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ESSAYS ON GROWTH AND DEVELOPMENT

BY

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DISSERTATION

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ABSTRACT

This dissertation is composed by three chapters evolving around the role of deindustrialization in the process of growth and development. This first chapter focuses on the manufacturing's share of employment, which is known to follow a hump-shaped pattern as economies structurally transform. Motivated by the observation that capital intensities in manufacturing increase over the development process, this chapter examines whether such changes are important in accounting for the hump-shaped pattern in manufacturing employment shares as well as the decline in agriculture and the rise in services. It does this by putting forth a model of the structural transformation that allows for varying rates of technological rates, long-run Engel curves, international trade, as well as time-varying capital intensities. The model is calibrated to the experience of South Korea between 1970 and 2010 and the importance of these four factors for the structural transformation is analyzed. The main finding is that whereas heterogeneous rates of technological change, long-run Engel curves and international trade are important for accounting for various elements of the structural transformation, only time-varying capital intensities are critical for generating the hump-shaped pattern in manufacturing employment fairly close. Time-varying capital intensities are the additional "labor push" needed to explain the observed movement of labor out of manufacturing.

The second chapter provides quantitative evidence of the Ricardian Effect, namely the replacement of labor in the production process when capital is introduced. Based on a unique plant-level longitudinal dataset for Colombian manufacturing establishments for the period 1982-1998, this article exploits the disaggregation of the labor force between non-production (managers) and production (workers) employees to test whether there is supporting evidence of the Ricardian Effect in Colombia; whether this effect varies between two qualitatively different types of labor; and whether this effect was influenced

by the so-called “market oriented reforms” that Colombia experienced during the early 1990s. After estimating input demands for capital, managers, and workers instrumenting output with demand shocks, I found that the output elasticities for the three inputs are close to 0.6, while the price elasticities for capital, managers, and workers are -0.28, -0.32, and -0.21 respectively. Based on a simulated arrival of cheaper capital goods, these input demand coefficients are used to predict that, on average, when a plant increases its capital stock by about 67 per cent, it will reduce its payroll by one manager and 4 workers. Capital replaces labor, and this replacement is stronger for employees that perform routine tasks in the work place. This replacement is significantly stronger during the post-reform years since these reforms turned input demands to be more elastic with respect to prices. Importantly, these effects are not driven by plant’s observable characteristics.

The last chapter, written in collaboration with Cesare Buiatti and Joao Duarte, seeks to explain labor productivity differences of the service sector between Europe and the U.S. through the labor allocation taking place within the service sector. We are interested in understanding why is Europe falling behind the United States in terms of aggregate labor productivity. We measure labor productivity *levels* using a multi-sector structural transformation model that decomposes services into 11 sub-sectors comparable across Europe and the U.S. It is well known that the underperformance of Europe *vis-à-vis* the U.S. is related to services. We use our structural transformation model to find which service sectors are largely responsible for the lagging behind. We identify wholesale and retail trade as well as business services as the two sectors responsible for most of the lack of catch up in labor productivity between Europe and the U.S.

To Rebekah, who redefines the concept of unconditional support.

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Working toward a Ph.D. in economics is a humbling experience. As the days go by, you accumulate so many debts of gratitude that you reach a point where you are no longer sure how much of the progress you have made is your own. This has certainly been my case at Illinois. I would like to thank my advisor Stephen Parente for helping me to fulfill my dreams by showing me the rugged path toward finishing this dissertation, and for supporting me during each stage. He taught me that to become an economist is like “crossing the river by feeling the stones under the feet”, as Den Xiaoping supposedly once said. Steve Parente was always available for discussion, and he tried to make the best out of our meetings even when my ideas were still far from sound. It was a privilege to work under his advice, and I know that a simple thank you does not do justice in expressing my gratitude towards him.

I gratefully acknowledge the rest of the members of my dissertation committee for their support and timely feedback. I would like to thank Anne Villamil for her words of encouragement and for always combining technical advice without sending me to get lost in the woods. I also thank Rui Zhao for her insightful and challenging comments on the technical aspects of the project. I learned a lot about my own research during my attempts to provide reasonable answers to her keen questions. Last, I would like to thank Marcelo Bucheli for his insights on my findings, which motivated me to start thinking about myself as a scholar even at early stages of the Ph.D. My relation with Marcelo goes back for more than a decade, when I enrolled in his Economic History class at Universidad de los Andes, in Bogotá (Colombia). Since then, I knew that I wanted to shape my life around academia, and it has been a privilege to work with him and get to know him as a colleague, a mentor, and a friend.

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I would like to thank my parents for their bulletproof confidence in me.

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TABLE OF CONTENTS

CHAPTER 1	TIME-VARYING CAPITAL INTENSITIES AND THE HUMP-SHAPED EVOLUTION OF ECONOMIC ACTIVITY IN MANUFACTURING	1
1.1	Introduction	1
1.2	Empirical Support	6
1.3	A Model of Structural Transformation	22
1.4	Calibration	41
1.5	Alternative Hypotheses and Numerical Experiments	50
1.6	Conclusion	64
CHAPTER 2	THE RICARDIAN EFFECT: WHERE CAPITAL REPLACES LABOR. EVIDENCE FROM COLOMBIA	66
2.1	Introduction	66
2.2	Data	74
2.3	Empirical Strategy	86
2.4	Results	90
2.5	Robustness Checks	102
2.6	Conclusion	105
CHAPTER 3	WHY IS EUROPE FALLING BEHIND? STRUCTURAL TRANSFORMATION AND SERVICES' PRODUCTIVITY DIFFERENCES BETWEEN EUROPE AND THE U.S.	108
3.1	Introduction	108
3.2	A Model of Structural Transformation	112
3.3	Calibration	117
3.4	Quantitative Results	122
3.5	Numerical Experiments	133
3.6	Conclusion	143
REFERENCES	145
APPENDIX A	ADDITIONAL MATERIAL FOR CHAPTER 1	150
A.1	Shooting Algorithm	150
A.2	Estimation of Income and Substitution Elasticities	153
A.3	Computation of Sectoral TFPs.	156

A.4	Model's Main Prediction with Exogenous Aggregate Time Series	157
A.5	Predicted Manufacturing Labor Share with Implied Balance of Trade	158
A.6	Pattern of Development in South Korea	159
A.7	Predicted Capital Income Shares for Other Countries	159
APPENDIX B ADDITIONAL MATERIAL FOR CHAPTER 2		164
B.1	EAM Classification of Production and Non-Production Personnel	164
B.2	Simulation Algorithm	165
B.3	Robustness Checks: Figures and Tables	167

CHAPTER 1

TIME-VARYING CAPITAL INTENSITIES AND THE HUMP-SHAPED EVOLUTION OF ECONOMIC ACTIVITY IN MANUFACTURING

1.1 Introduction

A puzzle in economic development is to explain why manufacturing shares of employment have a hump-shaped pattern among countries that have undergone structural transformations. Figure 1.1 shows this pattern by plotting manufacturing employment shares as a function of income for several countries during the period 1950 through 2010. The manufacturing employment share rises during early stages of development, but during later stages, it declines while services take off and dominate the employment participation. For countries that started their structural transformations during the 19th century, such as the United States and Great Britain, manufacturing employment shares were already in their declining phases during the post-WWII period, but for late starters, such as Korea, both the rising and declining part of the hump are evident. For India, a country that started its structural transformation even later, the employment share in manufacturing is still rising.

