that enroll at universities. Even more importantly, since low-income countries usually have low shares of college-educated populations, these findings help explain ”premature deindustrialization” in those countries. This is a process where, despite the potential of manufacturing to generate economic convergence, the sectors with fewer growth prospects (e.g., services) are expanding.

The paper is organized as follows. Section 1.2 provides an overview of the existing literature and discusses the contributions of this paper. Section 1.3 describes the variables used in the empirical specifications. In addition, Section 1.3 describes the strategy employed to recover convergence parameters by using nominal instead of real values . In Section 1.4, I discuss the convergence results and their implications. Section 1.5 addresses tertiary education's composition effect on employment shares. Finally, Section 1.6 summarizes the results and limitations with possible extensions for further research.

1.2 Related Literature

This paper is related to several significant strands of the economic growth literature. First, it is related to the research exploring convergence which dates back to Abramovitz (1986) and Baumol (1986), which Johnson and Papageorgiou (2020) recently reviewed. The question of whether developing countries tend to grow faster than their affluent counterparts and catch up has been one of the motivators of the original wave of empirical growth research since DeLong (1986) and Mankiw et al. (1992). The consensus that emerged is that absolute convergence, that is, unconditional faster growth by lagging economies, is not the case except among groups of highly homogeneous units, such as OECD countries, US states, and Japanese prefectures. Barro and Sala-i-Martin (1991) and Bernard and Jones (1996) are examples of findings in this direction.

In a broader sample, countries converge only to relative steady states, defined by characteristics such as institutions, education levels, openness to trade, or investment rates. My work is directly related to a new start in the literature, originating with the work of Rodrik (2013). This work looks at convergence at a more disaggregated level. It appears that within manufacturing, convergence is much more robust: it is faster, even in its absolute form, among a broader and more heterogeneous group of countries.[1] Recent work, such as Choi (2004) and Erten and Schwank (2021), has established that this behavior is more pronounced among high-tech manufacturing industries. I confirm and extend some of these results.

The presence of rapid convergence in manufacturing raises a natural question of why developing countries are not expanding those sections of their economies to reap the benefits of catch-up growth. In fact, there is evidence that the opposite has been happening, with more labor force moving to slower-growing service industries across much of the developing world, a process sometimes referred to as "premature deindustrialization" (Rodrik, 2015). This paper attempts to address this question by focusing on the role of education in shaping an economy's industrial landscape. In particular, I am motivated by two areas of research. One is the historical evidence of the role of education in transforming western economies from agriculture to manufacturing.

A classic example is Japan, which vigorously promoted education after the 1870s, a period that also matches its early industrial development.[2] Other examples include Mexico and Peru, which relied on foreign technical expertise to industrialize (Ota, 1997; Yamawaki, 2002). In contrast, India's British rulers viewed the sub-continent as a source of primary goods, leading to negligible investments in human capital in the area (Kohli, 2004). Similarly, Sub-Saharan African countries could only invest significantly in education after decolonization (Sender, 1999).[3] The lag in educational investments persists in the region (Moyo, 2018). Concomitantly, most of the region's countries are premature deindustrialisers.

The other motivation for studying the role of human capital in manufacturing convergence is a series of theoretical results in Aghion and Howitt (2005), Zeira (2009), and Zeira and Zoabi (2015). From an empirical perspective, Aghion et al. (2009), Squicciarini and Voigtländer (2015), Szirmai and Verspagen (2015), and Madsen and Martin (2017) also provide similar results. These results suggest that the high skills of the labor force and the expansion into modern industries are highly related. In other words, these works stress the importance of the "density in the upper tail of knowledge" in developing more innovative industries, as in Mokyr (2005a; 2009a). In particular, Aghion et al. (2009) develop a multi-state endogenous growth model based on Acemoglu et al.

[1] Herrendorf et al. (2022) find opposing results. Part of the discrepancy in results with Rodrik (2013) lies in their data collection.

[2] There is a debate on whether industrialization preceded the Meiji Era. However, there is a consensus in stating that significant human capital accumulation in terms of literacy rates preceded industrialization (Crawcour, 1974; 1997a).

[3] For example, the first Congolese university only opened its doors in 1954. A decade later, only thirteen Congolese students enrolled in engineering and natural sciences programs (Mantels, 2007).

(2003), in which "high brow" education fosters technological innovation and "low brow" education fosters technological imitation. Fundamentally, Aghion et al. (2009) posit that innovation makes intensive use of highly educated workers, while imitation relies more on combining physical capital with less educated labor. Similarly, the empirical findings of this paper support the fact that the effect of education is asymmetric across sectors, highlighting that this effect on growth relies strongly on the innovative nature of sectors.

This research is also related to the literature on the interaction between technology and human capital (Benhabib and Spigel, 1994). Nevertheless, this research focuses more squarely on the role of education in structural change. In a relatively recent article in the Handbook of Economic Growth, Herrendorf, Rogerson, and Valentinyi (2014) conclude that the role of human capital in structural transformation is one of the areas we know very little about. They conclude the article by calling for more quantitative studies. This paper is an attempt in this direction.

Finally, my work contributes to the more general question of the role of human capital in economic growth. The long list of theoretical models and anecdotal evidence suggesting that education should be central to growth has been matched by less unambiguous evidence. Especially surprising is the lack of evidence of any role of tertiary education, which would contribute to technology adoption and innovation, given that they are important engines of growth (Aghion and Howitt, 2005). My results contribute to this debate by showing that education may play a different role from previous explanations. It may contribute to growth by shaping the allocation of resources across sectors and industries, not by boosting productivity growth in any of the sectors themselves. This compositional effect may be strong at the margin. However, its economy-wide effect may be small if confined to a small section of the economy.

1.3 Data Description and Methods

The empirical analysis uses three primary sources: industry-level data on formal manufacturing employment and value-added and country-level data on educational attainment by levels (primary, secondary, and tertiary). I merge Barro and Lee (2013) and INDSTAT2 for the human capital variables specifications. In Section 1.3.3, I describe the variables used for the specifications of Section 1.4.4. Table 1.1 summarizes all the variables used and constructed and each data source. Finally, Section 1.3.4 describes the strategy used to recover convergence parameters using nominal instead of real productivity levels and the econometric to measure catching up.

1.3.1 Industry-Level Formal Manufacturing Data

I use data from UNIDO's INDSTAT2 database, which provides data on employment, value-added, wages, and the number of establishments at the industry level for an extensive range of countries. In this database, industries are classified following the International Standard Industrial Classification of All Economic Activities (ISIC) two-digit level of disaggregation (UNIDO 2021). The INDSTAT2 database covers up to 23 manufacturing industries for each country. This database goes back to the 1960s, including more than 100 countries. I use the information on value-added and employment to compute labor productivity and decadal growth rates in the upcoming specifications.

The coverage of developing countries, although quite extensive compared to other datasets, is still limited, making horizons longer than ten years impossible. To maximize observations, I group years into decades 1965-1975, 1975-1985, 1995-2005, and 2005-2015. In Sections 1.4.1 and 1.4.2, I also group years into 5-year periods.

It is essential to state that UNIDO gathers data from industrial surveys. In general, industrial surveys exclude microenterprises and informal firms. For developing nations, this exclusion is non-trivial, given the size of the informal sector in those economies. In addition, these industrial surveys generally exclude firms with less than ten employees. Hence, findings should be read as applying to more formal, organized parts of manufacturing and not to micro-enterprises or informal firms.[4]

Furthermore, I use the technology intensity definition proposed by the OECD and categorize industries into three groups based on R&D intensities (i.e., direct research and development expenditures as a percentage of gross output): low, medium, and high-technology intensive industries (Galindo-Rueda and Verger, 2016). The logic behind the classification is that, on average, high-technology-intensive industries invest more in R&D relative to their sales than medium and low-tech industries. Hence, high-technology-intensive industries are more innovative than medium and low, with medium industries being more innovative than low industries. The current database's industrial classification allows me to group industries following the technology intensity definition proposed by the Organization for Economic Cooperation and Development (OECD) (Galindo-Rueda and Verger, 2016). Table 1.2 shows the classification of industries in this framework.

[4] Diao et al. (2021) find significant differences in labor productivity between informal/small and formal manufacturing firms in Tanzania and Ethiopia. This paper will not address such issues.

The low-technology-intensive industries are food and beverages; tobacco products; textiles; wearing apparel and fur, leather; leather products and footwear; wood products; paper and paper products; printing and publishing; furniture; and recycling. Medium-technology-intensive industries include coke, refined petroleum products, nuclear fuel; rubber and plastics products; other non-metallic mineral products; basic metals; and fabricated metal products. Finally, high-technology-intensive industries include chemical and chemical products; machinery and equipment; office, accounting, and computing machinery; electrical machinery and apparatus; radio, television, and communication equipment; medical precision and optical instruments; motor vehicles, trailers and semi-trailers; and other transport equipment.

1.3.2 Country-Level Educational Attainment Data

The educational variables are measures of educational attainment for the entire population across countries. This information is extracted from Barro and Lee's (2013) Education Attainment Dataset. In this paper, I use the variables indicating percent of people within countries with completed primary, secondary, and tertiary education. In addition, I use average years of schooling in primary, secondary, and tertiary education. These variables are available for developed and developing countries. The dataset with human capital variables merges INDSTAT2 and Barro and Lee's (2013) dataset. This merged dataset contains 103 countries between 1965 and 2015.

1.3.3 Worldwide Governance and World Development Indicators

In Section 4.4, I use data from the World Development Indicators (WDI) (The World Bank, 2020a) and from the Worldwide Governance Indicators (WGI) (The World Bank, 20218a) database to assess whether growth determinants other than education levels have a similar effect on convergence. Specifically, I use exports plus imports as a percent of Gross Domestic Product (GDP) from the WDI to proxy for trade openness. Moreover, I use institutional quality variables measuring voice and accountability, political stability, the rule of law, and regulatory quality from the WGI to account for the role of institutions.

After merging UNIDO's INDSTAT2 database with the WDI, the final dataset contains 80 countries between 1965 and 2015.

After merging UNIDO's INDSTAT2 database with the WGI, the final dataset contains 65 countries between 1965 and 2015.

1.3.4 Convergence Regression and Labor Productivity Measures

In its broadest form, the convergence hypothesis states that economic growth favors the followers relative to the leaders or that there is "an advantage to backwardness." In its extreme form, it implies that in the long run, all countries achieve the same standard of living. At the same time, a restricted version might state that conditional on some characteristics, economies further behind the frontier grow faster and catch up (Papageorgiou and Johnson, 2020). A convergence regression is one of the most direct tools for investigating convergence in a sample of economic units. This is a regression of growth over a period of time on the level at the initial date of the interval over which the growth is computed (perhaps relative to the frontier level at that initial time). In the context of aggregate output, the researcher would regress the real GDP growth per worker for the sample on the (log) level of real GDP per worker in the initial year of the sample. A negative and significant estimate of the coefficient on the initial condition variable would indicate a tendency for convergence. A panel structure allows the use of multiple periods.

A convergence test of this kind will serve as the basis for the investigation in this paper. However, before turning to the empirical specifications, I will briefly discuss one way in which the industry-level analysis departs for aggregate convergence studies, namely the use of nominal as opposed to real productivity levels.

Dividing nominal value added by employment in nominal US dollars, I calculate nominal labor productivity for each industry i in country j in year t. Call y_{ijt} the log of nominal labor productivity in industry i in country j in year t. Following Rodrik (2013), the real growth of labor productivity Δq_{ijt} is given by $\Delta q_{ijt} = \Delta y_{ijt} - \pi_{ijt}$. In this setup, π_{ijt} represents the increase in the industry-level deflator and Δ denotes percent changes. To estimate industrial productivity growth, I assume that each industry's real labor productivity growth is a function of country-specific conditions and a convergence effect. This convergence effect is proportional to the gap between each industry's productivity and the frontier technology, represented by q^*_{it}. Thus,

$$\Delta q_{ij,t} = \beta(q_{ijt} - q^*_{it}) + D_j, \tag{1.1}$$

where $\Delta q_{ij,t}$ is labor productivity growth (measured in US dollars) over a time period, and D_j

is a dummy variable that stands for all time-and industry-invariant country-specific factors. The convergence coefficient of interest is given by β.

As in Rodrik (2013), I assume a common global (US dollar) inflation rate for each individual industry up to an idiosyncratic (random) error term ϵ_{ijt}, such that $\pi_{ijt} = \pi_{it} + \epsilon_{ijt}$. This assumption is crucial since it builds from the fact that manufactures are tradable goods and face common world prices. In addition, I assume that US dollar inflation rates are not systematically correlated with an industry's distance from the technological frontier.

Hence, by adding π_{ijt} on both sides of Equation (1.1), I can express the growth rate of nominal labor productivity as

$$\Delta y_{ij,t} = \beta(q_{ijt} - q^*_{it}) + \pi_{ijt} + D_j. \tag{1.2}$$

Substituting $\pi_{it} + \epsilon_{ijt}$ for π_{ijt} in Equation (1.2), I obtain

$$\Delta y_{ij,t} = \beta(q_{ijt} - q^*_{it}) + \pi_{it} + D_j + \epsilon_{ijt}. \tag{1.3}$$

Equivalently, I can express Equation (3) as

$$\Delta y_{ij,t} = \beta q_{ijt} + D_{it} + D_j + \epsilon_{ij,t}, \tag{1.4}$$

where D_{it}, which stands for (π_{it} - βq^*_{it}), represents a set of industry and period dummies. This strategy allows me to regress labor productivity growth in nominal US dollar terms on the initial levels of labor productivity. In this framework, the more negative the β, the larger the magnitude of the estimated convergence coefficient. In other words, the larger the coefficient β in absolute terms, the larger the estimated productivity growth. The coefficient β in Equation (1.4) measures the conditional convergence coefficient given country fixed effects D_j. To obtain the unconditional convergence rate, I drop country fixed effects. In Section 1.4, I test the variables of interest by interacting them with the initial log of nominal value added per worker, y_{ijt}.

1.4 Convergence Results

1.4.1 Convergence in Manufacturing

To obtain a visual representation of convergence in aggregate manufacturing, I plot the growth rate of labor productivity for 2000-2019 on the vertical axis over the initial log level of labor productivity for the same period on the horizontal axis. I show this in Figure 1.1. As can be seen, Figure 1.1 shows a steep slope indicating the evident signs of unconditional convergence in the data for aggregate manufacturing. In other words, Figure 1 shows that manufacturing industries that started with lower labor productivity experienced faster growth at the end of the period. Nevertheless, this figure lacks a set of needed controls presented in the upcoming specifications.

Following the strategy previously described in Section 1.3.4, I estimate a model along the lines of Equation (1.4) to assess convergence within overall manufacturing. The model is given by

$$\Delta y_{ij,t} = \alpha + \beta_1 y_{ijt} + D_{it} + D_j + D_t + \epsilon_{ij,t}, \tag{1.5}$$

where $\Delta y_{ij,t}$ represents the growth rate of labor productivity over a time period in industry i, country j at time period t; Δ represents the period change and y_{ijt} is the log of initial labor productivity at the beginning of the time period. In this empirical analysis, I utilize 5 and 10-year periods. D_j represents country fixed effects that control for the country's time-invariant heterogeneity, and D_t represents period fixed effects controlling for changes in each period. Finally, D_{it} controls for period $\times$ industry fixed effects.

As shown in Section 1.3.4, β_1 represents measures of the conditional convergence coefficient with country fixed effects. I only drop the country fixed effects to measure the unconditional convergence coefficient. In this framework, the country fixed effects represent the policies, institutions, and other country-specific circumstances. In other words, the country fixed effects account for the relative steady states defined by countries' characteristics. Hence, dropping the country fixed effects would imply evaluating convergence to a common steady state level. Table 3 shows results in the unconditional and conditional scenarios.

In the unconditional and conditional scenarios, it is possible to observe that labor productivity in manufacturing exhibits convergence. In other words, results indicate that countries further behind the technological frontier tend to catch up with the leaders. The convergence rate in the unconditional scenario using 10-year periods is approximately 2.11 %. The convergence rate in the same scenario using 5-year periods is approximately 2.71 %. The convergence rate in the conditional scenario using 10-year periods is approximately 5.73 %. The convergence rate for the same scenario but using 5-year periods is approximately 8.02%.[5] The present results support the existing literature (Madsen and Timol, 2011; Rodrik, 2013) confirming that labor productivity in manufacturing- unlike its economy-wide counterpart- exhibits convergence.