This paper proposes a new theory whereby changes in capital intensities across time in manufacturing account for the hump-shaped pattern in manufacturing employment shares as well as the decline in agriculture and the rise in services. The theory is motivated by an observation of time-varying capital intensities in the manufacturing sector, which is consistent with the modernization observed during industrialization that is documented extensively by researchers such as Rostow (1960) and O'Donnell (1973). To test my hypothesis, I use the workhorse model of the structural transformation process developed by Herrendorf, Rogerson, and Valentinyi (2014), to which I adapt the preferences crafted by Comin, Lashkari, and Mestieri (2015). The advantage of adding this preference structure is that the implied Engel curves

generated in the model do not level off as long as an economy grows richer.¹ With this model structure, it is possible to consider income effects driven by non-homothetic preferences, price effects due to varying rates of technological rates, and the role of trade in shaping the structural transformation separately. Although extant literature considers these factors as plausible candidates to understanding labor reallocation across sectors, the possibility of time-varying capital intensities in each of the three production sectors as an additional driver of the structural transformation has not been considered, and is the novel feature of this paper.

The conclusion of the analysis is that time-varying capital intensities are the missing component needed to generate the manufacturing hump-shaped pattern; it is the additional driver necessary to generate deindustrialization observed after the manufacturing peak. Accounting for the growing bias to-

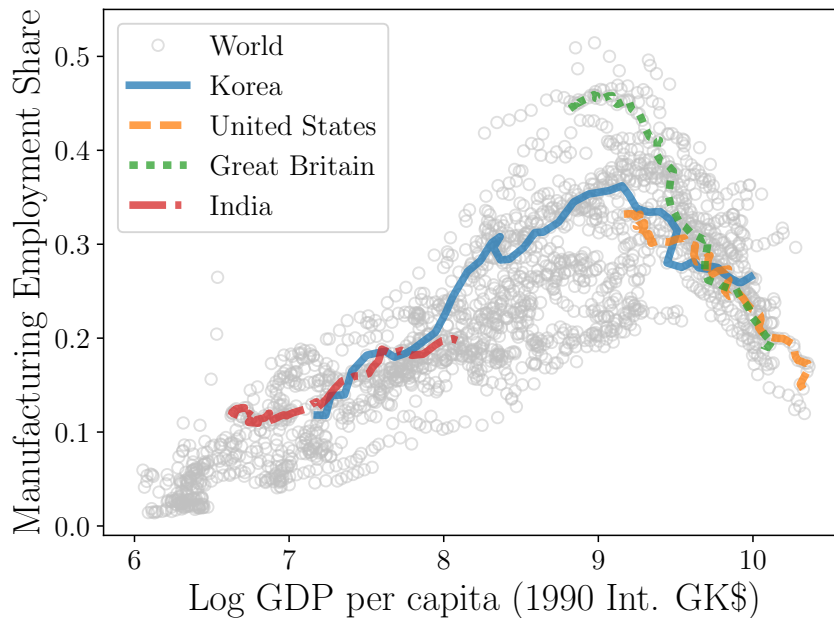


Figure 1.1: Manufacturing employment shares worldwide, 1950 – 2010. Manufacturing employment is constructed as the sum of total employment in mining, manufacturing, utilities, and construction. Income per capita is measured in 1990 international Geary-Khamis dollars. Sources: Timmer et al. (2014); The Maddison-Project (2013).

¹A recurrent problem with extant models of structural transformation is that most rely on Stoney-Geary preferences to account for income effects, and Engel curves generated by these preferences level off quickly.

ward capital in the production of manufacturing output, the model generates the additional “labor push”² of (redundant) workers out of manufacturing to explain the declining part of the hump. Whereas income effects through non-homothetic preferences, trade effects, and differences in technological growth rates across sectors are important to explaining the rise in the manufacturing employment share, they are unable to generate a hump-shaped pattern that follows the data closely. This paper closes this gap in macro-development literature.

I reach this conclusion by calibrating the model to the development experience of South Korea between 1970 and 2010. I use independent estimates of income and price elasticities, and calibrate the model to match the employment shares of the initial period perfectly. I then feed in capital income share values for each sector to identify the capital intensities, combined with data on growth in sectoral labor productivity and aggregate time-paths for consumption, wages and the real interest rate obtained with a shooting algorithm, to compute the model’s predictions for the time-paths of the employment shares of agriculture, manufacturing, and services. I find that with time-varying capital intensities, the model is capable of generating the observed hump-shaped pattern in South Korea. I also show that in absence of time-varying capital intensities, the model fails to account for the decline of the manufacturing employment share. My results confirm the conclusion of Buera and Kaboski (2009) that the standard theories of structural transformation cannot explain the steep decline in manufacturing observed in the data. Time-varying capital intensities are the additional “labor push” needed to explain the observed movement of labor out of manufacturing.

Using a set of counterfactual experiments, I demonstrate that traditional drivers of the structural transformation (i.e., Engel curves, heterogeneous technological rates, and trade) do not deliver the hump-shaped path of manufacturing share of economic activity, though they do matter when matching other dimensions of the structural transformation. I conclude that time-varying capital intensities are necessary but insufficient to address the evolution of economic activity in manufacturing. In particular, a counterfactual experiment for trade illustrates that South Korea would need to have been a

²Consistent with Alvarez-Cuadrado and Poschke (2011), labor push is a driver of the structural transformation in which redundant units of labor are released out of manufacturing.

net importer to account for the observed deindustrialization, without changes in capital intensity. As a further test, I calibrate the model to the United States to illustrate that time-varying capital intensities help account for U.S. labor share paths. A trade counterfactual with constant capital intensities over time suggests that the United States would have needed to more than double its trade deficit to account for the observed manufacturing employment share in 2010.

Recently, several models have been constructed to reconcile the structural transformation's stylized facts documented by Kuznets (1966) with the so-called Kaldor facts where the shares of labor and capital income, the capital-output ratio, the growth of capital and output per worker, and the real interest rate are constant (Kaldor, 1961). The notion of different capital intensities over time and across sectors that is supported in this paper does not contradict the Kaldor facts since rising capital intensities in manufacturing are accompanied by changing capital intensities in the service sector, and a greater prevalence of services in the economy. Consequently, the capital income share in manufacturing represents a smaller fraction of the aggregate capital income share. More specifically, capital income shares are not growing at the same pace in each sector. For Korea and the United States, the capital income share as a whole in the service sector is declining, and services are dominating participation of employment in the economy.³

Several articles relate to this paper.⁴ Noted above, from the income side of the structural transformation, the non-homothetic structure used here departs from standard use of Stoney-Geary preferences that were pioneered by Kongsamut, Rebelo, and Xie (2001), and follows Comin et al. (2015). With the introduction of long-run Engel curves, Comin et al. (2015) do account for the rise in services during later stages of development, but their model does not generate a *steep* deindustrialization after the peak of the hump-shape. These preferences also relate to Boppart (2014), who considers different marginal propensities for goods and services between rich and poor households, and to Foellmi and Zweimüller (2008), who introduced hierar-

³See Section 1.2 for details on the relationship between time-varying capital intensities and the Kaldor facts.

⁴Literature on structural transformation stands on the shoulders of the traditional development literature, such as W. A. Lewis (1954), Chenery (1960), Rostow (1960), Kuznets (1966, 1968), Baumol (1967), and Harris and Todaro (1970), among many others. For a detailed survey, see Matsuyama (2008) and Herrendorf et al. (2014).

chic preferences making the income elasticity of each good to deliver structural transformation as households get richer.

This paper belongs to supply-side explanations of the structural transformation, which focuses mainly on disparities in rates of technological changes and their influences through price effects, but has overlooked the observation of capital intensities changing over time. The seminal contribution in this area is Ngai and Pissarides (2007), who formalize the “Baumol cost disease” to explain labor reallocation due to heterogeneous technological rates in each production sector. It also relates closely to Acemoglu and Guerrieri (2008) who introduced differences in capital intensity as a static feature across sectors that delivers structural transformation through heterogeneous increments in the capital-to-labor ratio. Echevarria (1997) also considers a model in which sectors have differences in technology growth rates and time-invariant but heterogeneous factor intensities.

This paper also investigates the connection between trade and structural transformation, a research agenda influenced heavily by Matsuyama (2009). Uy, Yi, and Zhang (2013) recently claimed that the hump-shaped manufacturing employment share in South Korea is a consequence of greater openness and international trade. Their argument incorporates income and price explanations for the structural transformation in an open economy with a variation of the Ricardian theory of comparative advantages developed by Eaton and Kortum (2002). Although their model explains salient features of the structural transformation, it fails to generate the hump-shape for manufacturing employment. Betts, Giri, and Verma (2013) also account for trade liberalizations in a structural transformation model calibrated for Korea. Trade and trade reforms are quantitatively relevant when accounting for the structural transformation, but the model still fails to deliver the hump-shaped pattern in manufacturing employment.

This paper is organized as follows: Section 1.2 provides empirical support for the relevance of time-varying capital intensities for the structural transformation and its relation to the Kaldor Facts. Section 1.3 describes a model economy that accounts for structural transformation with varying capital intensities over time and across sectors. Section 1.4 presents the calibration strategy, discusses the test of the theory, and illustrates the prediction of the model for South Korea and the United States. Section 1.5 describes alternative hypotheses to account for the structural transformation, and employs

the model to address numerical experiments to recover the time series of capital income shares of other countries that display a well-defined hump-shape in manufacturing employment, but for which no comprehensive measures of capital income shares across sectors exist. Section 2.6 concludes the paper.

1.2 Empirical Support

1.2.1 Structural Transformation Stylized Facts: The Hump-Shaped Manufacturing Employment Share

The process known as structural transformation is characterized by sweeping changes in the structure of its productive apparatus from agricultural activities toward manufacturing and later toward services at advanced stages of development. Figure 1.2 illustrates the structural transformation patterns, known in the literature as the Kuznets facts.⁵ The solid line plots the fitted values from a regression of the labor share of each sector on the level, square, and cube of income per capita to summarize the structural transformation patterns in the data. Each panel of Figure 1.2 presents the coefficients of the estimation used to plot the fitted curve. Panel 1.2a shows that as long as economies grow richer, the participation of employment in agriculture falls asymptotically converging to employment shares below 4 per cent. Panel 1.2b illustrates that while economies grow richer, the employment share of services grows and even accelerates after an economy reaches, on average, over 9,000 international (Geary-Khamis) dollars of 1990.

Panel 1.2c shows the object of interest of this paper: A well-defined hump-shaped pattern for the employment share of manufactures with respect to the level of development: At early stages of development the industrial employment share grows and at later stages – above the 9,000 International (Geary-Khamis) dollars of 1990 mentioned before – it declines. In spite of the heterogeneity observed across countries,⁶ the fitted values are capable

⁵Kuznets (1973) considered the labor allocation out of agriculture as one of the six critical characteristics observed in the growth of developed nations. Quoting Kuznets (1973, p. 248), “(...) [m]ajor aspects of structural change include the shift away from agriculture to nonagricultural pursuits and, recently, away from industry to services”

⁶Including country fixed effects would have the effect of controlling for levels and therefore the residuals would be closer to the fitted line.

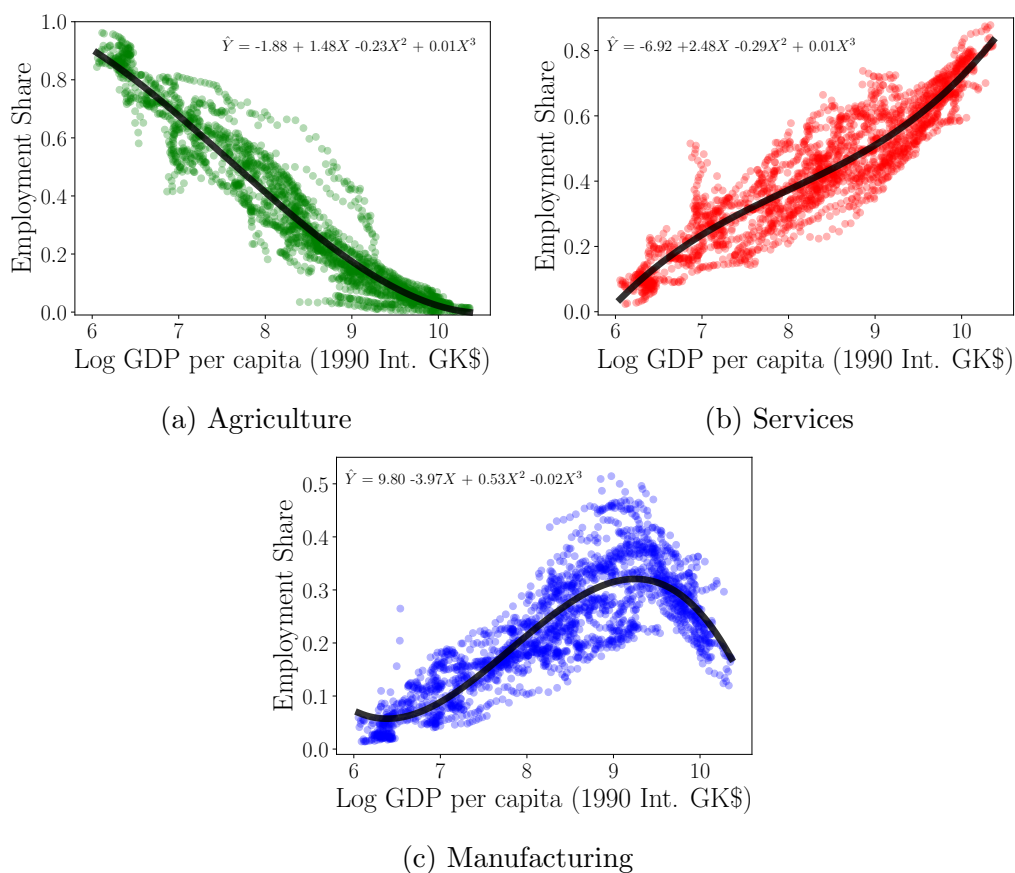


Figure 1.2: Structural transformation patterns. Employment shares of agriculture, manufacturing, and services. Manufacturing employment is constructed as the sum of total employment in mining, manufacturing, utilities, and construction. Services is the sum of whole sale and retail trade; hotels and restaurants; transport, storage, and communications; finance, real state, and business services; and community, social, and personal services. Income per capita is measured in 1990 international Geary-Khamis dollars. Sources: Timmer et al. (2014); The Maddison-Project (2013).

of summarizing the main patterns of structural transformation that nations experience in their development paths.