1.4.2 Convergence in Manufacturing by R&D Intensity

In Section 1.4.1, I confirm previous findings, showing that labor productivity in manufacturing exhibits convergence. Madsen and Timol (2011) suggest that this convergence in manufacturing has been driven by R&D spillovers as predicted by the Schumpeterian theories of growth (Aghion and Howitt, 2005). Consequently, this implies that more innovative industries should converge faster than less innovative ones. To obtain a visual representation of convergence among manufacturing industries, I plot the growth rate of labor productivity for the period 2000-2019 on the vertical axis over the initial log level of labor productivity on the horizontal axis. Nevertheless, as opposed to Figure 1.1, I subdivide industries by their technology intensity categories.

As can be seen, Figures 1.2 to 1.4 show steep slopes indicating evident signs of unconditional convergence for each subset of industries. In other words, these figures show that manufacturing industries with lower initial log levels of labor productivity experienced faster growth at the end of the period. In particular, Figure 1.4 (high-tech) shows a steeper slope than Figure 1.2 (low-tech). Although the figures undeniably show differential convergence rates among the subsets of industries, they do not account for many controls presented in the upcoming specifications.

Finally, I can test whether industries show differential convergence rates given their R&D intensity categories given the OECD definition. To capture these differential convergence rates, I employ a fixed effects specification with an interaction coefficient between the log of initial labor productivity and the indicators variables representing R&D intensity categories. The specification is given by

$$\Delta y_{ij,t} = \alpha_0 + \beta_1 y_{i,j,t} + \beta_2 y_{i,j,t} \times TECH + D_t + D_{it} + D_j + \epsilon_{ij,t}, \tag{1.6}$$

[5] As noted by Barro (2012), growth regressions with country fixed effects yield upward estimates as the time horizon in the analysis becomes shorter. This is due to the Hurwicz-Nickell bias (Hurwicz ,1950; Nickell, 1981). As the period grows, the bias tends to zero asymptotically. As in Rodrik (2013), I treat conditional regressions as upper bounds, focusing on the unconditional results.

where $\Delta y_{ij,t}$ represents the growth rate of labor productivity over a time period in industry i, country j at time period t; Δ represents the period change, and y_{ijt} is the log of initial labor productivity at the beginning of the time period. In this specification, I utilize 5 and 10-year periods. Then, I interact y_{ijt} with the technological intensity categories proposed by the OECD. The categories are low, medium, and high technologically-intensive industries. In addition, D_j represents country fixed effects that control for the country's time-invariant heterogeneity, and D_t represents period fixed effects controlling for changes in each period. Finally, D_{it} controls for the unobserved factors affecting industries in each period.

The coefficients of interest are β_1 and β_2, which are measures of conditional convergence in this specification. The coefficient β_1 shows the convergence coefficient for low technologically intensive industries. The coefficient β_2 captures the differential effect between low and medium, low and high technologically intensive industries.

In Table 1.4, it is possible to observe that these industries differ in their convergence rates. Medium and high-tech manufacturing converge faster than low-tech manufacturing in the unconditional and conditional scenarios. In the first column, the estimated coefficient for unconditional convergence using 10-year periods for low-technologically intensive industries is 1.77 %.The estimated coefficient for unconditional convergence in the same scenario under 5-year periods is approximately 2.26 %. Table 1.4 also shows that high-tech industries, in particular, converge faster than low-tech industries, closing the technology gap at a higher rate. A salient fact of Table 1.4 is that using 10-year periods, the differential convergence coefficient for medium-tech industries becomes statistically insignificant in the conditional convergence scenario.

These differential convergence rates show that heterogeneities across industries are significant because they suggest that countries that focus their manufacturing on more R&D-intensive industries catch up more rapidly toward the technology frontier. Erten and Schwank (2021) find similar results with regional variations across the globe. These results are updated and extended in this section.

1.4.3 Human Capital and Convergence in Manufacturing

Motivated by the existing literature on human capital and industrialization, I extend the previous analysis by measuring the role of human capital in explaining labor productivity convergence. One objective of this paper is to capture the effect of human capital on labor productivity convergence in manufacturing. To assess the proposed relationship, I use a fixed effects specification. The specification takes the form

$$\Delta y_{ij,t} = \alpha + \beta_1 y_{ijt} + \beta_2 y_{ijt} \times EDUC_{jt} + D_{it} + D_j + D_t + \epsilon_{ij,t}, \tag{1.7}$$

where $\Delta y_{ij,t}$ represents the growth rate of labor productivity over ten years in industry i, country j at period t; Δ represents 10-year change, and y_{ijt} is the log of initial labor productivity at the beginning of the period. I interact the term y_{ijt} with two measures of educational attainment: percent of people with primary, secondary, and tertiary education completed in a country and average years of schooling by primary, secondary, and tertiary categories in country j in period t. The variable $EDUC_{jt}$ represents the educational variables. In addition, D_j represents country fixed effects that control for the country's time-invariant heterogeneity, and D_t represent period-fixed effects controlling for changes in each period. Finally, D_{it} controls for period $\times$ industry fixed effects.

The coefficients of interest are β_1 and β_2. The coefficient β_1 is the convergence coefficient as in previous estimations, and the coefficient β_2 represents the interaction between the initial log of labor productivity and the distinct educational attainment categories. This interaction measures the effect of the distinct levels of educational attainment on decadal growth rates. A negative β_2 indicates that educational attainment contributes to convergence.

Results in Tables 1.5 and 1.6 show the effects of the different levels of educational attainment on the convergence of labor productivity. In Table 1.5, the proxy for the stock of human capital is the percent of people with complete levels of primary, secondary, and tertiary education. Table 1.6 shows the results in terms of average years of schooling in primary, secondary, and tertiary.

Results in Table 1.5 indicate that the different categories for educational attainment play a minor role in explaining labor productivity convergence for overall manufacturing. Nevertheless, results vary based on categories of educational attainments. In the second column (2), for instance, the variable with percent of people with completed primary education is not robust to changes in country fixed effects. In other words, the effect of complete primary education vanishes with the exclusion of country fixed effects. The magnitudes of the interactions with secondary and tertiary education from Columns (3) to (6) are substantially higher, particularly for tertiary education. Although the magnitudes of these interactions are significantly small in terms of their role in influencing convergence rates, they support Mokyr's hypothesis of the importance of the density in the upper tail of knowledge. Namely, in this context, the importance of high skills in explaining labor productivity growth convergence.

Table 1.6 shows that the coefficients associated with primary and secondary average years of schooling are not statistically significant once the convergence scenario changes from conditional to unconditional. Namely, when the scenario changes from country to no country fixed effects. For tertiary education, average years of schooling remains statistically significant at all levels though quantitatively small in terms of its contribution. As opposed to primary and secondary education, tertiary education shows statistical significance under all measures of human capital. This result supports Mokyr's hypothesis on the importance of the density in the upper tail of knowledge.

1.4.4 Institutions, Trade, and Convergence in Manufacturing

To assess the role of growth determinants other than education levels in explaining convergence in manufacturing, I substitute the educational variables in Equation (1.7) for other potential drivers of convergence. More specifically, I substitute the education levels for measures of institutional quality from the WGI and trade openness from the WDI.

As it is possible to verify from Table 1.7, all different measures of institutional quality and trade openness are statistically insignificant. As shown in Section 1.4.7, the relationship that holds under the unconditional and conditional scenario is tertiary education. It is important to emphasize that although these findings suggest no statistical significance, this does not imply that institutions play no role in aggregate growth. Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), for instance, document that sector-specific distortions, in the form of taxes, play a detrimental role in growth. More recently, Sinha (2021) finds that the quality of institutions positively impacts allocative efficiency. However, the present results indicate that none of the measures of institutional quality and trade openness play a role in fostering convergence rates within manufacturing.

1.4.5 Convergence by R&D Intensity and Tertiary Education

Previous results provide two critical findings. First, they show that education speeds up convergence within manufacturing. Second, they show that R&D-intensive industries converge faster. A natural question that follows these findings is whether education, particularly tertiary education, disproportionally affects growth in high-tech industries. To test this hypothesis, I use a fixed effects specification. The specification is given by

$$\Delta y_{ij,t} = \alpha_0 + \beta_1 y_{i,j,t} + \beta_2 y_{i,j,t} \times TECH \times EDUC_{jt} + D_t + D_{it} + D_j + \epsilon_{ij,t}, \tag{1.8}$$

where $\Delta y_{ij,t}$ represents the growth rate of labor productivity over a 10-year period in industry i, country j at time t; Δ represents the 10-year change, and y_{ijt} is the log of initial labor productivity at the beginning of the period. I interact this variable with the technology intensity categories proposed by the OECD and with the measures of tertiary education levels from Barro and Lee (2013). In this framework, D_j, D_t, and D_{it} represent country, period, and period $\times$ industry fixed effects. In the specification, the coefficient of interest is β_2. This coefficient measures the convergence rate conditional on countries' tertiary education levels and industries' R&D intensity. As in Section 1.4.2, the dummy $TECH$ captures the differential effect between low and medium and low and high technologically intensive industries. Hence, the omitted category is low. Table 1.8 shows the results of the estimation.

Table 1.8 shows the results for the specification in Equation (1.8) using two alternative measures of levels of tertiary education. Columns (1) and (2) show the triple interaction of the percent of countries' population with tertiary degrees, technological intensity categories, and the initial logarithm of labor productivity. Similarly, Columns (3) and (4) exhibit the same triple interaction but with an alternative measure of the levels of tertiary education: average years of tertiary schooling.

All columns in Table 1.8 use different measures of tertiary education. The results support that countries' tertiary education levels have no direct impact on the rate of convergence in any of the industries. In other words, results indicate that tertiary education does not disproportionately affect growth in any industry category.

1.5 Composition Effect of Tertiary Education

Results in Section 1.4 reveal two significant findings: First, they show that countries' tertiary education levels somewhat accelerate manufacturing convergence. Second, they show that convergence is faster in high-tech industries. Nevertheless, results in Section 1.4.5 indicate that tertiary education does not drive high-tech industries' relatively accelerated convergence rates. The synthesis of these findings implies that tertiary education affects convergence in manufacturing differently.

Previous theoretical works, such as Zeira (2009), propose an additional channel in which education affects economic growth. If industrialization drives economic growth, the transition from traditional to modern modes of production requires workers who know beyond basic skills such as reading and arithmetic. In other words, these works suggest that education has a composition effect in which countries' higher-level skills increase the share of labor allocated to the most modern industries. To examine this channel, I test whether tertiary education has this composition effect on manufacturing. More precisely, I test whether countries' tertiary education levels increase the share of labor allocated to the fast-converging, more innovative high-tech industries.

Preliminarily, Figure 1.5 depicts the employment shares within manufacturing by R&D intensity classification. This figure divides the world into seven regions: North America, Latin America and the Caribbean, Sub-Saharan Africa, Europe and Central Asia, Middle East and North Africa, South Asia, and East Asia and the Pacific. As can be seen, more developed areas, such as North America, have a higher share of high-tech employment. In contrast, less developed areas, such as Sub-Saharan Africa, have lower shares of high-tech employment and higher shares of low-tech employment. As it is known, these regions have dramatically different levels of secondary and tertiary schooling. These descriptive figures signal that education may contribute to growth by shaping the allocation of workers across industries.

In order to test whether countries' tertiary education levels increase the share of labor allocated to high-tech industries, I use a fractional logit estimator.[6] In this analysis, the dependent variable is the share of workers employed in each R&D intensity category i in country j in year t. This approach examines whether changes in countries' tertiary education levels lead to increases in the proportion of people working in each R&D intensity category within the manufacturing sector. For this section, I create two categories of R&D intensity, low and non-high-tech manufacturing. The low category corresponds to the low-tech manufacturing industries, as in the OECD R&D intensity classification. The non-high-tech category corresponds to the low-tech plus the medium-tech industries. In other words, I separately estimate the effect of tertiary education level measures on these two new R&D intensity categories, low and non-high (low plus medium-tech). In the empirical analysis, a positive coefficient indicates a direct relationship between tertiary education levels in country j and the share

[6]The two-limit Tobit could be applied to fractional logit variables. Nevertheless, this model would only apply provided a high concentration of observations at exactly zero and one. In the present dataset, there is a minimal number of observations at exactly zero and one (Papke and Wooldridge, 1996; Wooldridge, 2010; Villadsen and Wulff, 2018).

of workers in R&D intensity category i in year t and vice-versa.

Regarding the empirical strategy, I model $E(SHARE_{ij} \mid EDUC_j)$ as a logistic function. Hence, the conditional expectation takes the form

$$E(SHARE_{ij} \mid EDUC_j) = \frac{e^{(EDUC_j \beta)}}{1 + e^{(EDUC_j \beta)}}. \tag{1.9}$$

This form ensures that the predicted employment shares fall within the unit interval $[0, 1]$. Thus, the partial effect of increasing countries' tertiary education levels is given by

$$\frac{\partial E(SHARE_{ij} \mid EDUC_j)}{\partial EDUC_j}, \tag{1.10}$$

where the partial effects are evaluated at the βs. These partial effects measure the effect of a one percentage point increase in countries' tertiary education levels on the mentioned share of workers in low and non-high tech manufacturing.

Table 1.9 depicts the relation between the share of workers in the two established R&D intensity categories (low and non-high) and countries' percent of people with tertiary education. In Column (1), Table 1.9 shows that increases in countries' percent of people with complete tertiary education are associated with a lower share of workers in low-tech. Column (2) of the same table shows that increases in countries' percent of people with complete tertiary education are associated with a lower share of workers in non-high-tech (low plus medium-tech).

Column (1) in Table 1.10 shows the partial effects. In other words, it shows that a one percentage point increase in population with tertiary decreases the share of low-tech workers in manufacturing with a coefficient of approximately -0.00629 (or approximately 0.6 percentage points). Conversely, Column (2) in the same table shows that the same increment decreases the share of non-high tech workers with a coefficient of approximately -0.00383 (or approximately 0.3 percentage points).The results in Table 10 show a relatively small negative effect of increases in population with tertiary in the shares of low and non-high-tech industries. Nevertheless, these results suggest that tertiary education affects economic growth not necessarily by increasing labor productivity growth in fast-converging industries but by allocating workers to fast-converging industries (in this case, high-tech industries). Since low-income countries usually possess lower shares of college-educated workers, these findings provide suggestive evidence that the low shares of college-educated workers might potentially explain why sectors with fewer growth prospects are expanding in those countries.

1.6 Conclusions

This paper investigates the role of human capital in generating economic convergence through its impact on manufacturing productivity growth. Thus, I rely on industry-level data on formal manufacturing employment and value-added and country-level data on educational attainment by different levels (primary, secondary, and tertiary). Confirming and extending existing results, I show that productivity in manufacturing has exhibited convergence. In other words, countries further behind tend to catch up to those on the technology frontier. In addition, I show that this convergence is faster in high-tech industries, confirming existing results.

Most importantly, I show that country's level of human capital, particularly tertiary education, accelerates convergence in manufacturing. Surprisingly, empirical results in this paper indicate that the faster convergence in high-tech industries is not driven by tertiary education's impact on the rate of catching up. Nevertheless, this does not imply that education has no role in growth. Results suggest that tertiary education increases the share of labor allocated to the fast-converging high-tech sector.

Empirical results support that transitioning from traditional (e.g., low-tech) to modern (e.g., high-tech) manufacturing relies on the supply of a high-skilled labor force. In other words, results in this paper indicate that the lack of a high-skilled labor force constitutes a bottleneck for countries that ought to make this transition. Although this problem is palpable in developing economies, it is not exclusive to them. A recent example that validates the statement is the shortage of skilled workers arising as a consequence of the United States government's plan of relocating manufacturing in their borders by implementing microchip and semiconductor plants in the country's midwest.[7]

Unsurprisingly, this paper has limitations. One limitation is not being able to capture the effect of multinational corporations (MNCs) in the convergence process. There is empirical evidence suggesting that high-tech and low-tech multinational firms within manufacturing show different patterns of knowledge spillovers, with high-tech multinationals catching up relatively fast to the technology frontier (Choi, 2014). This paper cannot capture those effects given how industrial data is aggregated into industries regardless of the origins of firms that compose each industry. In

[7]Information from the article titled "Biden wants an industrial renaissance". He cannot do it without immigration reform" in Politico magazine.

addition, the present work does not address the role of foreign employees as a channel for convergence via technological transfers (Santacreu-Vasut and Teshima, 2016).