Figure 1.3 distinguishes the manufacturing employment shares by regions. Panel 1.3a shows that the United States and most of the European economies are already in their “postindustrial era” (the declining part of the hump-shape) while most African and some Asian countries are at their early stages of development where the hump is rising. The case of Latin America as a region is not conclusive: it does not display a clear pattern as a whole, since

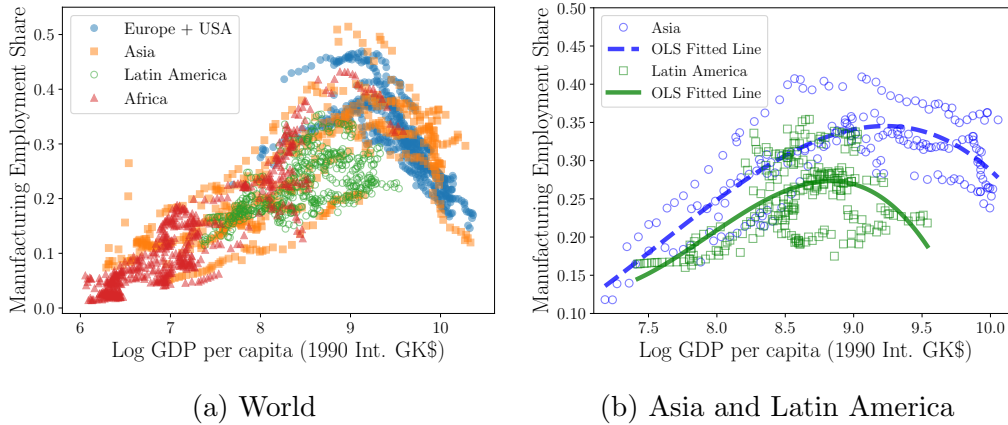


Figure 1.3: Manufacturing employment shares by regions, 1950 – 2010. Manufacturing employment is constructed as the sum of total employment in mining, manufacturing, utilities, and construction. Income per capita is measured in 1990 international Geary-Khamis dollars. For plotting panel 1.3b, the criteria of selection is that the country displays a well-defined hump in the manufacturing share of employment. The Asian economies selected are Japan, Korea, Malaysia, and Taiwan. Hong Kong and Singapore were excluded because in spite of their well-defined hump-shape in manufacturing employment, these economies are city-states with negligible agricultural sectors. The Latin American countries selected are Argentina, Brazil, Chile, and Mexico. Sources: Timmer et al. (2014); The Maddison-Project (2013).

there are countries such as Bolivia and Colombia for which a manufacturing peak is not evident.

To shed some light on the Latin American case, Panel 1.3b plots a set of Asian and Latin American countries that do have a well-defined manufacturing hump-shape in the data and plots the fitted curve for each set of countries derived from a regression of manufacturing labor shares on a cubic polynomial of income per capita. The evidence supports Rodrik’s (2015) claim that Latin America’s industrial experience has been a case of “premature deindustrialization”, namely a process in which the industrial share peaked at a modest stage of development – far below the 9,000 dollars discussed above – compared with advanced economies and with late starters such as Japan, Korea, Malaysia and Taiwan. The message delivered by the comparison of the fitted curves should be taken with a grain of salt since they do not capture the heterogeneity observed for each country, but one can compare each case in Latin America individually and realize that indeed this region experienced

a premature deindustrialization.

1.2.2 Capital Income Shares as Evidence of Time-Varying Capital Intensities

Acemoglu and Guerrieri (2008) proposed a theory of structural transformation based on static differences in factor proportions across sectors and suggest that capital income shares reflect the proportion, or intensity of capital in the production function.⁷ Following a long tradition in macroeconomics, I consider as well capital income shares as evidence of the capital intensity in the production function. As in Acemoglu and Guerrieri (2008), I measure the capital intensity of each industry as the ratio of value added minus total labor compensation to value added in each sector.⁸ The critical departure here is that I do not consider averages across time for these measures to interpret them as evidence of static differences in factor proportions, but I illustrate the time series of factor shares as evidence of time-varying capital intensities.

Figure 1.4 provides evidence for the main building block of the paper: Capital income shares across sectors do change over time. Panel 1.4a illustrates that in the United States the manufacturing capital income share – defined as the non-labor income share of value added – was falling from about 34 per cent in 1948 to levels below 30 per cent in the early 1980s both for manufacturing and for the whole industrial sector composed by manufacturing, mining, construction and utilities. In the mid-1980s the capital income share rose sharply and by 2010 the capital income share was above 47 per cent while the whole industrial sector had a capital income share of 42 per cent. The capital income share in the manufacturing sector since the late 1980s rose over 50 percent in the United States in less than three decades.

Panel 1.4b considers the case of South Korea. From the 1970s up to the early 1990s the capital income share was also declining, although at a faster pace compared to the United States (from about 60 per cent to levels below

⁷As Acemoglu and Guerrieri (2008, p. 468) write: “(...) [d]ifferences in factor proportions across sectors (*i.e.*, different shares of capital) combined with capital deepening lead to nonbalanced growth because an increase in the capital-to-labor ratio raises output more in sectors with greater capital intensity.”

⁸The data comes from the World KLEMS project, available at <http://www.worldklems.net/>.

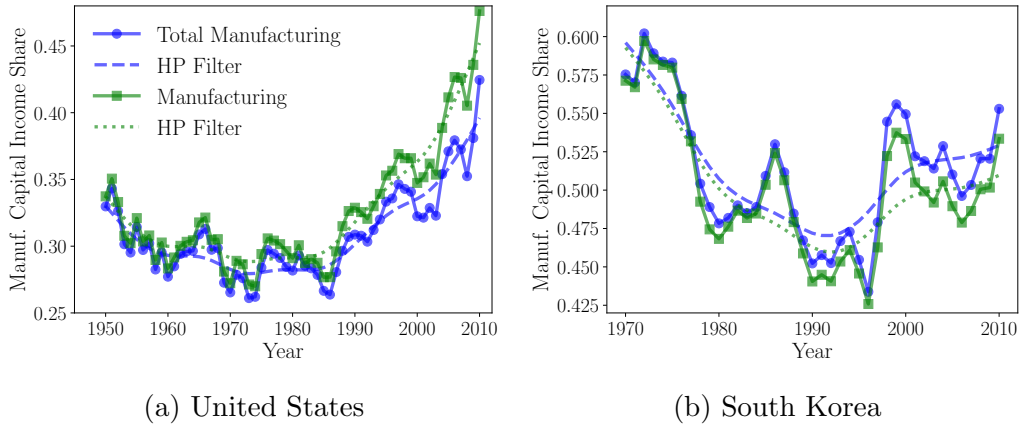


Figure 1.4: Manufacturing capital income shares for United States and South Korea. Capital income is computed as the value added per sector minus the total labor compensation. Manufacturing is constructed as the sum of mining, manufacturing, utilities, and construction. The dashed lines represent the trended capital income shares using the Hodrick–Prescott filter with a smoothing parameter of $\lambda = 100$. Source: The World KLEMS.

45 per cent), but after the early 1990s the manufacturing capital income share started a rising trend and the capital income share rose above 55 per cent for the manufacturing sector and about 53 per cent for the whole industry. Overall, after the 1990s the capital income share in South Korea increased about 25 per cent. Capital intensities in manufacturing do change over time, and the order of magnitude of these changes is substantial.

It is worth emphasizing that heterogeneous capital income shares across sectors but fixed over time as a sufficient measure of capital intensity is misleading because it assumes that one sector in particular can be ranked as more (or less) capital intensive compare to another sector. Figure 1.5 presents the trended capital income shares for United States and Korea for agriculture, manufacturing and services and shows that for both countries the capital income share for services was higher at early stages of development, and sometimes even higher than the capital income share in manufacturing. Using a measure of capital income shares that neglects the time variation provides an inaccurate ordering of the capital intensity across sectors.