By providing a unified analysis of the role of education in explaining labor productivity convergence in manufacturing, this paper suggests that schooling's impact on manufacturing has been meaningful. First, it has been critical in explaining overall manufacturing catching-up. Second, it provides the labor force needed for modern industries to expand. This second finding suggests that human capital, particularly tertiary education, may contribute to growth by shaping the allocation of workers across industries, not by necessarily boosting productivity growth within industries.

Future work may extend this analysis by quantifying the gains in labor productivity within manufacturing arising from reallocating workers from low-tech to high-tech manufacturing. In particular, it would be interesting to investigate these gains in light of the Asian Miracle countries. Finally, studying the detailed mechanisms through which education fosters (or encourages/accelerates) the expansion of high-tech manufacturing.

Table 1.1: Description of Variables

Variable	Definition and Source
Log of Initial Labor Productivity	Log of nominal value added per worker for industry i in country j in year t. Calculation from information retrieved from INDSTAT2 (2021). The logarithm of labor productivity is given by $$ly = log(\frac{\text{Value Added}_{ijt}}{\text{Employment}_{ijt}}). \quad (1.11)$$
Growth rate of labor productivity	10-year growth rate of labor productivity. Growth rate calculated with information retrieved from INDSTAT (2021). The decadal growth rate of labor productivity is given by $$g = \frac{ly_t - ly_{t-10}}{10}. \quad (1.12)$$ 5-year growth rates are calculated analogously.
Percentage of Primary Complete	Percentage of population with complete primary schooling attainment in country j and year t. Information retrieved from Barro and Lee (2013).
Percentage of Secondary Complete	Percentage of population with complete secondary schooling attainment in country j and year t. Information retrieved from Barro and Lee (2013).
Percentage of Tertiary Complete	Percentage of population with complete tertiary schooling attainment in country j and year t. Information retrieved from Barro and Lee (2013).
Average Years of Primary Schooling	Average years of primary schooling attained in country j and year t. Information retrieved from Barro and Lee (2013).
Average Years of Secondary Schooling	Average years of secondary schooling attained in country j and year t. Information retrieved from Barro and Lee (2013).
Average Years of Tertiary Schooling	Average years of tertiary schooling attained in country j and year t. Information retrieved from Barro and Lee (2013).

Variable	Definition and source
Voice and Accountability	Indicator that captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Information retrieved from the World Governance Indicators (2018).
Political Stability	Indicator that captures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. Information retrieved from the World Governance Indicators (2018).
Regulatory Quality	Indicator that captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Information retrieved from the World Governance Indicators (2018).
Rule of Law	Indicator that captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Information retrieved from the World Governance Indicators (2018).
Control of Corruption	Indicator that captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Information retrieved from the World Governance Indicators (2018).
Trade Openness	Ratio between the sum of total goods and services imported and exported by country j in year t over its gross domestic product in year t. Information retrieved from the World Development Indicators (2020).

Variable	Definition and source
Employment Shares	Number of people working in industry with technological intensity i in country j in year t over the number of people working in overall manufacturing in country j in year t. Calculation with information retrieved from INDSTAT2 (2021). The employment shares are given by $$\text{Share}_{ijt} = \frac{\text{Total Employment}_{ijt}}{\text{Total Employment}_{jt}}. \quad (1.13)$$

Table 1.2: R&D Intensity Classification

Low-Tech	**Medium-Tech**	**High-Tech**
Food and beverages (15)	Coke, refined petroleum products, nuclear fuel (23)	Chemical and chemical products (24)
Tobacco Products (16)	Rubber and plastics products (25)	Machinery and equipment (29)
Textiles (17)	Non-metallic mineral products (26)	Office, accounting, and computing machinery (30)
Wearing apparel and fur (18)	Basic metals (27)	Electrical machinery and apparatus (31)
Leather; leather products and footwear (19)	Fabricated metal products (28)	Radio, television, and communication equipment (32)
Wood products (20)		Medical,precision, and optical instruments (33)
Paper and paper products (21)		Motor vehicles, trailers and semi-trailer (34)
Printing and publishing (22)		Other transport equipment (35)
Furniture; manufacturing n.e.c (36)		
Recycling (37)		

Table 1.3: Overall Convergence in Manufacturing

	(1)	(2)	(3)	(4)
	10 years	10 years	5 years	5 years
Log of Initial Labor Productivity	-0.0211***	-0.0573***	-0.0271***	-0.0802***
	(0.00319)	(0.00289)	(0.00418)	(0.00781)
_cons	0.266***	0.462***	0.280***	0.607***
	(0.02718)	(0.0200)	(0.0347)	(0.0507)
Country fixed effects	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes
Number of Countries	110	110	120	120
Number of Observations	5222	5222	11928	11928

Note: Panel specification for overall manufacturing convergence from 1965-2015 in 10 and 5 year periods. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.4: Convergence by R&D Intensity Category

	(1) 10 years	(2) 10 years	(3) 5 years	(4) 5 years
Log of Initial Labor Productivity	-0.0177***	-0.0542***	-0.0226***	-0.0758***
	(0.00337)	(0.02825)	(0.00392)	(0.00736)
Log of Initial Labor Productivity × MEDIUM	-0.00905***	-0.00615	-0.00700**	-0.00744**
	(0.00153)	(0.00326)	(0.00436)	(0.00353)
Log of Initial Labor Productivity × HIGH	-0.00402**	-0.00490**	-0.01010**	-0.00919**
	(0.00161)	(0.00188)	(0.00441)	(0.00436)
_cons	0.238***	0.438***	0.243***	0.573***
	(0.0284)	(0.01816)	(0.03326)	(0.0478)
Country fixed effects	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes
Number of Countries	110	110	120	120
Number of Observations	5222	5222	11928	11928

Note: Panel specification for labor productivity convergence by groups of industries with different R&D intensity classification for the period 1965-2015. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.5: Convergence Regressions by Percent of Population with Complete Education

	(1) Primary	(2) Primary	(3) Secondary	(4) Secondary	(5) Tertiary	(6) Tertiary
Log of Initial Labor Productivity	-0.0166***	-0.0575***	-0.0209***	-0.0537***	-0.0233***	-0.0531***
	(0.015943)	(0.00527)	(0.001985)	(0.00657)	(0.0020)	(0.00452)
Log of Initial Labor Productivity × EDUC	-0.000371***	-0.00000471	-0.000128**	-0.000128	-0.000492***	-0.000456***
	(0.0000537)	(0.0000729)	(0.000047)	(0.0000901)	(0.001127)	(0.00113)
_cons	0.229***	0.469***	0.248***	0.416***	0.272***	0.422***
	(0.0134)	(0.0393)	(0.0165)	(0.0514)	(0.0164)	(0.03316)
Country fixed effects	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Periods × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	103	103	103	103	103	103
Number of Observations	4987	4987	4987	4987	4987	4987

Note: Panel specification for labor productivity convergence with different levels of education attainment for the period 1965-2015. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.6: Convergence Regressions by Average Years of Schooling

	(1) Primary	(2) Primary	(3) Secondary	(4) Secondary	(5) Tertiary	(6) Tertiary
Log of Initial Labor Productivity	-0.0244***	-0.0489***	-0.0310***	-0.0534***	-0.0253***	-0.0541***
	(0.00211)	(0.00717)	(0.00227)	(0.00597)	(0.00208)	(0.00427)
Log of Initial Labor Productivity × EDUC	-0.0000601	-0.00179**	-0.000426	-0.00133**	-0.00727***	-0.00627**
	(0.000367)	(0.000694)	(0.0004131)	(0.0006246)	(0.00140)	(0.00228)
_cons	0.258***	0.417***	0.315***	0.412***	0.287***	0.431***
	(0.0176)	(0.0552)	(0.0185)	(0.0450)	(0.0168)	(0.0308)
Country fixed effects	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Periods × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	103	103	103	103	103	103
Number of Observations	4987	4987	4987	4987	4987	4987

Note: Panel specification for labor productivity convergence with different levels of education attainment for the period 1965-2015. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.7: Other Potential Sources of Convergence

	(1) Voice and Acct	(2) Political Stab	(3) Reg Quality	(4) Rule of Law	(5) Corruption	(6) Trade
Log of Initial Labor Productivity	-0.0840***	-0.0871***	-0.0831***	-0.0831***	-0.0853***	-0.0592***
	(0.00699)	(0.00682)	(0.00636)	(0.00636)	(0.00661)	(0.00646)
Log of Initial Labor Productivity × Variable	0.00323	-0.00677	0.00329	0.0006	-0.00297	0.00190
	(0.00764)	(0.00512)	(0.00714)	(0.00692)	(0.00402)	(0.00246)
_cons	0.6986***	0.7338***	0.6594***	0.6215***	0.6905***	0.524***
	(0.0748)	(0.0739)	(0.0692)	(0.0742)	(0.0664)	(0.05957)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Periods × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	65	65	65	65	65	80
Number of Observations	1986	1986	1986	1986	1986	2004

Note: Panel specification for labor productivity convergence with other potential covariates for the period 1965-2015. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.8: Convergence by R&D Intensity Category and Tertiary Education

	(1)	(2)	(3)	(4)
	% Population	% Population	Avg Years	Avg Years
Log of Initial Labor Productivity	-0.0843***	-0.244***	-0.0868***	-0.243***
	(0.01365)	(0.0379)	(0.0287)	(0.0361)
Log of Initial Labor Productivity × MEDIUM × EDUC	-0.00233	-0.00123	-0.0638	-0.0298
	(0.00136)	(0.00159)	(0.0497)	(0.05079)
Log of Initial Labor Productivity × HIGH × EDUC	0.00207	0.00283	0.0495	0.0571
	(0.00178)	(0.00185)	(0.0483)	(0.3758)
_cons	1.065***	2.125***	1.081***	2.118***
	(0.103)	(0.319)	(0.236)	(0.324)
Country fixed effects	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes
Periods × industry fixed effects	Yes	Yes	Yes	Yes
Number of Countries	103	103	103	103
Number of Observations	4987	4987	4987	4987

Note: Panel specification for labor productivity convergence by R&D intensity category with different levels of education attainment for the period 1965-2015. Robust standard errors clustered at the country level are shown in parenthesis.

Table 1.9: Fractional Logit Regressions with Employment Shares by R&D Intensity Category

	(1)	(2)
	Low	Non-High
Percent of Tertiary Complete	-0.0308***	-0.0219***
	(0.00101)	(0.0011)
_cons	-0.694***	-1.087***
	(0.01305)	(0.0227)
Number of Observations	10010	11012

Note: Fractional logit regressions with the shares of employment by manufacturing R&D intensity as the dependent variable. Regressions cover the period between 1965-2021. Delta-Method standard errors in parenthesis. The non-high tech category includes low plus medium tech industries.

Table 1.10: Fractional Logit Regressions with Employment Shares - Marginal Effects

	(1) Low	(2) Non-High
Percent of Tertiary Complete	-0.00629***	-0.00383***
	(0.00022)	(0.00020)
Number of Observations	10010	11012

Note: Marginal effects of fractional logit regressions with the shares of employment by manufacturing R&D intensity as the dependent variable. Regressions cover the period between 1965-2021. Delta-Method standard errors in parenthesis. The non-high tech category includes low and medium-tech industries.

Figure 1.1: Labor Productivity Convergence in Aggregate Manufacturing (2000-2019)

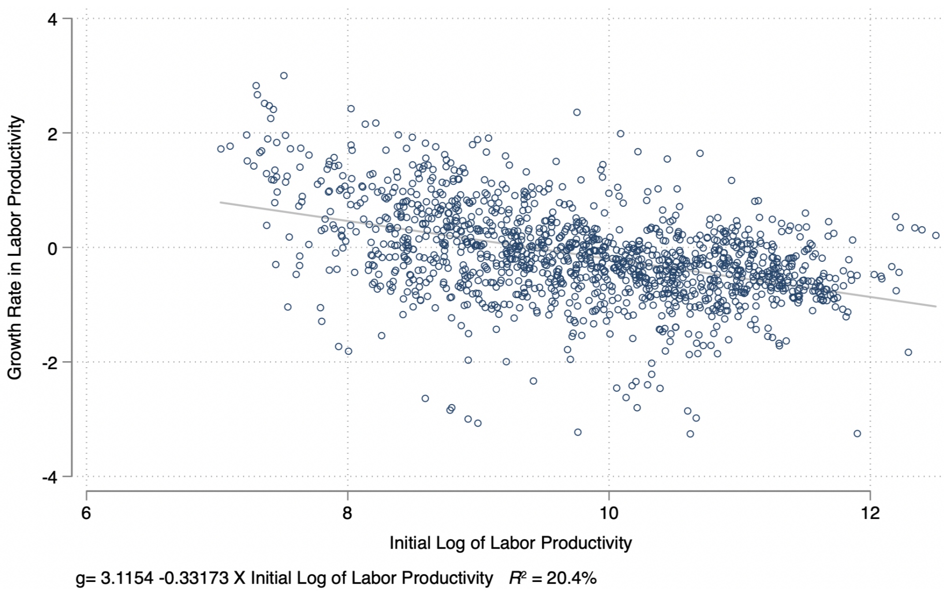


Figure 1.2: Labor Productivity Convergence in Low Tech Manufacturing (2000-2019)

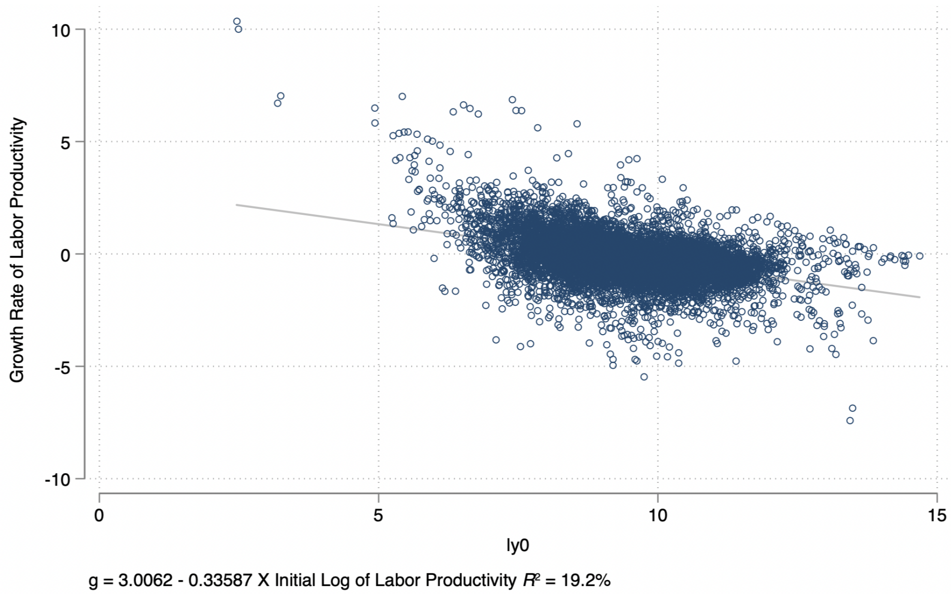


Figure 1.3: Labor Productivity Convergence in Medium Tech Manufacturing (2000-2019)