Time-Varying Capital Intensities and the Kaldor Facts

Is the notion of time-varying capital intensities consistent with the Kaldor facts? Kaldor (1961) suggested that the shares of labor and capital income, the capital-output ratio, the growth of capital and output per worker, and the real interest rate are roughly constant over time, and several studies in modern macroeconomics argue that indeed once the economy abandons the Malthusian trap and enters into a period of modern economic growth, the capital and labor shares remain constant.⁹

In fact, Gollin (2002) argues that much of the variation observed in labor income shares across countries is due to mismeasurement problems mostly in agriculture. In particular, for poor countries the official statistics used to compute labor income shares are based on employee compensations and

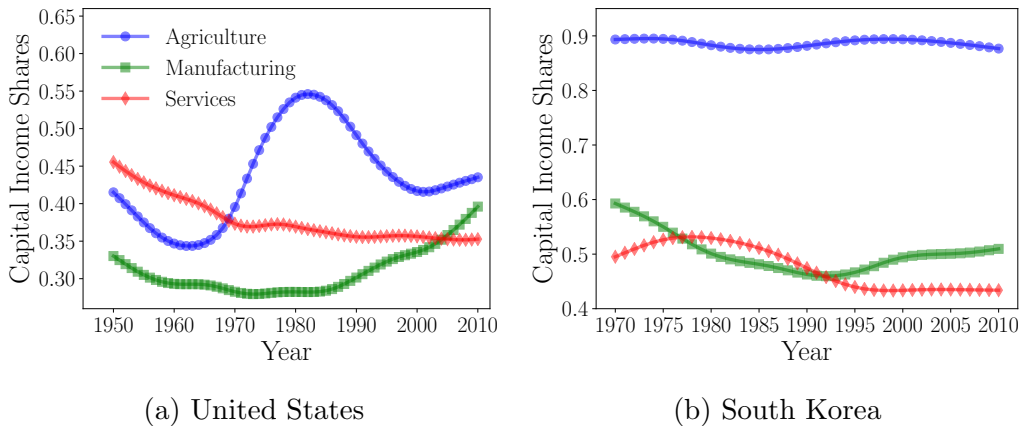


Figure 1.5: Capital income shares for United States and South Korea in agriculture, manufacturing and services. Capital income is computed as the value added per sector minus the total labor compensation. Manufacturing includes mining, utilities, and construction. Services is the sum of whole sale and retail trade; hotels and restaurants; transport, storage, and communications; finance, real state, and business services; and community, social, and personal services. The lines represent trended capital income shares using the Hodrick–Prescott filter with a smoothing parameter of $\lambda = 100$. Source: World KLEMS.

⁹The seminal work in this area is the unified theory of development by Hansen and Prescott (2002), which integrates in a single framework a model that explains the stagnation during the Malthusian era and the transition to Solow technologies (the modern period of economic growth). Hansen and Prescott (2002) show that once the economy abandons the Malthusian trap, the economy converges asymptotically to the neoclassical growth model where *aggregate* capital income shares are constant.

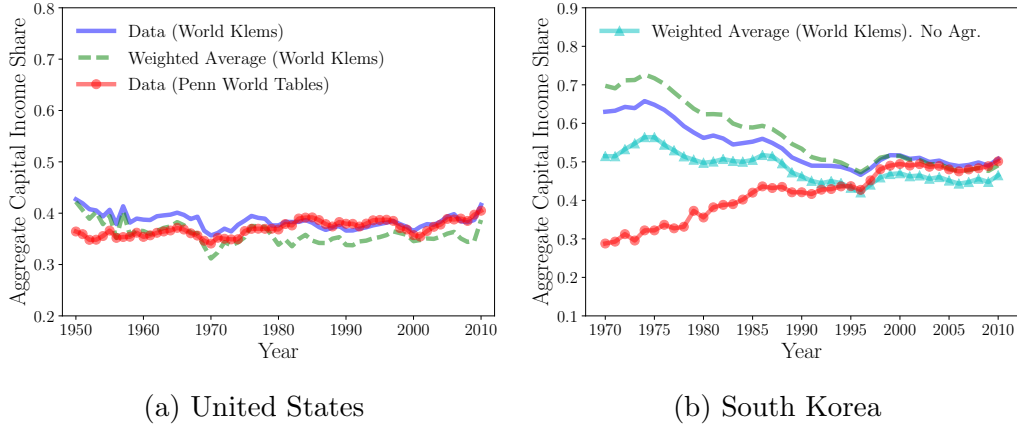


Figure 1.6: Structural transformation and the Kaldor Facts for United States and South Korea. Capital income shares from World Klems are computed as the value added per sector minus the total labor compensation. The weighted average from World Klems is the sum of the observed capital income shares for agriculture, manufacturing and services weighted by their respective employment shares. Capital income shares from Penn World Tables are computed as one minus the reported labor income shares. Source: The World KLEMS and Penn World Tables 9.0.

attributes the self-employment compensation as capital earnings. This mis-measurement is more problematic in rural activities where self-employment is more prevalent. Once labor income shares are adjusted using operating surplus to account for self-employment earnings, Gollin (2002) shows the labor income shares fall in the range between 0.6 and 0.85 and labor income shares seem to be stable across countries regardless of their level of development.

In line with Gollin (2002), Figure 1.6 suggests that the variation observed for capital income shares across sectors is consistent with the constancy of aggregate capital income shares. Panel 1.6a compares the observed capital income shares in the United States from Penn World Tables and World Klems to a weighted average of capital income shares across sectors using the labor shares of employment, *i.e.* the structural transformation, as weights. Aggregate capital income shares are roughly constant over time, and their levels are similar to the findings of Gollin (2002). Time-varying capital intensities across sectors and the Kaldor facts are consistent for the United States' development experience precisely because, as this paper suggest, the increasing capital intensity in manufacturing is an additional push of labor out of manufacturing balancing the effects with the absorption of labor in

services, which is more labor intensive, as the data suggests.

Panel 1.6b considers the Korean case. The Kaldor facts seem to hold only after 1990, but before this date there is important variation in aggregate capital income shares between the different sources. As Gollin (2002) suggests, this could be because of the prevalence of self-employment in agriculture together with its weight in the economy at early stages of development.¹⁰ Nevertheless, Panel 1.6b shows that if one neglects the agricultural sector and computes the capital income share as the weighted average of the capital income shares of manufacturing and services the “rough” constancy of the aggregate capital income share is back. As Hansen and Prescott (2002) suggest, the constancy of capital income shares in line with the neoclassical growth model do hold for periods of modern economic growth in which the participation of agriculture is shrinking. Whether observed capital income shares are constant when the economies still have an important participation of labor in agriculture is still open since it can be either measurement error in agriculture or simply that the constancy of capital income shares are a feature of modern economic growth but not necessarily a stylized fact that holds for Malthusian periods where land is still an important production input. Either way, the key message of Figures 1.5 and 1.6 for the purposes of this paper is that capital income shares *do* change over time and across sectors, and this fact does not necessarily contradict Kaldor’s (1961) observation that on aggregate, the capital income share is roughly constant.

Is There A Global Decline in the Labor Income Share?

Recently, Karabarbounis and Neiman (2014) contribute to the discussion on factor income shares following Gollin (2002) and analyse the labor shares within the corporate sector, arguing that mismeasurement problems are far beyond the agricultural sector. The virtue of the corporate labor share is that “(...) aggregate labor share measures are influenced by the methods

¹⁰The direction of the bias in capital income shares in agriculture is positive due to self-employment since the remuneration is accounted as capital income, but there are also negative biases on the capital share in agriculture due to the treatment of land and natural resources, which are not considered in World Klems as capital inputs. It is hard to conclude which bias dominates, although the evidence presented here suggests that for World KLEMS it is the self-employment nature of agriculture the most prevalent bias at early stages of development whereas for Penn World Tables the measures underestimate the role of capital when agriculture is still an important share of the economy.

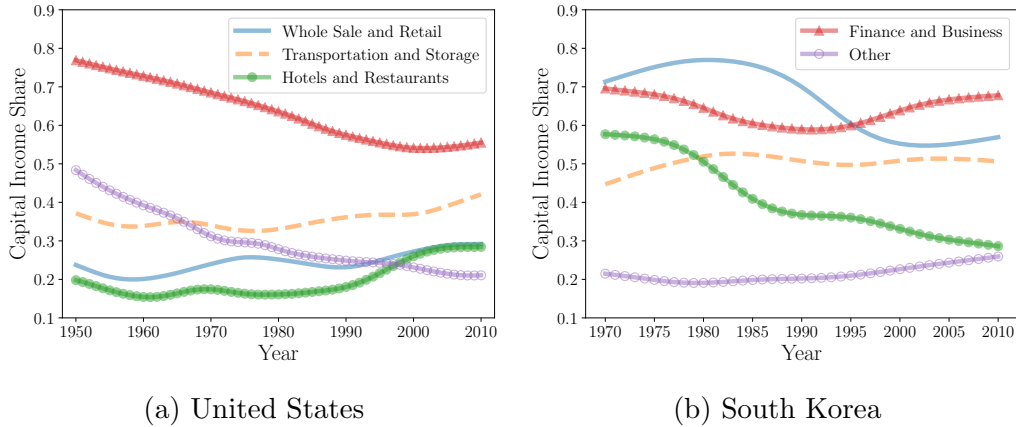


Figure 1.7: Capital income shares in services for United States and South Korea. Capital income shares from are computed as the value added per sector minus the total labor compensation. The lines represent trended capital income shares using the Hodrick–Prescott filter with a smoothing parameter of $\lambda = 100$. Source: The World KLEMS.

used to separate the labor and capital income earned by entrepreneurs, sole proprietors, and unincorporated businesses. The corporate labor share is not subject to such imputations” Karabarbounis and Neiman (2014, p. 62). Unlike Gollin (2002) however, Karabarbounis and Neiman (2014) interpret their findings as a 5 percentage point decline in the labor share over the past 35 years globally and argue that the aggregate labor share is falling due mostly to the decline in the relative price of investment goods.

Karabarbounis and Neiman (2014) estimate that labor shares are declining in the manufacturing sectors, in transportation, and to a lesser degree in whole sale/retail and public services, while they are growing in agriculture as well as in financial and business services. With the exception of transportation, all the sectors experiencing important declines in the labor share belong to manufacturing, whose participation in the economy is declining at later stages of development. It is not straightforward to extrapolate the evidence of time-varying capital intensities in the industrial sectors (and in some but not all services) as evidence against the Kaldor facts. In line with Karabarbounis and Neiman (2014), this paper also presents evidence suggesting that labor shares are falling in *some* sectors, but not in all of them. And it is precisely in those sectors that are not experiencing a decline in the labor share the ones that are increasing its employment share participation in the economy.

Figure 1.7 shows the capital income shares (the complement of the labor income shares) and provides further evidence on the heterogeneity observed within services to support the argument presented above. Time-varying capital intensities in manufacturing does not mean that labor income shares falling in each and every sector in the economy. In the United States the services that are experiencing an increase in the capital income share (or a decline in the labor income share) are hotels and restaurants; transport, storage, and communications and to a lesser degree whole sale and retail services, whereas finance and business services experienced a decline in capital income share up to 2000, confirming the finding of Karabarbounis and Neiman (2014) for this particular sector. Other services, which include community, social, and personal services have had experienced an increase in the labor income share as well.

For Korea, hotels and restaurants display the most dramatic reduction in the capital income share, closer to a 50 percent decline. Whole sale and retail trade also experienced an important reduction in its capital income share since the 1980s. The sectors in which capital income shares are growing are finance and business since the 1990s as well as transportation, storage and communications and other services. As Karabarbounis and Neiman (2014) suggest, there are sectors outside manufacturing experiencing increments in the capital income share, like transportation, but this fact does not imply that the aggregate capital income share in the economy is growing, as the evidence suggest for United States after WWII and for Korea if one excludes agriculture or only considers the period after 1990s where the employment share in agriculture was similar to the agricultural employment shares for the United States in the 1950s.¹¹

Biases in *Levels* of Capital Income Shares

A common concern in Gollin (2002) and Karabarbounis and Neiman (2014) is that factor income shares are potentially biased if one attributes self-employment earnings as capital income. The data on capital income shares from World KLEMS are constructed as the value added minus the labor compensation after correcting the self-employment bias by assuming that a

¹¹See section 1.4 for the time series of employment shares in agriculture, manufacturing, and services in United States and Korea.

self-employed worker does receive an hourly wage equal to an employee.¹² In principle, the measures of capital income shares used here capture the concerns Gollin (2002) and Karabarbounis and Neiman (2014). Nevertheless, Karabarbounis and Neiman (2014) show that once they use corporate labor shares, the correction of the biased measures of labor income shares is in *levels*,¹³ and even if the levels of capital income shares are biased, the key tenet of this paper is that capital income shares do change over time. In other words, even with biased *levels* for the measures of capital income shares, one can address their changes over time as evidence of a heterogeneous and dynamic process of capital intensity across sectors. The next subsection explores whether the *variation* in these measures of capital intensity are associated with the manufacturing labor shares of employment.

1.2.3 Time-Varying Capital Intensities and Manufacturing Labor Shares

The critical element of the theory proposed in this paper is that capital income shares and labor shares in the manufacturing sector are related. The theory suggest that increases in capital intensity in the production of manufacturing output – measured with manufacturing capital income shares – are negatively associated with the employment shares in this sector, posing time-varying capital intensities as a candidate to explain the observed deindustrialization patterns. Figure 1.8 shows a scatter plot for these two variables. Panel 1.8a illustrates the plot for Korea and United States. There are important differences in levels between these two countries, although the patterns are similar. These differences are possibly due to the fact that the Unites States is at a more advanced development stage during the sample period, in which labor manufacturing shares are lower compared to South Korea. Therefore, Panel 1.8a illustrates that a scatter plot with more countries will not deliver useful insights because the association between capital income shares and manufacturing employment shares will be performed across different development stages.

¹²See Jäger (2016) for detailed description of the EU KLEMS database, which shares the same methodology used in World KLEMS.

¹³Gollin (2002) also discusses the bias of labor income shares in terms of the differences in *levels* across countries.