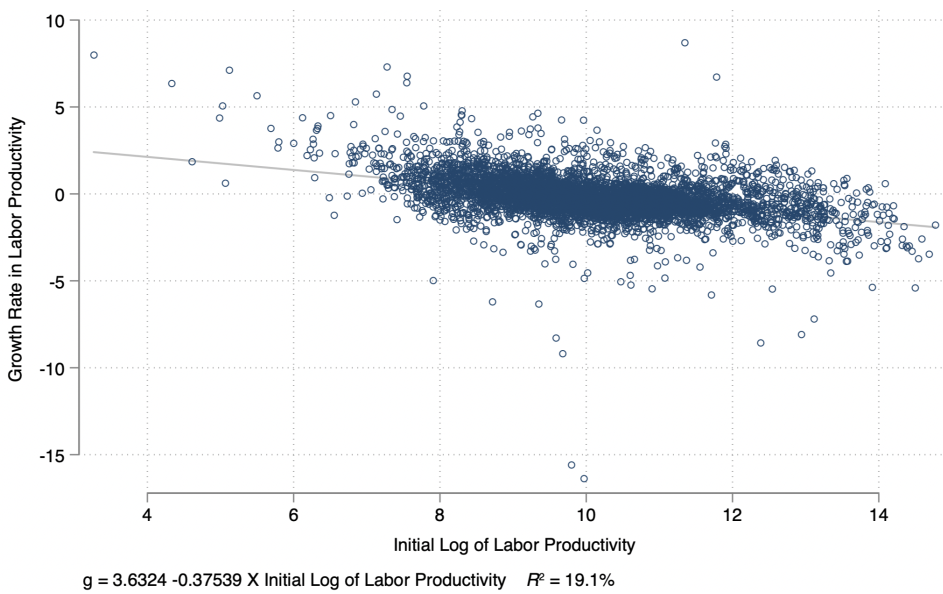


Figure 1.4: Labor Productivity Convergence in High Tech Manufacturing (2000-2019)

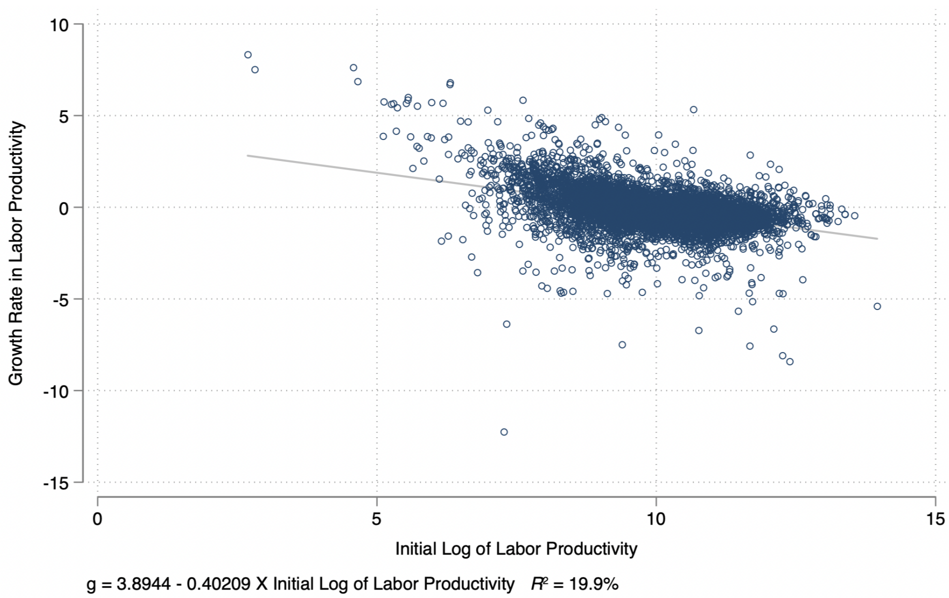
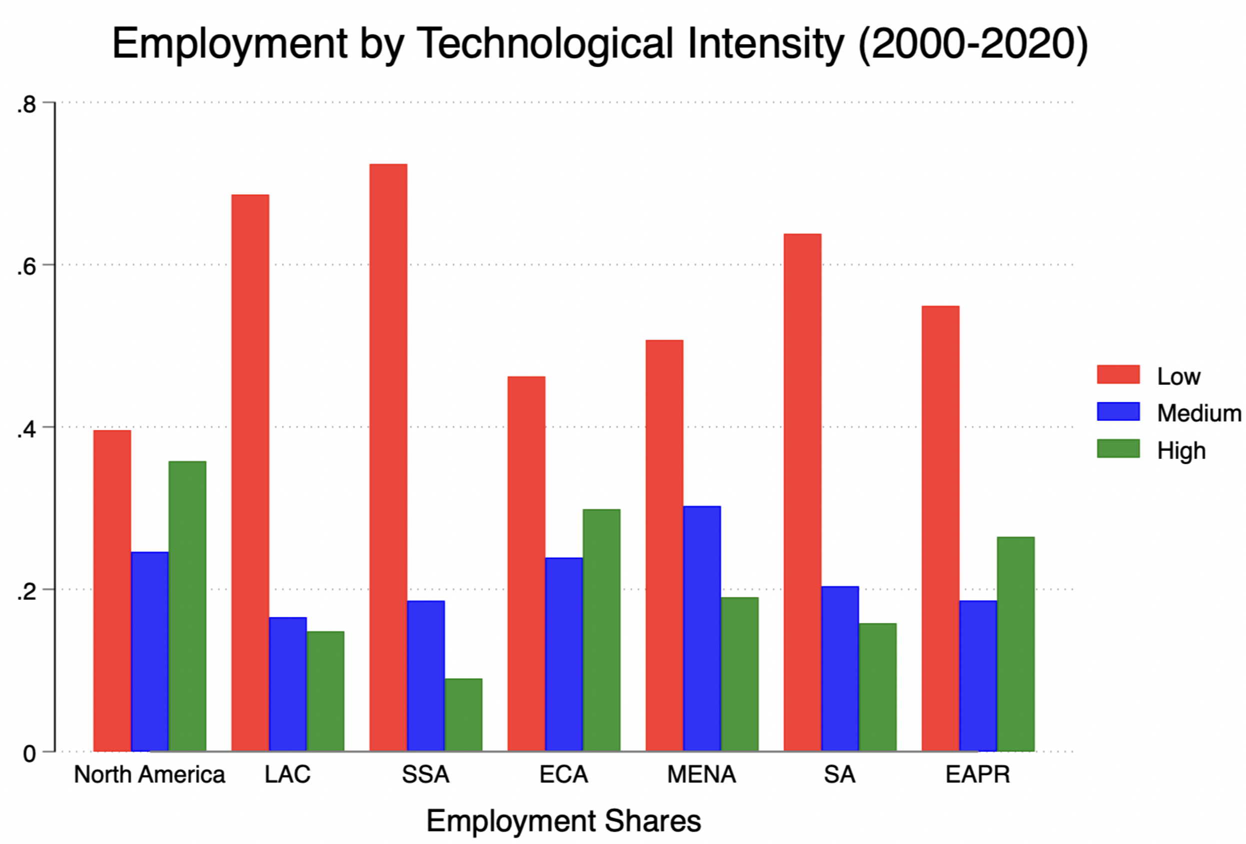


Figure 1.5: Shares of Employment within manufacturing by regions (2000-2020)



Chapter 2

FDI, Structural Change and Labor Allocation: Evidence from Asia and Latin America

2.1 Introduction

The activities of multinational enterprises (MNEs) have increased substantially in the recent years and are associated with foreign direct investment (FDI), particularly in emerging and developing economies. Between 2000 and 2018, world FDI inflows amount to an annual average of 1.28 trillion US dollars, corresponding to a ratio of 2.3 percent relative to world GDP as documented by the United Nations Conference on Trade and Development in 2020.

The circumstances of these flows vary significantly. The resulting effects are heterogeneous across countries receiving these FDI inflows. Nevertheless, one feature is salient regardless of the circumstances and effects: FDI alters host economies' landscapes and structures. Given that MNEs shift investments towards sectors where host economies have some form of comparative advantage, a question that naturally arises is whether FDI inflows have an effect in structural change or transformation in host economies. That is, whether FDI inflows have a significant impact in the process of reallocation of overall economic activity across sectors.[1]

The relationship between FDI and structural change has not been studied extensively in the literature. This fact is relatively surprising given the effects of FDI in sectoral composition of host economies in the long run. Intuitively, productive MNEs firms may change sectoral composition in host economies by inducing a reallocation of labor from low to high productivity sectors. As shown by Redding,Schott and Bernard (2013), MNEs firms tend to pay higher real wages, potentially bringing labor from different sectors. Jude and Silaghi (2016) find evidence of statistically

[1] The terms structural change and structural transformation are used interchangeably along this work.

significant effects from FDI on employment. In addition, Amendolagine, Coniglio and Seric (2017) investigate the impact of foreign investors on structural change through knowledge spillovers using firm-level data in Africa. Mühlen and Escobar (2019), for instance, study the role of multinationals on a structural change scenario. They find that FDI inflows in Mexico were, on average, growth-enhancing though considerably disparate across Mexican states. However, a complete analysis and comparison of the effects of FDI on structural transformation across countries is still missing. Given that structural change can have a determinant role in promoting productivity growth and economic development, it is of vital importance to understand a potential link between FDI and structural change. If FDI affects structural change positively, then it also contributes to productivity growth. However, if FDI affects structural change negatively or, in contrast, does not affect structural change, then it is of vital importance to understand why that is the case and what drives this potential misallocation across sectors.

In this paper, I conduct a cross-country analysis that attempts to investigate the impact of FDI inflows on growth-enhancing structural change across and within-sectors. More specifically, I explore an empirical strategy that measures the effects of inward FDI inflows using de Vries, Timmer and de Vries (2013) decomposition framework for labor productivity change in Latin America and Asia. Both regions provide interesting cases given their relatively recent episodes of FDI liberalization. Moreover, I use a simple model to calculate the allocation of labor that equalizes value added per worker across sectors. The result is contrasted with the allocation of labor found in the data. Then, I conduct an empirical strategy that assesses the effects of inward FDI inflows on the gap between the optimal allocation of labor predicted by the presented simple model and the actual allocation of labor across sectors.

Latin America and Asia are case studies of interest for research. McMillan and Rodrik (2013), for instance, find that since the 1990s structural change has been growth reducing in Latin America in contrast with Asia that had a relatively better structural growth pattern during same period. Interestingly, this period coincides with the period when trade and foreign direct investment barriers were softened. McMillan and Rodrik (2013) also report that Latin American countries' reliance on natural resources played a detrimental role in enhancing positive structural change growth. A puzzling fact ignored in the literature is that both Latin America and Asia liberalized FDI investments during the 1990s, receiving substantial inflows. Hence, it is natural to question whether these inflows played a significant role in defining structural change patterns.

The remainder of this paper is structured as follows. In Section 2, I use descriptive figures to introduce a motivation for FDI and sectoral patterns in both regions. Section 2.3 shows the decomposition of labor productivity change used in the analysis along with some empirical patterns in the data. Section 2.4 describes the Groningen Growth and Development Center (GGDC) 10-Sector Database and the data on inward FDI inflows from the United Nations Conference on Trade and Development (UNCTAD). In addition, I explain the datasets used for specifications in sections 2.5 and 2.7. In Section 2.5, I also discuss the methodology employed to evaluate the effects of inward FDI inflows on each of labor productivity change's components. In the same section, I discuss the empirical results of the analysis. In order to capture the role of FDI on inter-sectoral labor allocation, I employ a simple model that calculates optimal employment shares by sector. This model is presented in Section 2.6 along with some empirical patterns in the data. In Section 2.7, I introduce the empirical strategy used to assess the effects of inward FDI inflows in the allocation of labor by sector. In the end of this section, I discuss the empirical results. Finally, Section 2.8 provides the conclusion with possible extensions for further research.

2.2 Structural change and FDI patterns

First, I show long-run patterns for FDI and structural change for both Latin America and Asia. These patterns serve as a motivation that reveals insights about both regions. More specifically, I employ the common broad distinction between broad sectors (agriculture, manufacturing, and services) to depict these patterns from a structural change perspective. Following the same objective, I also present inward FDI numbers for both regions.

Second, I integrate the mentioned patterns into whether FDI inflows influence the allocation of labor across agriculture, manufacturing, and services.

2.2.1 Long run structural change

Figures 2.1 and 2.2 suggest signs of structural change in Latin America and Asia. This is particularly noticeable in the agricultural sector whose share of employment declines substantially starting from the 1950s. For instance, in Latin America, the share of agricultural employment relative to total employment drops from approximately 55 percent in 1951 to approximately 17 percent in 2013.[2] In other hand, the share of services employment increased substantially after the 1970s.[3] The share of services relative to total employment increased from approximately 17 percent in 1951 to approximately 43 percent in 2013. The share of manufacturing employment presents particular patterns in the region. In 1951, it is approximately 15 percent. During the period 1960-1990, the share of manufacturing employment relative to total employment reached approximately 18 percent during the 1970s. This is in part explained by the process of industrialization and import substitution in the postwar era. The scarcity of imported goods generated incentives for Latin American economies to promote substituting foreign industrial goods with their domestic counterparts. Later, this systematic process of substitution became a policy goal and was named Import Substitution System (ISS). This process was at the heart of industrial policy in many Latin American economies, particularly in Argentina, Brazil, and Mexico as documented by Baer and Kerstenetzky (1964) and Abreu (2004). In the 1990s, many economies in the region removed trade barriers and promoted FDI. The openning process induced by trade and investments liberalization caused a drop in the share of manufacturing employment due to the removal of protection towards specific industrial sectors. In 2013, the share of manufacturing relative to total employment was approximately 13 percent in some Latin American countries.

[2]For many countries, points after 2013 were not available at the time of data extraction. For instance,some countries only had observations until 2011 at the time of the analysis. Countries in the sample are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Peru, and Venezuela. Some sectors such as government, public utilities, and mining are excluded from the paper.

[3]In this paper, I add wholesale and retail trade, transport, storage, communications, financial intermediation, personal services, and government services to account for overall services for Latin America and Asia.

In Asia, the share of agricultural employment relative to total employment did not decrease substantially. In 1960, for instance, it was approximately 48 percent while that, in 2013, it was approximately 45 percent. Nevertheless, it is important to emphasize that there is considerable dispersion in the shares of employment by sector in the sample for Asian countries.[4] For instance, in 1951, the share of agricultural employment relative to total employment in South Korea was approximately 62 percent in 1951 while the same share was approximately 7 percent in 2013. In other hand, India's share of agricultural employment was approximately 72 percent in 1951 and approximately 53 percent in 2013. Nevertheless, long run trend depict a clear decline in the share of agricultural employment in Asian countries, more noticeable after the 1980s. Regarding the manufacturing sector, there is a consistent decline in the share of manufacturing employment. In 1960, for instance, this share was approximately 16.5 percent. In 2013, it was around 14 percent. However, it is important to reemphasize that there is considerable dispersion in the shares. For example, South Korea's share of manufacturing was around 8 percent in 1961. It increased substantially during the period between 1960 and 1980, reaching a share in the neighborhood of more than 28 percent. This is partly due to an aggressive industrialization policy with an outward-looking strategy as documented by Rodrik, Grossman and Norman (1995). In 2013, the share of manufacturing employment was approximately 17 percent. For those same years, India's share of manufacturing employment, for instance, was around 8 percent and 11 percent despite an aggressive state-oriented industrialization process with a heavy emphasis in machinery and capital-intensive sectors during the 1960s as shown by Felipe, Kumar and Abdon (2010). The share of services employment had a noticeable increase, increasing from approximately 18 percent in the 1960s to approximately 30 percent in 2013.

Overall, the long run picture in Latin America and Asia mirrors to some extent the rationale of the dual economy approach documented first by Lewis (1954), where labor moves from a traditional sector (agriculture) to modern sectors (manufacturing and services) characterized by high productivity levels. The goal of this paper is to understand what the role of FDI is in the context of sectoral allocation of labor.

2.2.2 Inward FDI patterns

In figures 3 and 4, inward FDI inflows show a clear positive trend in the long run for Latin America and Asia. These FDI inward inflows increase substantially and permanently, particularly after the 1990s, for both Latin America and Asia. Most countries in both regions had processes of FDI liberalization during the 1990s. In Latin America, for instance, Argentina,Brazil, Mexico, Chile, Colombia and Peru promoted the entry of foreign firms by removing existing barriers. In 1993, Argentina promoted FDI liberalization by allowing foreign firms to transfer profits abroad.[5] In 1993, Mexico also followed the same course of action by liberalizing FDI. Nevertheless, the Mexican law was more restrictive than the Argentinian law.[6] This process of liberalization accelerated with Mexico's entry into the North American Free Trade Agreement (NAFTA) in the same year with the US being the main investing country in Mexico,

[4] Countries in the sample are China, Indonesia, India, Japan, South Korea, Malaysia, Philippines, Singapore, and Thailand.
[5] Ley 21.382 de Inversiones Extranjeras en Argentina. 5th Article.
[6] The Ley of Inversión Extranjera in Mexico restricted participation of foreign firms in some sectors such as electricity and oil & gas.

concentrating 36.8 percent of Mexico's FDI inflows in 2019.[7] Brazil did not promote FDI liberalization explicitly with changes in legislation. However, after 1991, Brazil promoted a process of opening up the economy by drastically reducing tariffs and removing protection to specific sectors. In addition, Brazil promoted a process of privatization of some state-owned enterprises that allowed the participation of foreign firms. Chile, Colombia, and Peru changed existing legislation by liberalizing FDI investments.[8] Finally, although some countries in the sample did not change their FDI legislation, they promoted structural and pro-market reforms that stimulated the entry of foreign firms.

In Asia, FDI inflows patterns are relatively similar to Latin America given that many countries in the region experienced a process of structural reforms and liberalization. For instance,in 1978, China promoted a policy of FDI liberalization with foreign firms in special economic zones (SEZs). Later, in the 1990s, China also passed legislation that removed barriers on FDI. In 2002, China's entrance into the World Trade Organization (WTO) further removed FDI barriers. During the 1960s, as documented by Rodrik, Grossman, and Norman (1995), South Korea and Taiwan pushed their firms onto world markets by subsidizing them heavily. Nonetheless, after the 1980s, South Korea and Taiwan removed protection to specific sectors and allowed competition among local and foreign firms. India also started FDI liberalization policies in the early 1990s by welcoming MNEs. This process of FDI liberalization was followed by considerable inflows and sectoral reallocation. For example, the retail sector in India went through a gigantic transformation in the decades following FDI liberalization policies. In 2013, according to Masharu and Ali Nasir (2018), the market value of the Indian retail sector was 500 billion US dollars with a population of 40 million engaged in it. Hence, it is possible to, at least, question a potential link between FDI and structural transformation.

2.3 Decomposition of labor productivity change

The general framework of economy-wide labor productivity change applied by de Vries, Timmer and de Vries (2013) reads as follows:

$$\Delta Y_t = \underbrace{\sum_{i=1}^{n}(y^i_{t_1} - y^i_{t_1})\theta^i_{t_1}}_{\text{within sector}} + \underbrace{\sum_{i=1}^{n}(\theta^i_{t_1} - \theta^i_{t_0})y^i_{t_0}}_{\text{static reallocation}} + \underbrace{\sum_{i=1}^{n}(y^i_{t_1} - y^i_{t_0})(\theta^i_{t_1} - \theta^i_{t_0})}_{\text{dynamic reallocation}} \tag{2.1}$$

where Y_t, y^i_{t0}, and y^i_{t1} refer to economy-wide and sectoral labor productivity levels in terms of real value added per worker of sector i in years $t_0$and t_1, respectively; θ{t}^i_0, and θ{t}^i_1 represent the employment shares of sector i in years t_0 and t_1 given n sectors in the economy.

The first term represents the sum of changes in real value added per worker in sector i, $i = 1, 2, ..., n$. The second and third terms are the components of labor productivity change arising from inter-sectoral employment changes (i.e., net movements of workers across sectors). More specifically, the second term "static reallocation" measures whether

[7] OECD FDI Report 2020.

[8] Chile promoted changes in previous FDI legislation in 1993. Peru liberalized FDI with an explicit new law in 1991. In 1991, Colombia also changed FDI legislation following the pattern in the region.

workers move to above-average productivity *level* sectors while the third term "dynamic reallocation" measures the joint effect of changes in employment shares and sectoral labor productivity. It is positive if workers are moving to sectors that are experiencing positive labor productivity growth and vice-versa.

2.3.1 Average mean change in decomposition components

The patterns in figures 2.5 and 2.6 for Latin America clearly depict patterns of structural change that have served to reduce rather than increase labor productivity. This effect is particularly more noticeable after the 1990s. As noted along Section 2.2, this is exactly the period when most developing economies, particularly Latin America and Asia, have become integrated with the world economy by drastically reducing tariffs and liberalizing FDI investments. Nevertheless, what Figure 2.6 shows is a reduction on growth-enhancing structural change relative to Figure 2.5. This reduction is more pronounced on the static portion of labor reallocation of Equation (2.1). Interestingly, the portion of labor productivity change that does not rely on inter-sectoral movements of workers across sectors (*within sector change*) increases in some economies, especially in Argentina and Chile. The portion of labor productivity change pertaining to the dynamic portion decreases but not substantially. These preliminary findings indicate, as Rodrik and McMillan (2013) state, that the consequences of globalization depend on the *manner* in which countries integrate into the global economy rather than the simplistic dichotomy of *closed vs open* economies.

Regarding Asia, figures 2.7 and 2.8 show a more ambiguous scenario relative to figures 2.6 and 2.7. Clearly, the process of integration with the world economy via tariff reduction and, more specifically, FDI liberalization have been positive for some Asian economies in the sample. For instance, China and India show considerable average increases for the *within sector* and the *static reallocation* components of labor productivity change. However, all Asian economies in the sample exhibit a decline in the *dynamic reallocation* components after the 1990s. As in figures 2.5 and 2.6, some economies show considerable gains in *within sector* growth, particularly China, India, Indonesia, Malaysia and South Korea.

Conclusively, it is possible to say that the gains in labor productivity change are clearly ambiguous (especially in Asia). This paper attempts to generalize results in a cohesive manner by attempting to find a causal link between inward FDI inflows and structural change.

2.4 Data description

In order to to answer the research question, I use the Groningen Growth and Development Centre (GGDC) 10-Sector database (2014 release) developed by the University of Groningen. This database contains annual data on gross value added at current and constant prices in terms of national currencies. Moreover, the 10-Sector Database contains annual data on number of workers employed by sector. The data on gross value added and number of workers employed allows the derivation of labor productivity (gross value added per worker). It is important to mention that gross value added is found in 2005 constant prices in the database. However, this is measured by national currency. To make derivations with labor productivity comparable across countries, I convert gross value added in constant prices to US dollars using 2005 Purchasing Power Parity (PPP) exchange rates. In addition, the database covers ten sectors of the economy as defined by the International Standard Industrial Classification, Revision 3.1 (ISIC rev 3.1). For the purpose of this paper, some sectors were excluded (such as public utilities and construction). The remaining sectors were classified among three broad categories (agriculture, manufacturing and services). The control covariates in the dataset are composed by information on inward Foreign Direct Investment (FDI) over Gross Domestic Product (GDP). This information obtained through the United Nations Conference on Trade and Development (UNCTAD). UNCTAD statistics has relevant data on annual FDI inflows from 1970 until 2019. Therefore, in the process of merging the two mentioned sources, all information before 1970 present in GGDC Database is excluded from the econometric analysis. The complete description and summary statistics of the variables used can be found in Section 2.10.

2.5 Assessing the role of FDI for structural change

The main objective of this paper is to investigate a potential relationship between FDI and structural transformation. More importantly, the main goal is to find a potential causal link between FDI and structural change. In order to analyze this potential link, I run a regression analysis where the units of observation are countries in Asia and Latin America.

2.5.1 Methodology

In terms of the econometric strategy, I estimate the following model

$$y_{s,t} = \alpha_0 + \alpha fdi_{s,t} + \lambda_t + \mu_s + \epsilon_{st} \tag{2.2}$$

where the dependent variable $y_{s,t}$ represents the five-year average of each of the labor productivity change components in Equation (2.1) in section 2.3 by country s. The main justification for taking five year periods averages for the dependent and independent variables is to remove time series noise in the data. Moreover, as pointed documented by Helpman, Melitz and Yeaple (2004), Jude and Silaghi (2014) and Mühlen and Escobar (2019), FDI can promote different effects for the overall economy in the short and long-run. Given that structural transformation is a long-run process, it is natural to attempt to the exclude any short-run fluctuations represented by time series noise. The independent variables are represented by the terms $fdi_{s,t}$ where t is the five-year average of inward FDI inflows in percent of Gross Domestic Product (GDP). For instance, the term $fdi_{s,2010}$ represents the five-year average of inward FDI inflows as a percent of GDP for the period 2005-2010 for country s. Similarly, the term $fdi_{s,2005}$ represents the five-year average of inward FDI inflows for the period 2000-2005 and so forth.The terms λ_t and μ_s control for period-specific and country fixed-effects while the term α is the constant and ϵ_{st} is the error term of the estimation.

In terms of the estimation method, I employ a fixed effects estimator. Hence, I exploit the panel structure of the data and the within variation. Moreover, after merging the FDI data from the United Nations Conference on Trade and Development (UNCTAD) with the sectoral data available, I am able to consider periods of structural change on annual basis between 1970 and 2011. The results and analysis of the regression estimation are presented in the following section.

2.5.2 Empirical Results

In Table 2.4, I report the baseline results based on estimating Equation (2.2) on each of the components of labor productivity change in Equation (1). In columns (1), (2), and (3), the dependent variables are the *within sector*, *static reallocation*, and *dynamic reallocation* components, respectively. From column (1), it is possible to see that the independent variables in the form of inward FDI inflows as percent of GDP have no statistically significant effect on *within sector* labor productivity change. This result is in line with recent results such as Kalemli-Ozcan et al. (2004) and Kalemli-Ozcan el al. (2021). In the mentioned studies, the authors find that even large increases are not important for country-level productivity growth. Although the mentioned authors focus on total factor productivity (TFP) growth while I focus on labor productivity changes, findings in Table 2.4 still support their findings. Moreover, for developing countries, Kalemli-Ozcan et al. (2021) find declines in TFP productivity levels after FDI although they do not focus on inter-sectoral reallocation.

From a structural change perspective, columns (2) and (3) provide more interesting insights given that these columns involve inter-sectoral movements of workers across sectors. Column (2) shows that, on average and holding all else equal, a one percent increase in FDI inflows over GDP during the period 2000-2006, led to -0.145 percent decline in static reallocation with a ten percent significance level. Furthermore, FDI inflows during the period 1995-2000 also had a negative effect on static reallocation at a five percent significance level. Interestingly, FDI inflows over the period 1990-1995 had a positive effect on static reallocation at a one percent significance. Overall, it is clear that FDI inflows had a negative effect on static reallocation. In other words, FDI inflows, particularly after the 1990s, contributed to workers moving from high to low productivity level sectors, indicating statistically significant signals of labor misallocation across sectors. Nevertheless, FDI inflows had a positive effect before the 1990s (as the coefficient *FDIinflow_1995* indicates). More specifically, the coefficient associated with $FDIinflow\_1990$ is 0.0697, which is statistically significant at the five percent level. This coefficient clearly indicates a positive effect of inflows during this period on static reallocation. This can be explained, at least partially, by two reasons: first, many Latin American countries in the sample stabilized inflation rates during this period, thus increasing businesses' confidence and, second, and most importantly, the sectoral composition of FDI during the 1990-1995 period favored the manufacturing sector. In particular, the mentioned five-year period was a time of substantial mergers and acquisition ($M\&A$) in the manufacturing sector in many of the countries in the sample. Dias, Robalo and Richmond (2020)) find that the allocation of resources is more efficient in manufacturing relative to service sector . Therefore, a prevalence of manufacturing FDI should, on average, lead to a more efficient allocation of workers given that they are a vital factor of production. FDI sectoral patterns only started to change substantially in the late 1990s and early 2000s.

Regarding Column (3), it is possible to see that that FDI inflows had a detrimental and statistically significant effect on dynamic reallocation. The coefficient *FDIinflow_2000* and *FDIinflow_1980* had both negative effects on dynamic reallocation at a one percent level of statistical significance. In a few words, FDI inflows played a detrimental role on structural change. The mentioned coefficients indicate that, on average, workers moved from high productivity to low productivity growth sectors. Possible hypotheses for this could include the interaction of substantial FDI inflows with rigid institutional structures such as rigid labor laws among other factors. Rodrik and McMillan (2013) use a different decomposition framework and find that employment rigidity has a negative effect on structural change. Previously, Hopenhayn and Rogerson (1993), among others, find that hiring costs play an important role in explaining labor misallocation. Moreover, Mühlen and Escobar (2019) also find a negative relationship between labor conflicts (as a *proxy* for labor rigidity) and structural change using Mexican data. Results in Column (3) also show a link between labor misallocation and negative structural change and FDI inflows. The key finding of the results presented are the similar effects of FDI inflows on static and dynamic reallocation of workers. In both cases, FDI inflows plays mostly a negative role. In particular, this negative role is more salient in more recent decades. A possible explanation for this negative role is the shift from a predominantly manufacturing to a predominantly services FDI. Moreover, the decline of FDI inflows in the primary sector (e.g agriculture and/or natural resources) could also play a role in negative structural change given high productivity in sectors such as mining as documented by Rodrik and McMillan (2013).

2.6 Optimal allocation of labor across sectors

An alternative approach to measure the effects of FDI inflows on structural change is to use a benchmark scenario. In this benchmark scenario, I depict the allocation of labor that equalizes value added per worker across sectors. To analyze this, I develop a simple model based on Adeyinka, Salau and Vollrath (2013). In Section 2.6.2, I contrast these results with the actual sectoral shares found in the data over time. I compare them, with optimal sectoral shares in the model. Then, I calculate the percentage change difference between the model's shares ("optimal") minus the actual shares per sector. Finally, in Section 2.7, I regress these differences by sector (agriculture, manufacturing, and services, respectively) on inward FDI inflows. As in Section 2.5.1, I use five-year averages for the dependent and independent variables.

The key objective of sections 2.6 and 2.7 is to identify the source of the misallocation (negative structural change) of estimates in Table 2.4. This is achieved by verifying how changes in inward FDI cause statistically significant deviations from optimal employment shares per sector analyzed.

2.6.1 Benchmark allocation of labor across sectors

Initially, it is possible to the describe each sector *i's* value added by the following Cobb-Douglas production function:

$$VA_i = X_i L_i^{1-\alpha} \tag{2.3}$$

where X_i is a fixed productivity term specific to sector i. One can interpret this parameter as a factor that combines the role of physical capital and total factor productivity. [9] Given the scope of this paper, both terms are held constant and combined in a single term.[10]

L_i is the amount of labor employed in a sector i while L represents the amount of all labor employed in the economy. The exponent $(1-\alpha)$ can be interpreted as elasticity of value-added with respect to labor. This exponent is vital due to the fact that it indicates how much labor productivity will fall as labor is added to a sector and vice-versa. As in the rest of this paper, the standard measure of labor productivity is

$$\frac{VA_i}{L_i} = \frac{X_i}{L_i^{\alpha}} \tag{2.4}$$

From the GGDC 10-Sector database, it is possible to see that there is considerable variation of value-added per worker across sectors within countries. The implication of equalizing value-added per worker across sectors within countries is that ideally labor will move from low-productivity sectors to high-productivity sectors and vice-versa until there are no gains for exploiting.

With n sectors, it is possible to show that the allocation of labor that equalizes value-added per worker is[11]

$$\frac{L_i}{L} = \frac{X_i^{1/\alpha}}{\sum_{i=1}^{n} X_i^{1/\alpha}} \tag{2.5}$$

A higher X_i for a particular sector implies that more labor should be allocated to it. Following Gollin, Lagakos and Waugh (2011) and Adeyinka, Salau and Vollrath (2013), I assumed $\alpha = 0.3$ given that this value matches estimates of own price elasticity of labor demand as in Hamermesh (1993). I also use the employment share per sector i in Equation (2.5) as a reference benchmark to evaluate to what extent FDI inflows facilitated positive or negative structural change in terms of labor allocation. More precisely, I compare the employment shares of agriculture, manufacturing, and services found in the data with the optimal shares implied by Equation (2.5). Subsequently, I attempt to find a relationship between the gap between the mentioned employment shares with inward FDI inflows. Finally, my interest is to study whether FDI inflows play a role in determining the existing gap between optimal

[9] A very important absence in this model is that changes in relative prices are not present. This could occurr from the changes in labor across sectors.