Panel 1.8b plots the partial residuals of a correlation between manufacturing employment shares and capital income shares for Belgium, Canada, Spain, Great Britain, Japan, South Korea and the United States.¹⁴ Controlling for country fixed effects, as a first crude approximation to account for differences in the stage of development,¹⁵ yields a correlation between capital intensity and manufacturing employment negative and statistically significant. The point estimate is -0.47 and the standard error is .07, which

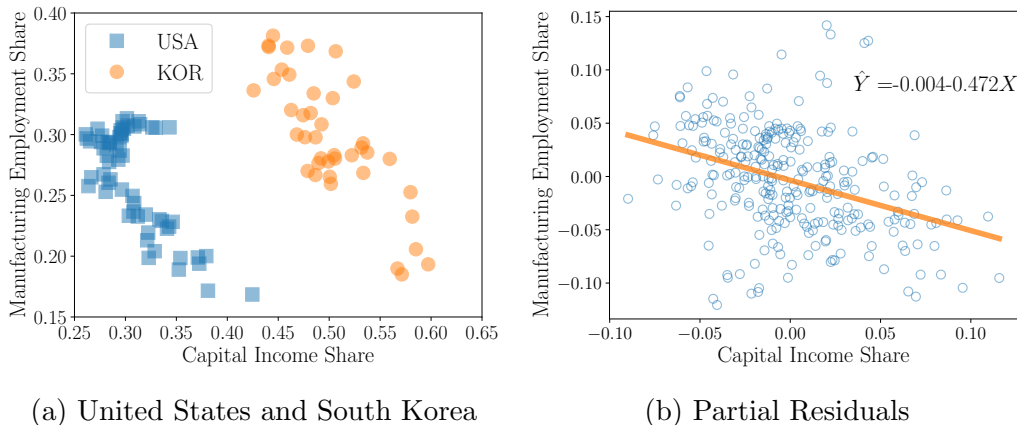


Figure 1.8: Manufacturing labor shares vs. capital income shares. Capital income is computed as the value added per sector minus the total labor compensation. Manufacturing labor is computed as the sum of hours employed in mining, manufacturing, utilities, and construction. Panel 1.8a plots the capital income shares against the manufacturing employment shares for United States and South Korea. Panel 1.8b plots the partial residuals of a correlation between capital income shares and manufacturing employment shares after controlling for country fixed effects for the following economies: Belgium, Canada, Spain, Great Britain, Japan, South Korea and the United States. Panel 1.8b also plots the fitted line of the residuals.

¹⁴The selection of these particular countries is limited due to data availability from the World KLEMS (<http://www.worldklems.net/>). There are a few more countries available with time series of capital income shares across sectors (Austria, Germany, Finland, France, Italy and The Netherlands) but I decided not to use these observations because some of their values for the agricultural capital income share are negative. It is important to emphasize however that the values of the capital income shares in manufacturing and services are positive, but negative capital income shares in agriculture indicate either important biases in the construction of labor income measures or agricultural sectors highly subsidized to sustain a value added inferior to the labor income.

¹⁵Since it is a fixed effect this control can be interpreted as the time invariant condition that describes whether the country entered to a modernization stage early or late compared to the United States as well as all the time invariant characteristics of a country that might have a role in the structural transformation.

documents a substantial negative association, as the theory suggest.

Table 1.1 uses the World KLEMS data for countries that display positive capital income shares in agriculture as well as in the aggregate manufacturing and services. The countries used in the panel are Belgium, Canada, Spain, Great Britain, Japan, South Korea and the United States. All the columns from Table 1.1 are estimated with the employment share of total hours per sector (agriculture, manufacturing and services). The manufacturing sector includes construction, utilities and mining whereas the service economy includes whole sale and retail trade; hotels and restaurants; transport, storage, and communications; finance, real state, and business services; and community, social, and personal services.

Column 1 of Table 1.1 considers the capital income share and its interactions with the binary identifiers of manufacturing and services as independent variables. The binary variables are also included in order to interpret correctly the interactions. For the first three columns country fixed effects are included to be able to control for time invariant characteristics such as the starting date of the modernization relative to the leader. Year fixed effects are excluded. The elasticity for capital income share is positive and statistically significant. This result should be interpreted with caution. This positive elasticity is present only when the binary variables of manufacturing and services take zero (when the sector in question is agriculture). Most of the economies of the sample display very low agricultural employment shares at late stages of development which are not controlled for in Column 1. The coefficient of interest is the interaction between capital income share and the binary variable for manufacturing. The elasticity is negative and statistically significant, and it counteracts the positive elasticity for agriculture. The effect of being in manufacturing alone is positive, but the interaction yields an overall negative effect as long as capital income shares grow. The effect of the interaction between capital income shares and services is also negative although less strong, which suggest that the observed rise in services should be consistent with reductions in the capital income share in services, which is precisely what Figure 1.5 documents for the cases of United States and Korea. For the case of services, the effect of the binary variable alone seems to be stronger than the case of manufacturing

Column 2 of Table 1.1 includes the GDP per capita and its square following Herrendorf et al. (2014) and Rodrik (2015) in order to capture the effects of

	(1)	(2)	(3)	(4)	(5)	(6)
Capital Income Share	0.259** (0.127)	0.0830 (0.051)	0.0271 (0.049)	0.398*** (0.118)	0.0876 (0.054)	0.0322 (0.051)
Capital Income Share × Manufacturing	-1.173*** (0.140)	-0.622*** (0.066)	-0.617*** (0.064)	-1.153*** (0.126)	-0.650*** (0.069)	-0.647*** (0.067)
Capital Income Share × Services	-0.997*** (0.180)	-0.472*** (0.085)	-0.346*** (0.084)	-1.052*** (0.184)	-0.499*** (0.088)	-0.373*** (0.087)
Manufacturing	0.376*** (0.134)	-12.82*** (2.649)	-13.70*** (2.766)	0.446*** (0.124)	-12.36*** (2.906)	-13.14*** (2.987)
Services	1.276*** (0.190)	10.64*** (3.235)	4.437 (3.533)	1.277*** (0.201)	11.30*** (3.204)	5.200 (3.490)
GDP pc		3.717*** (0.579)	2.894*** (0.588)		2.054** (0.816)	1.223 (0.840)
Squared GDP pc		-0.273*** (0.032)	-0.229*** (0.032)		-0.174*** (0.047)	-0.129*** (0.048)
GDP pc × Manufac- turing		1.690*** (0.586)	1.874*** (0.611)		1.590** (0.639)	1.754*** (0.656)
Squared GDP pc × Manufacturing		-0.0270 (0.032)	-0.0369 (0.034)		-0.0219 (0.035)	-0.0307 (0.036)
GDP pc × Services		-3.869*** (0.713)	-2.534*** (0.776)		-4.016*** (0.705)	-2.701*** (0.766)
Squared GDP pc × Services		0.307*** (0.039)	0.236*** (0.042)		0.314*** (0.038)	0.245*** (0.042)
Trade Balance			1.205*** (0.323)			1.206*** (0.360)
Trade Balance × Manufacturing			-0.347 (0.270)			-0.301 (0.266)
Trade Balance × Services			-2.034*** (0.344)			-1.976*** (0.353)
Constant	-2.945*** (0.115)	-13.33*** (2.589)	-9.523*** (2.644)	-2.092*** (0.315)	-6.189* (3.587)	-2.349 (3.714)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	852	852	852	852	852	852
Adjusted R^2	0.84	0.97	0.97	0.85	0.97	0.97

Table 1.1: OLS estimations. The dependent variable is the employment share of total hours worked per sector. Manufacturing is a binary variable that takes one for manufacturing sectors, zero otherwise. Services is a binary variable that takes one for services sectors, zero otherwise. The countries included are Belgium, Canada, Spain, Great Britain, Japan, South Korea and the United States. All remaining variables are in logs. Heteroscedasticity robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

development on the structural transformation process.¹⁶ The positive elasticity of capital income share for agriculture is no longer significant while the elasticities of capital income shares for manufacturing and services are negative and statistically significant, although less strong compared to Column 1. Adding the terms for manufacturing the income elasticities deliver the hump-shaped pattern for employment with a positive income elasticity and a negative elasticity for its square. Additionally, for agriculture income also predicts a hump-shape which is at odds with the stylized facts of structural transformation, but recall that these countries display very low agricultural shares throughout the sample period with the exception of South Korea. For services, the rising pattern is captured reasonably well by the income elasticities.