[10] More specifically, the GGDC 10-Sector Database does not provide information on physical capital at a sectoral level. If I explicitly model the role of physical capital and capital accumulation, labor optimal employment shares would be different as gains from structural change would be greater. Moreover, I would be able to capture in greater detail the effects of factor shares on structural change by using a Constant Elasticity of Substitution (CES) production function as it is typically done in this literature.

[11] In this analysis, I assume three sectors only: agriculture, manufacturing, and services

and actual shares. Essentially, the question is to what extent FDI inflows played a role in explaining the existing misallocation of workers across sectors within countries. Summarizing, the comparison between the mentioned shares is the following:

$$Gap_{s,t} = \left(\frac{\theta_{s,t}^{optimal} - \theta_{s,t}^{actual}}{\theta_{s,t}^{actual}} \right) 100 \tag{2.6}$$

where $\theta_{s,t}^{optimal}$ represents the optimal employment share predicted by Equation (2.5) of sector i in year t (the ratio $\frac{L_i}{L}$). The term $\theta_{s,t}^{actual}$ represents the actual employment share found in the data. The interpretation of the variable $Gap_{s,t}$ is in percentage change relative to $\theta_{s,t}^{actual}$. The main objective is to investigate whether $Gap_{s,t}$ increases or decreases over time and its potential interaction with FDI inflows. In the next section, I attempt to compare shares of employment implied by Equation (5) (optimal) and actual shares to hypothesize about possible interactions with FDI.

2.6.2 Optimal shares of sectoral employment vs actual shares

In figures 2.9, 2.10, and 2.11, it is possible to observe the evolution of employment shares by sectors across countries. Figure 2.9 shows no substantial change in the gap for agriculture share of employment. This pattern seems in accordance with recent trends in FDI. From 1990 to 2001, for instance, FDI in primary sector (agriculture included) decreased from 10 to 6 percent (UNCTAD 2003).

Regarding Figure 2.10 , it is interesting to notice the change in trends for manufacturing and services after the 1990s. For instance, in Figure 2.10, it can be noted that after the 1990s, there is a substantial increase in the gap between the optimal and actual shares of manufacturing employment in countries such as Brazil, China, Costa Rica, Peru, and South Korea. As mentioned before in Section 2.2, this is the decade when many of these countries liberalize FDI leading to a positive net movement of many MNE's. For other countries, such as India and Bolivia, the gap decreases after the 1990s. In essence, one can see heterogeneous effects of liberalization in the manufacturing sector.

With respect to the service sector in Figure 2.11, one can note a gradual decline in the optimal service employment share in Figure 2.11 after the 1990s. Interestingly, this fact comes with an expansion of service sector as predicted by Lewis (1956). The only country where the gap does not decline or increase substantially is India. In fact, in India the gap is almost constant over time. This seems natural given that FDI in the service sector increased substantially in recent decades. For instance, the share of FDI stock in the service sector increased from less than 50 percent in 1993 to more than 60 percent in 2003 (UNCTAD 2003).

Conclusively, patterns in manufacturing and services sectors indicate a role played by FDI inflows. Given the recent trend of FDI in the last decades, agriculture share of employment is driven more by other structural factors rather than FDI or liberalization.

2.7 Assessing the role of FDI for labor allocation gaps

As an alternative approach to investigate a potential relationship between FDI and structural transformation is to use $Gap_{s,t}$ term in Equation (2.6) as a dependent variable and evaluate whether inward FDI inflows as a percent of GDP played a role in widening or shrinking the optimal and actual sectoral employment shares. To analyze this, I run a regression analysis following the same strategy as Equation (2.2).

2.7.1 Methodology

For the econometric approach is given as a fixed effects regression in the following Equation (2.3):

$$Gap_{s,t} = \alpha_0 + \alpha fdi_{s,t} + \lambda_t + \mu_s + \epsilon_{st} \tag{2.7}$$

I model the dependent variable as the sectoral $Gap_{s,t}$ of Equation (6) of country s in year t in terms of five year averages. The independent variables $fdi_{s,t}$ are also represented by the five year means of inward FDI inflows as a percent of GDP. The reason to proceed with five year means is, as in Section 2.4.1, to remove time series noise and focus on long-run patterns given that structural transformation is a long-run process. The terms α_0, λ_t, μ_s, and ϵ_{st} represent the constant, period-specific effects, country fixed-effects and the error term, respectively. Results for this specification are presented in Table 5 and discussed in the following section.

2.7.2 Empirical Results

From Table 2.5, it can be observed that FDI inflows play no statistically significant role in explaining the gap between the optimal and actual shares of agriculture employment. As noted previously, in recent decades, FDI inflows to the primary sector have declined substantially (UNCTAD 2003). During the period 2005-2007, for instance, FDI accounted for approximately 8 percent of total FDI while manufacturing and services accounted, respectively, for 41 and 50 percent of total FDI (UNCTAD 2012). Hence, the effects of primary sector's FDI should have no major implications on structural transformation.

Regarding the gap between optimal and actual shares of manufacturing employment, it is possible to see that FDI contributed to a shrinkage of the gap. The coefficient associated with inward FDI inflows over GDP during the period 1985-1990 show that, on average and *ceteris paribus*, a one percent increase in inflows over GDP depict a 1.068 percent decrease in the gap between the optimal and actual shares of employment. This coefficient is statistically significant at the 10 percent level. Regarding the existing gap between the optimal and actual shares of services employment, one can observe that, on average, increases on inward FDI inflows over GDP are associated with increase in the existing gap. The coefficient associated with FDI inflows over the period 1985-1990 is 1.237, which is statistically significant at the 5 percent level while the same coefficient associated with the period 1990-1995 is 0.571 being statistically significant at the 10 percent level. These results are aligned with existing literature. Existing studies show that the level of resource misallocation in the service sector is significantly higher than in manufacturing.

Dias, Robalo and Richmond (2020), for instance, find that closing the gap by reducing misallocation in the service sector would increase aggregate value-added by approximately 31 percent with Portuguese data. The novel aspect presented in Table 2.5 is that FDI inflows play an important role in explaining this misallocation of resources within sectors by showing that labor, a key input, "is not where it is supposed to be" in terms of maximizing aggregate value-added per worker.

Furthermore, findings in Column (2) in Table 2.5 support Rodrik (2013)'s hypothesis of unconditional convergence in manufacturing labor productivity. The relatively novel aspect is that FDI plays a role by contributing to the shrinkage of employment shares gaps.[12] Although Rodrik (2013) states that in "In an open global economy, access to foreign capital and foreign markets (which removes finance and market size as constraints) further strength- ens the presumption of convergence", he does not provide a causal link between FDI and unconditional labor productivity in the manufacturing sector. Findings in Table 2.5 attempt to find this causal link with a clear identification strategy, indicating that FDI could, at least, partially explain unconditional convergence in labor productivity in the manufacturing sector.

Ultimately, findings indicate that FDI inflows played an ambiguous role regarding structural transformation. More precisely, FDI played a positive role regarding a more optimal allocation of labor in the manufacturing. However, these inflows played a detrimental role regarding an optimal allocation of labor in the service sector.

2.8 Concluding Remarks

This paper shows that FDI inflows played, at an aggregate level, a detrimental role in structural transformation. This finding is robust with two different components of labor productivity change across sectors (*static and dynamic reallocation*). This detrimental role can be explained, at least partly, by a misallocation of workers in the service sector as showed in Table 2.5. Moreover, results in the paper suggests that FDI inflows contributed to a shrinkage of the gap between optimal and actual shares of manufacturing employment. This led to a more efficient allocation of manufacturing workers. Perhaps, due to the hypothesis of unconditional convergence in labor productivity for the manufacturing sector. More specifically, these results show that although the gap between optimal and actual manufacturing shares of employment is large in most countries in the sample, FDI contributed to a shrinkage of this gap, hence leading to a more efficient allocation of workers across sectors and positive structural change. The major issue that apparently drives negative structural change in section 2.5.2 and Table 2.4, as showed by results in Section 2.7.2 and Table 2.5, is the growth of the service sector.

There are two mechanisms to explain the findings in this paper. These mechanisms are explained by Helpman, Melitz and Yeaple (2004) and Rodrik and McMillan (2013). The first mechanism shows that, after FDI, unprofitable and least productive firms exit, leading to a more efficient allocation of labor. In the other hand, the second mechanism by Rodrik and McMillan (2013) points out that there is a potential problem when displaced workers after

[12]Possibly the same effect occurs with physical capital gaps if one thinks about capital misallocation.

FDI and trade end up in less productive activities due to large inter-sectoral gaps in developing nations. Results in sections 2.6 and 2.7 support both mechanisms in a unifying framework. More specifically, results indicate that unproductive firms exited the manufacturing sector (Helpman, Melitz, and Yeaple (2004)), leading to a more efficient allocation of workers in this sector. Nevertheless, displaced workers from the manufacturing sector moved to less productive activities in the service sector after FDI. The transition from a manufacturing to a services FDI in the late 1990s and early 2000s can also explain why FDI during those periods induced workers to move from high to low productivity activities (negative *static* and *dynamic reallocation*). More specifically, results in section 2.7.2 show that FDI inflows played a positive role in closing the gap between the optimal and actual share of manufacturing employment. In other words, FDI inflows induced a more efficient allocation of workers in the manufacturing sector. Nonetheless, these inflows also induced a less efficient allocation of workers in the services sector, causing negative *structural change* growth. The effects found in Table 2.2.4 are driven by an increase of the service sector found in Table 2.2.5. Conclusively, it is important to emphasize that the scope of this paper concerns the potential effects of FDI on structural change. There are other effects of FDI that are not addressed in this paper such as the creation of a more competitive environment among firms and spillover effects.

Finally, an interesting venue for further research includes studying the interactions between FDI, sectoral productivity shocks, and informality in developing nations.

Table 2.1: Description of Variables

Variable Name	**Variable Description**
Within sector	5-year mean of changes in value added with no reallocation of workers
Static reallocation	5-year mean of changes in value added with reallocation to high growth sectors
Dynamic reallocation	5-year mean of changes in value added with reallocation to higher growth sectors
FDIinflow_2010	5-year mean in FDI inflows as a % of GDP (2005-2010)
FDIinflow_2005	5-year mean in FDI inflows as a % of GDP (2000-2005)
FDIinflow_2000	5-year mean in FDI inflows as a % of GDP (1995-2000)
FDIinflow_1995	5-year mean in FDI inflows as a % of GDP (1990-1995)
FDIinflow_1990	5-year mean in FDI inflows as a % of GDP (1985-1990)
FDIinflow_1985	5-year mean in FDI inflows as a % of GDP (1980-1985)
FDIinflow_1980	5-year mean in FDI inflows as a % of GDP (1975-1980)
Gap_agriculture	5-year mean in gap between optimal and actual share of agriculture employment
Gap_manufacturing	5-year mean in gap between optimal and actual share of manufacturing employment
Gap_services	5-year mean in gap between optimal and actual share of services employment

Table 2.2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
Within sector	-1.726563	2.429153	-25	2.5	154
Static reallocation	-1.873958	1.659471	-5	3	154
Dynamic reallocation	-3.519792	1.54426	-8	0	154
FDIinflow_2010	0.6935818	2.730416	-5	16.6667	154
FDIinflow_2005	0.6979167	2.738433	-5	16.6667	154
FDIinflow_2000	0.7148847	2.738635	-5	16.6667	154
FDIinflow_1995	0.7194093	2.746747	-5	16.6667	154
FDIinflow_1990	0.7112527	2.753616	-5	16.6667	154
FDIinflow_1985	0.715812	2.76189	-5	16.6667	154
FDIinflow_1980	0.7268817	2.767368	-5	16.6667	154
Gap_agriculture	75.03219	3.310226	68.3	86.25	154
Gap_manufacturing	62.66693	2.349795	56.25	70.9	154
Gap_services	62.29036	2.938133	55.5	68.8	154

Table 2.3: Sectoral structure in the analysis (GGDC 10 - Sector Database 2014)

Sector	**Description**
AGR	**Agriculture**
MAN	**Manufacturing**
SER	**Services**
WRT	Wholesale and retail trade, hotels and restaurants
TRA	Transportation,storage and communication services
FIRE	Finance and insurance services
GOV	Government services
OTH	Other services

Table 2.4: Fixed effects estimation for labor productivity change components

	(1)	(2)	(3)
	Within sector	Static reallocation	Dynamic reallocation
FDIinflow_2010	0.169	0.0341	0.0512
	(0.135)	(0.0697)	(0.0651)
FDIinflow_2005	-0.224	-0.145*	0.0787
	(0.254)	(0.0765)	(0.0673)
FDIinflow_2000	-0.00664	-0.166**	-0.142***
	(0.0651)	(0.0574)	(0.0325)
FDIinflow_1995	-0.0801	0.0697**	0.0206
	(0.0829)	(0.0289)	(0.0594)
FDIinflow_1990	-0.127	0.0850	0.0425
	(0.161)	(0.0629)	(0.0782)
FDIinflow_1985	0.199	-0.00666	0.00987
	(0.194)	(0.0623)	(0.0462)
FDIinflow_1980	0.0651	0.0318	-0.170***
	(0.0726)	(0.0503)	(0.0565)
_cons	-1.805**	-0.977**	-3.651***
	(0.648)	(0.454)	(0.465)
Observations	154	154	154
Number of countries	18	18	18

Robust standard errors in parentheses. All regressions include year dummies not reported

* p<0.1, ** p<0.05, *** p<0.01

Table 2.5: Fixed effects estimation for gaps in sectoral employment shares

	(1) Gap_agriculture	(2) Gap_manufacturing	(3) Gap_services
FDIinflow_2010	0.315	1.582	-1.900
	(0.242)	(1.234)	(1.237)
FDIinflow_2005	0.0602	-0.101	0.0439
	(0.0694)	(0.324)	(0.347)
FDIinflow_2000	0.116	-0.158	0.0471
	(0.0947)	(0.329)	(0.399)
FDIinflow_1995	-0.0282	-0.538	0.571*
	(0.0940)	(0.321)	(0.316)
FDIinflow_1990	-0.172	-1.068*	1.232**
	(0.144)	(0.530)	(0.539)
FDIinflow_1985	-0.0693	-0.264	0.341
	(0.0566)	(0.482)	(0.461)
FDIinflow_1980	-0.0739	-0.420	0.490
	(0.0849)	(0.658)	(0.608)
_cons	-98.24***	-61.21***	-40.61***
	(0.632)	(5.314)	(5.096)
Observations	154	154	154
Number of countries	18	18	18

Robust standard errors in parentheses. All regressions include year dummies not reported
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

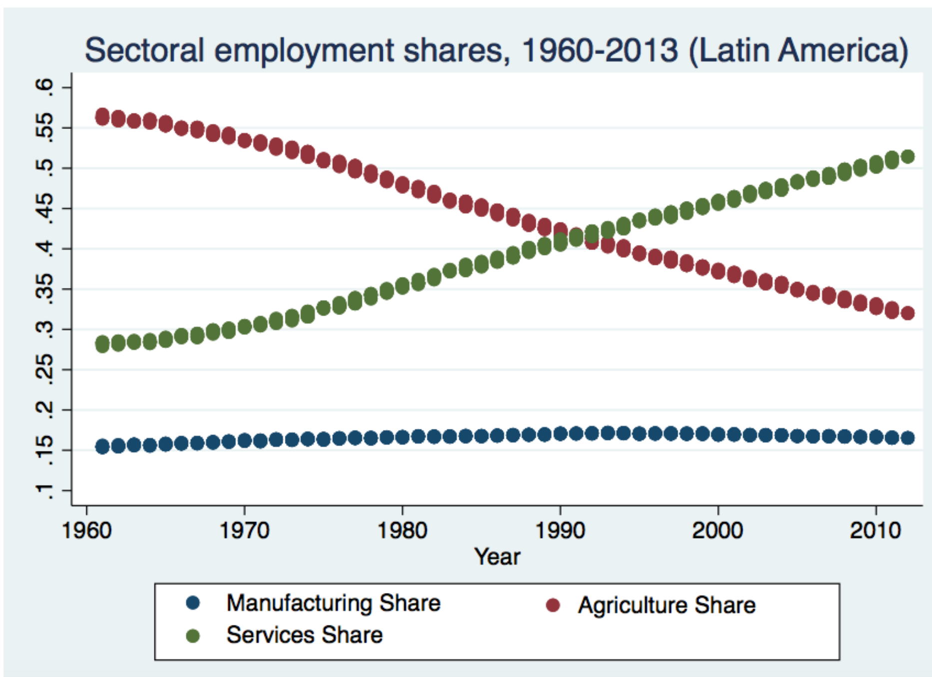


Figure 2.1: Long run structural change in terms of sectoral employment in Latin America. Countries in the sample are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Mexico, Peru and Venezuela

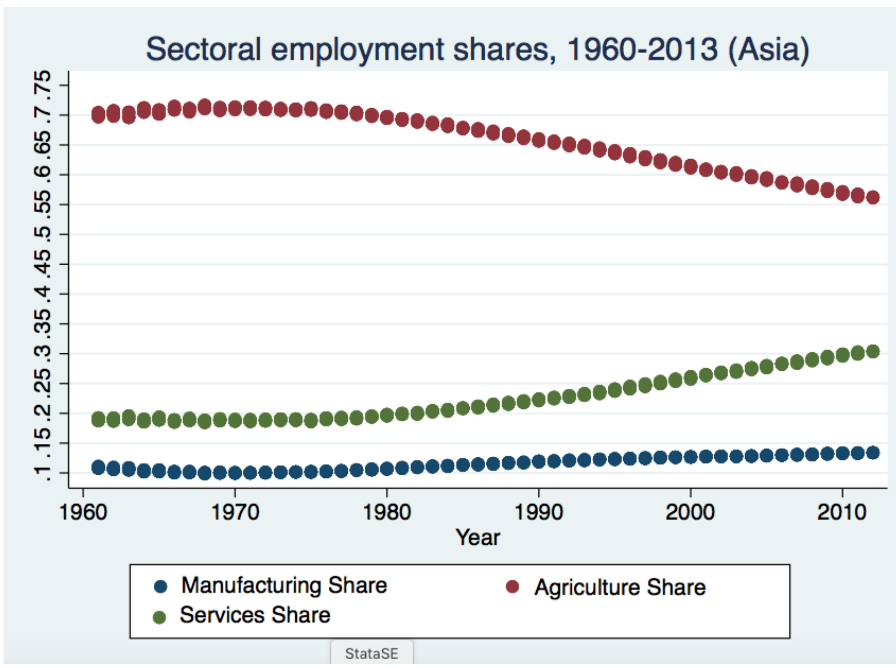


Figure 2.2: Long run structural change in terms of sectoral employment in Asia. Countries in the sample are China, Indonesia, India, Japan, South Korea, Malaysia, Philippines, Singapore, and Thailand.

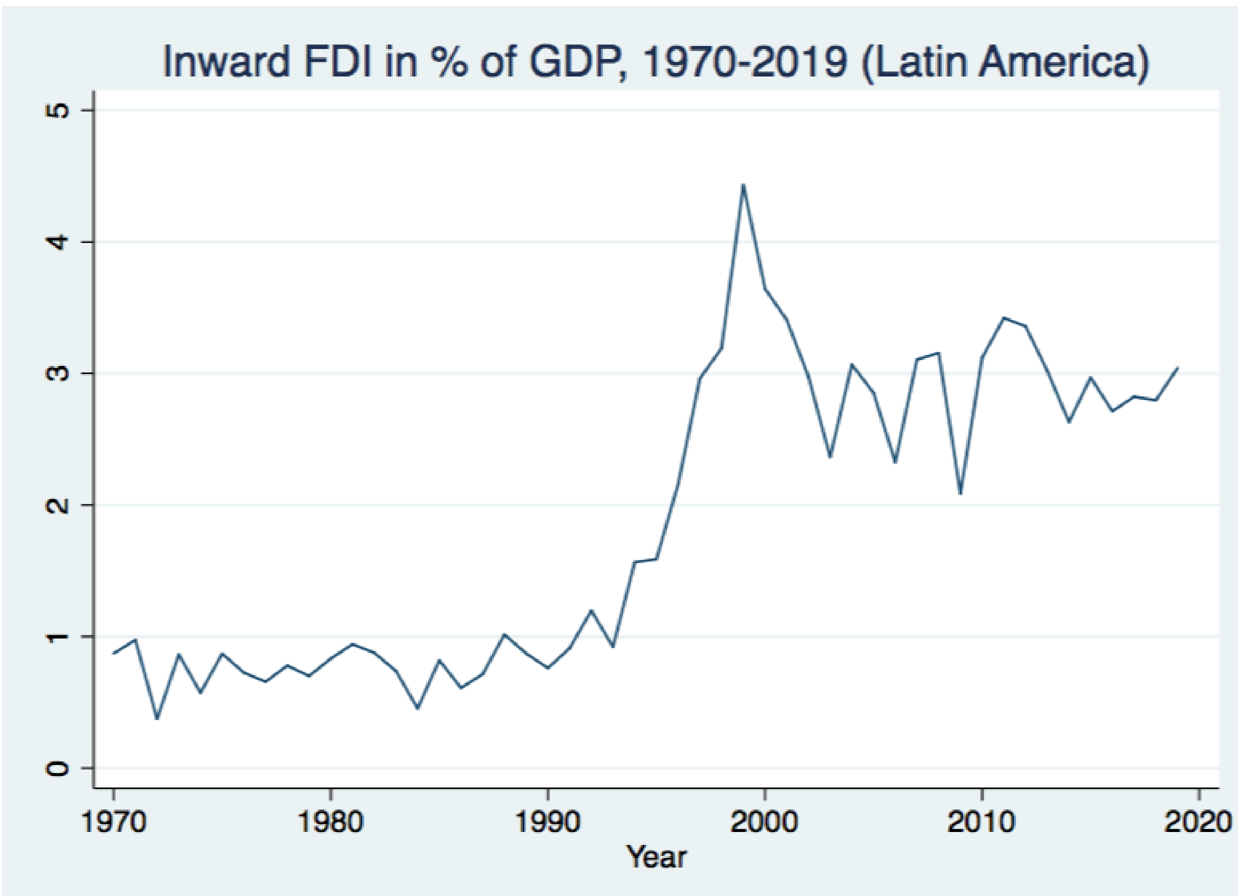


Figure 2.3: The relevance of foreign direct investments inward inflows in Latin America.

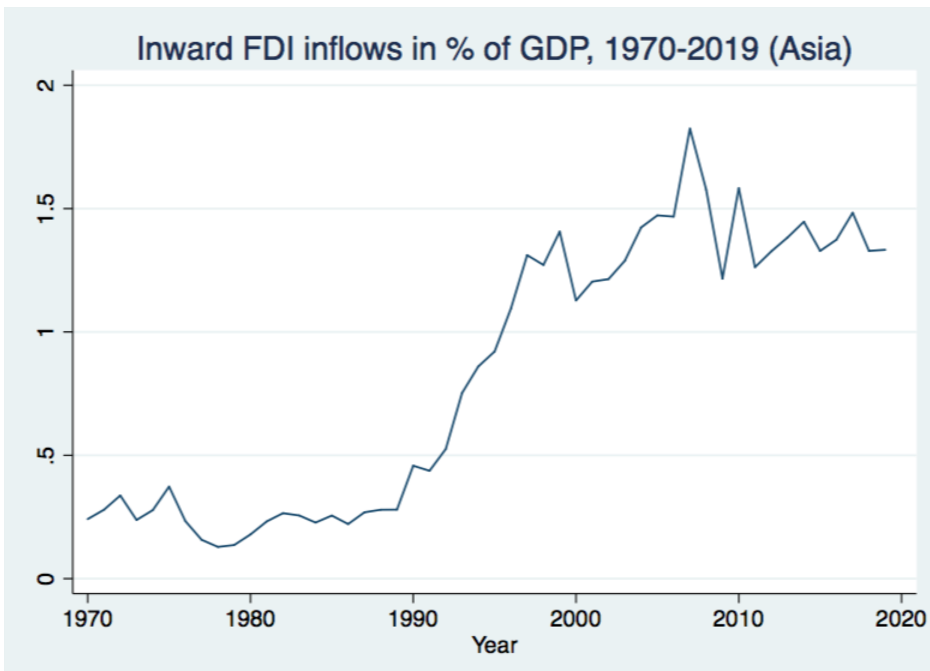


Figure 2.4: The relevance of foreign direct investments inward inflows in the Asian region.

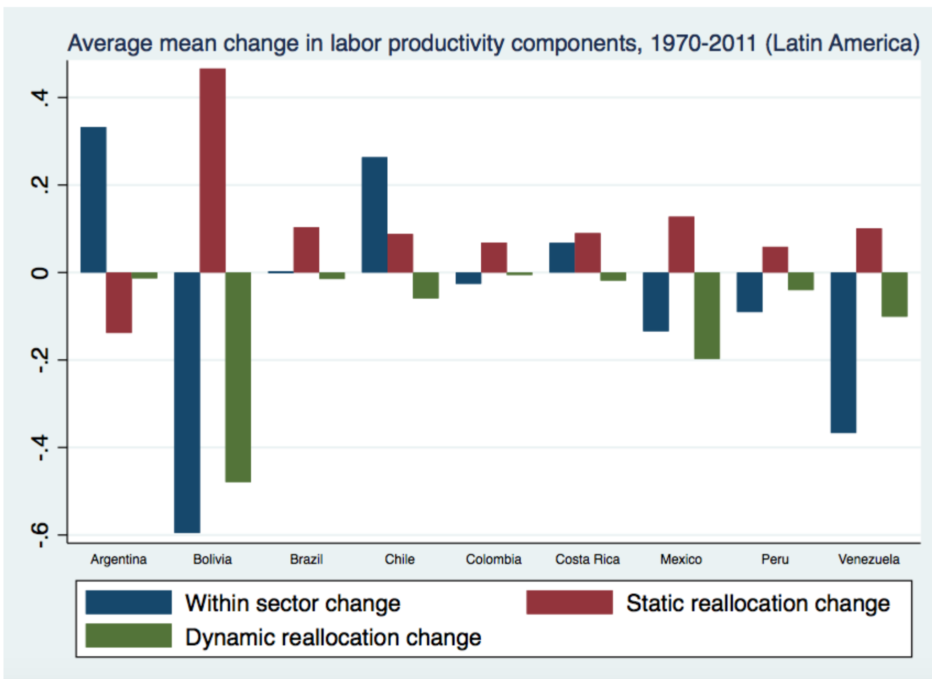


Figure 2.5: Average annual change of the three components of labor productivity change in Latin America for the period 1970-2011.

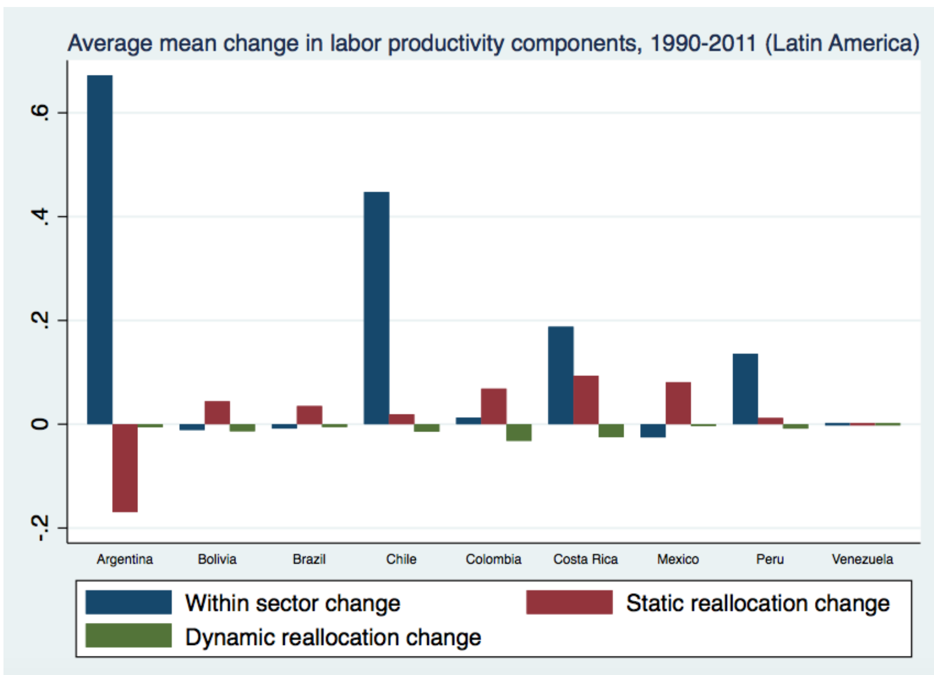


Figure 2.6: Average annual change of the three components of labor productivity change in Latin America for the period 1990-2011.

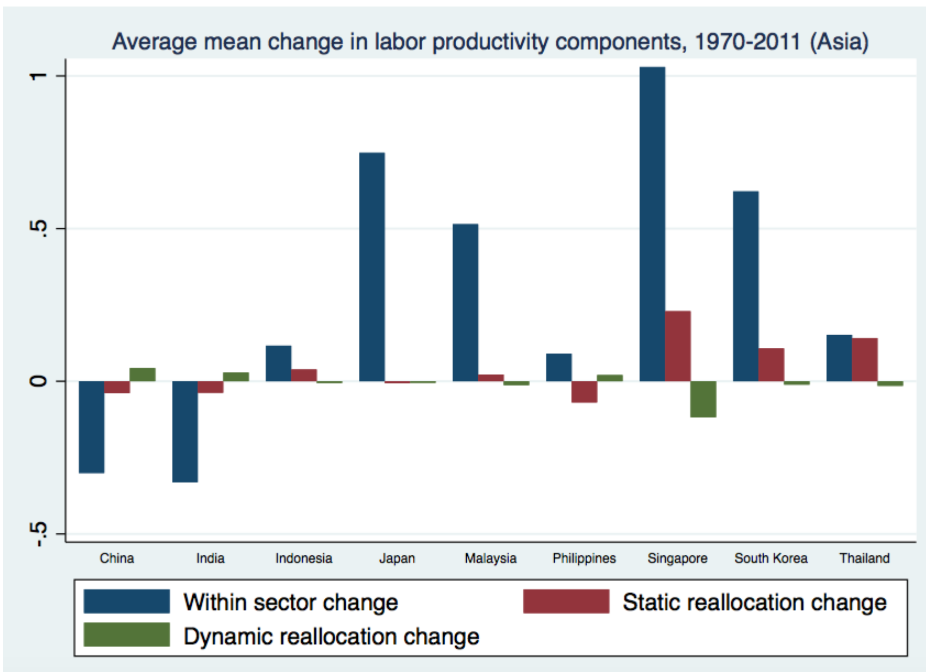


Figure 2.7: Average annual change of the three components of labor productivity change in Asia for the period 1990-2011.

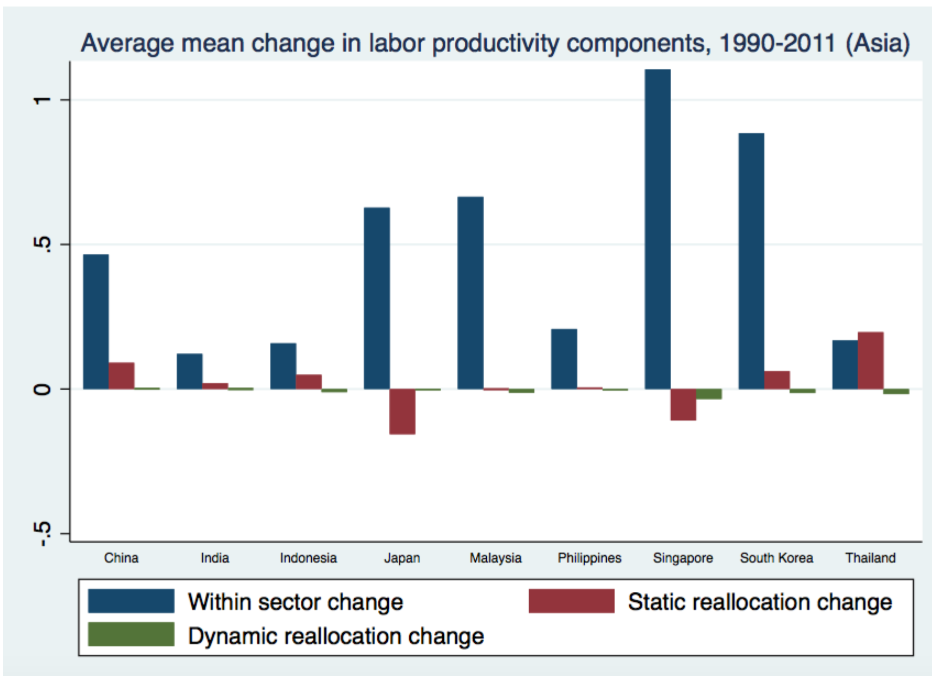


Figure 2.8: Average annual change of the three components of labor productivity change in Asia for the period 1990-2011.

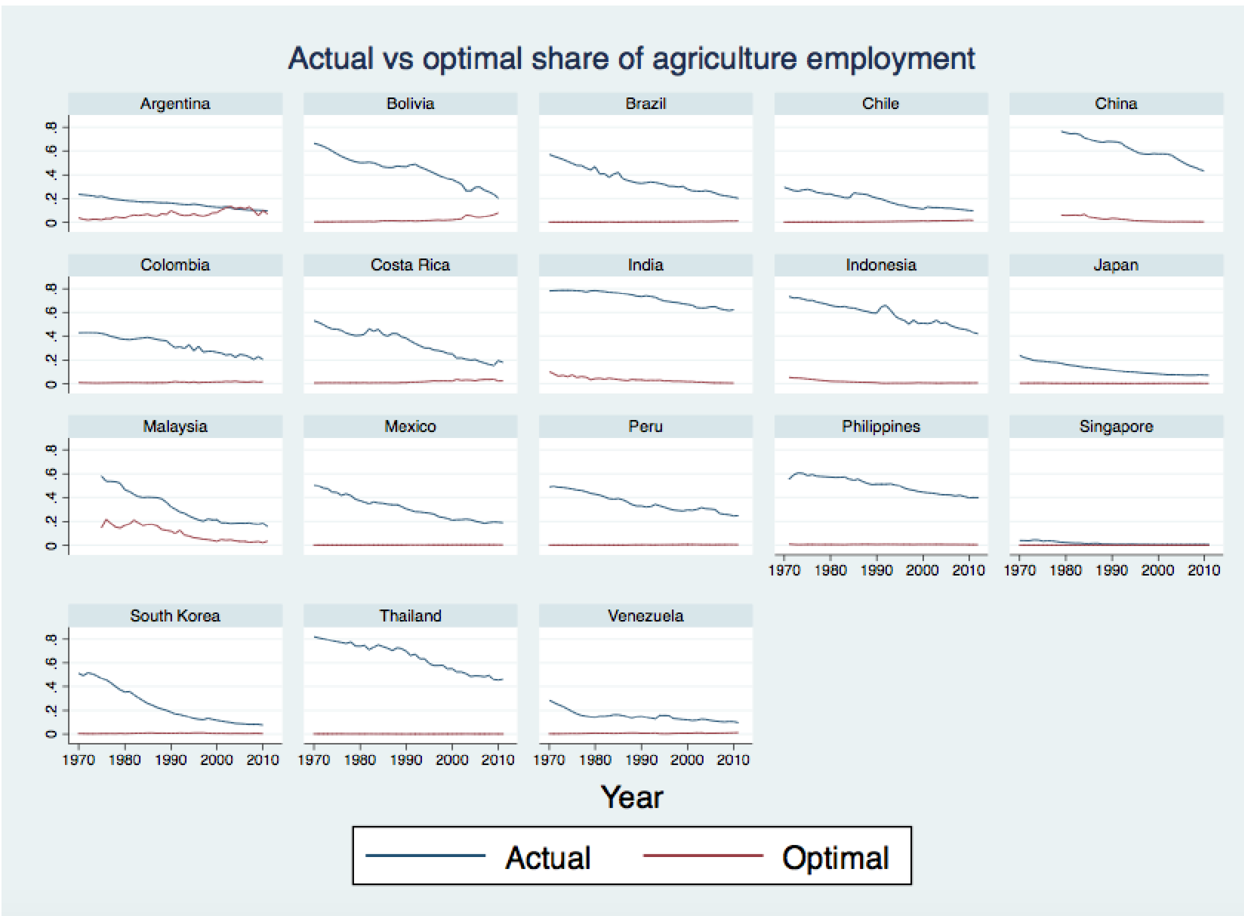


Figure 2.9: Shares of agriculture employment as predicted by model versus actual shares of agriculture employment in data.

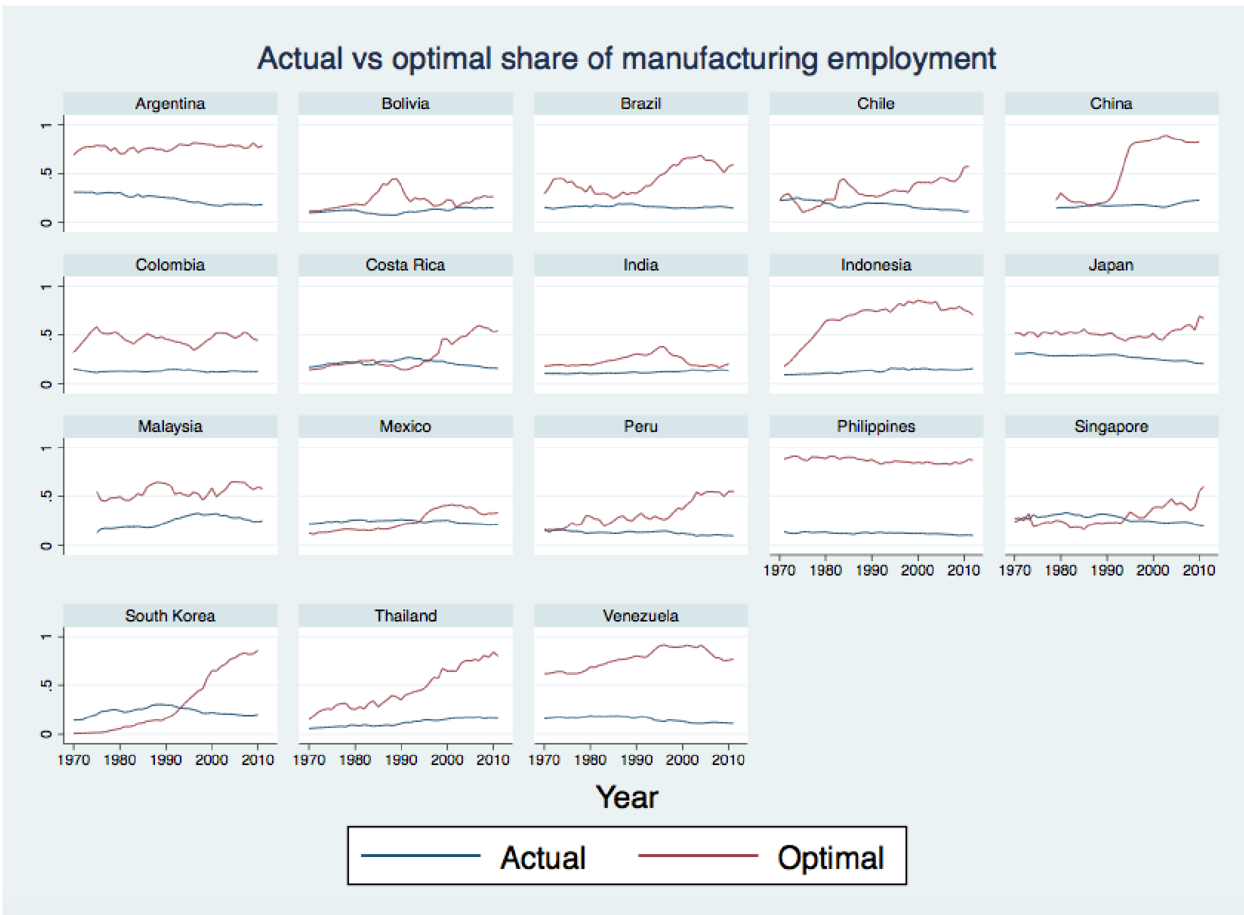


Figure 2.10: Shares of manufacturing employment as predicted by model versus actual shares of manufacturing employment in data.

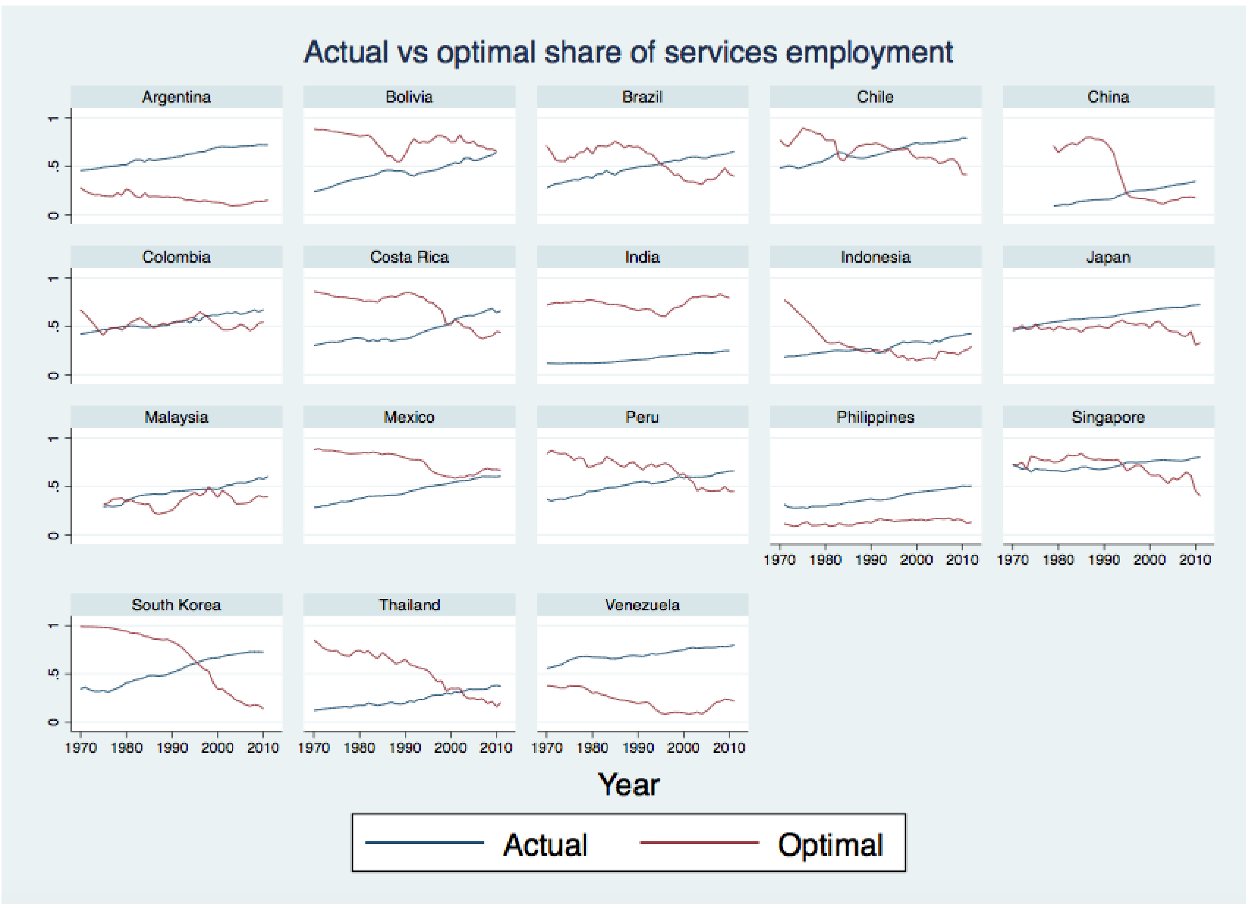


Figure 2.11: Shares of services employment as predicted by model versus actual shares of services employment in data.

Appendices

Appendix A- Countries included in Specifications for Chapter 1

Table 5: Countries for the period 1965-2015 (10-year growth rates)

8	Albania	417	Kyrgyzstan
12	Algeria	418	Lao People's Dem Rep
31	Azerbaijan	428	Latvia
32	Argentina	434	Libya
36	Australia	440	Lithuania
40	Austria	442	Luxembourg
50	Bangladesh	446	Macao
51	Armenia	450	Madagascar
52	Barbados	454	Malawi
56	Belgium	458	Malaysia
68	Bolivia	470	Malta
72	Botswana	480	Mauritius
76	Brazil	484	Mexico
100	Bulgaria	496	Mongolia
124	Canada	498	Republic of Moldova
140	Central African Republic	504	Morocco
152	Chile	512	Oman
156	China	528	Netherlands
158	Taiwan	554	New Zealand
170	Colombia	558	Nicaragua
188	Costa Rica	562	Niger
196	Cyprus	566	Nigeria
203	Czechia	578	Norway
208	Denmark	586	Pakistan
214	Dominican Republic	590	Panama
218	Ecuador	598	Papua New Guinea
222	El Salvador	604	Peru
231	Ethiopia	608	Philippines
232	Eritrea	616	Poland
233	Estonia	620	Portugal

242	Fiji	634	Qatar
246	Finland	642	Romania
250	France	643	Russian Federation
268	Georgia	682	Saudi Arabia
276	Germany	686	Senegal
288	Ghana	702	Singapore
300	Greece	703	Slovakia
320	Guatemala	705	Slovenia
340	Honduras	710	South Africa
344	Hong Kong	724	Spain
348	Hungary	748	Eswatini
352	Iceland	752	Sweeden
356	India	756	Switzerland
360	Indonesia	760	Syrian Arab Republic
364	Iran	764	Thailand
368	Iraq	780	Trinidad and Tobago
372	Ireland	788	Tunisia
376	Israel	792	Turkey
380	Italy	807	North Macedonia
388	Jamaica	818	Egypt
392	Japan	826	United Kingdom
400	Jordan	834	United Republic of Tanzania
404	Kenya	840	United States
410	Republic of Korea	858	Uruguay
414	Kuwait	894	Zambia

Number of Countries 110

Table 6: Countries for the period 1965-2015 (INDSTAT2- Barro and Lee (2013)

8	Albania	417	Kyrgyzstan
12	Algeria	418	Lao People's Dem Rep
32	Argentina	428	Latvia
36	Australia	434	Libya
40	Austria	440	Lithuania
50	Bangladesh	442	Luxembourg
51	Armenia	446	Macao
52	Barbados	454	Malawi
56	Belgium	458	Malaysia
68	Bolivia	470	Malta
72	Botswana	480	Mauritius
76	Brazil	484	Mexico
100	Bulgaria	496	Mongolia
124	Canada	498	Republic of Moldova
140	Central African Republic	504	Morocco
152	Chile	528	Netherlands
156	China	554	New Zealand
158	Taiwan	558	Nicaragua
170	Colombia	562	Niger
188	Costa Rica	566	Nigeria
196	Cyprus	578	Norway
203	Czechia	586	Pakistan
208	Denmark	590	Panama
214	Dominican Republic	598	Papua New Guinea
218	Ecuador	604	Peru
222	El Salvador	608	Philippines
233	Estonia	616	Poland
242	Fiji	620	Portugal
246	Finland	634	Qatar
250	France	642	Romania
276	Germany	643	Russian Federation
288	Ghana	682	Saudi Arabia

300	Greece	686	Senegal
320	Guatemala	702	Singapore
340	Honduras	703	Slovakia
344	Hong Kong	705	Slovenia
348	Hungary	710	South Africa
352	Iceland	724	Spain
356	India	752	Sweden
360	Indonesia	756	Switzerland
364	Iran	760	Syrian Arab Republic
368	Iraq	764	Thailand
372	Ireland	780	Trinidad and Tobago
376	Israel	788	Tunisia
380	Italy	792	Turkey
388	Jamaica	818	Egypt
392	Japan	826	United Kingdom
400	Jordan	834	United Republic of Tanzania
404	Kenya	840	United States
410	Republic of Korea	858	Uruguay
414	Kuwait	894	Zambia

Number of Countries 103

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