Column 3 of Table 1.1 includes the trade balance to control for openness, which plays an important role in the theory to follow closer the observed labor shares. The coefficient of interest, capital income shares in manufacturing, does not change with this control. The elasticities suggest that trade is important to understand the process of structural transformation, although seems to be less important for manufacturing compared to agriculture or services. This result is at odds with the notion that trade is more important in manufacturing for late starter countries. However, this sample is not representative of countries for which, arguably as a consequence of greater openness, trade played an important role in shaping the structural transformation. The only two countries whose period of modernization started relatively late are Japan and South Korea. Nevertheless, Column 3 does reveal that including trade does not change the elasticity of capital income share for manufacturing, which suggest that time-varying capital income shares rather than trade are critical to understand the process of deindustrialization at late stages of development.

Columns 4, 5, and 6 of Table 1.1 repeat the exercises of Columns 1, 2 and 3 respectively controlling for year fixed effects as well as country fixed effects. Column 6 presents the most complete exercise with country and year fixed effects and with controls for development levels and trade. Once time effects are included, the trade elasticities are roughly the same while

¹⁶I excluded the cubic term for income in these estimations with the purpose of presenting a cleaner interpretation of the income coefficients with regards to the structural transformation paths between agriculture, manufacturing and services.

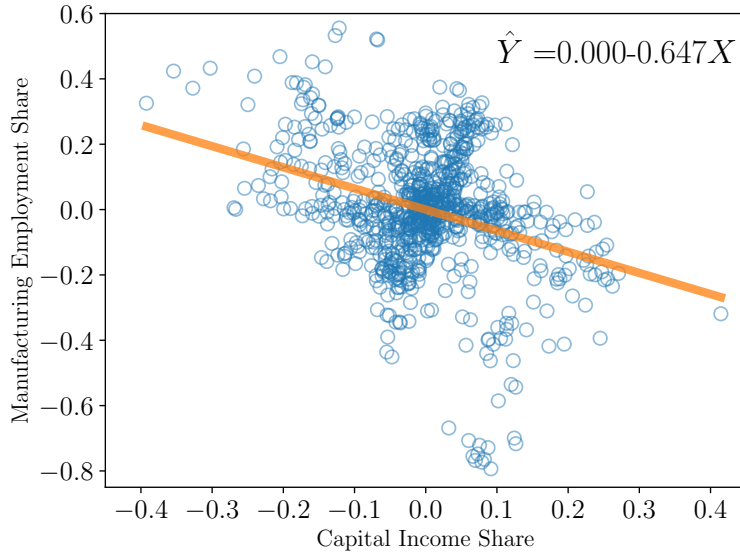


Figure 1.9: Manufacturing labor shares vs. capital income shares. Partial residual plots. The residuals are computed from the OLS estimation of equation of Column 6 of Table 1.1 in order to capture the correlation between capital income shares and employment shares for the manufacturing sector after isolating the controls suggested. Notice that the coefficient of the fitted line is the same as the coefficient for capital income shares for manufacturing sectors, as demonstrated by the Frisch-Waugh-Lovell Theorem.

the income elasticities for manufacturing are no longer useful to generate the hump-shaped pattern for industrial shares (the squared term loses its significance), and more importantly, the capital income share as a source of deindustrialization is robust.

Overall, the evidence suggest that there is a negative and statistically significant association between time-varying capital intensities and the employment shares in the manufacturing sector. This correlation is robust to controlling for time and fixed effects, for levels of economic development and for proxies of trade. Figure 1.9 uses partial residual plots to visualize the coefficient of interest presented in Column 6 of Table 1.1. An increase in 10 per cent in the manufacturing capital income share will lead to a reduction of the manufacturing employment share in about 6.5 per cent. These elasticities are just statistical associations and should not be interpreted as casual links, but it is clear from the scatter plot that there is a negative association between capital income shares and manufacturing labor shares. Time-varying capital

intensities seem to be a plausible candidate to understand the mechanics of deindustrialization. The next section presents a model of structural transformation to understand such mechanics.

1.3 A Model of Structural Transformation

Motivated by the evidence on capital income shares in manufacturing and its relation with the manufacturing employment share, in this section I present a theory whereby the process of labor allocations between agriculture, manufacturing and services depends on time-varying capital intensities in each of the three production sectors. The setup of the model borrows from Comin et al. (2015), who introduced long-run Engel curves to account for the demand side explanation of the structural transformation and include heterogeneous technological rates and differences in factors proportions to account for the supply side mechanisms of Ngai and Pissarides (2007) and Acemoglu and Guerrieri (2008) respectively. There are two important departures from Comin et al. (2015). First, factor proportions do change over time as well as across sectors to capture time-varying capital intensities as an additional supply driver. Second, there are only three sectors in the economy – agriculture, manufacturing, and services – and each of these sectors produce consumption *and* investment goods, as opposed to Comin et al. (2015) and Herrendorf et al. (2014) who consider that investment goods are produced in a separate investment sector. I assume differences in the production technologies between agriculture, manufacturing, and services, but that the same technology is used regardless of the destination of the output (toward consumption or investment goods). This assumption is important to be able to reconcile the theory of structural transformation with the two-sector neoclassical growth model.

I proceed in three steps. First, I describe the two-sector neoclassical growth model and show that if consumption and investment goods are produced using the same factor proportions, one can aggregate and reconcile the structural transformation theory with the one-sector neoclassical growth model that is consistent with the Kaldor facts.¹⁷ Second, I disaggregate the con-

¹⁷Or at least with the constancy of the real interest rate, which as weaker concept known in the literature as the generalized balanced growth path (GBGP).

sumption bundle between agriculture, manufacturing, and services to account for the labor allocations across sectors. Last, an additional step is required for the open economy implications of the model. Following Comin et al. (2015) and Sposi (2015), I consider trade in a reduced form to discipline the market clearing conditions when trade is not balanced and I assume that the only tradable good in the economy is produced in the manufacturing sector.

1.3.1 Two-Sector Neoclassical Growth Model

This section follows closely Herrendorf et al. (2014) exposition of the two-sector neoclassical growth model. In each period, there is an infinitely lived stand-in household of measure L . Households supply labor inelastically and are endowed with a positive but small capital stock at the beginning of the period. There are two constant-returns to scale sectors devoted to the production of consumption and investment goods respectively. Labor and capital are perfectly mobile across sectors.

Households

Each household is endowed with one unit of labor supplied inelastically in competitive labor markets and their income stream is generated through wages and capital rents product of their capital accumulation. Capital goods are the only means available to transfer present income to future consumption. The preferences over the consumption sequence $\{C_t\}$ are described by

$$\sum_t^{\infty} \beta^t \log C_t, \quad (1.1)$$

where β is the discount factor and belongs to the open interval $(0, 1)$. The objective of the household is to maximize their utility subject to its budget constraint described by

$$P_t C_t + X_t = W_t L_t + R_t K_t - 1 X N_t, \quad (1.2)$$

where P_t is the relative price of the consumption bundle in terms of the investment good, C_t represents the consumption bundle, X_t stands for in-

vestment in period t , W_t is the real wage, R_t is the real interest rate and L_t and K_t are the aggregate labor and capital in the economy respectively, $\mathbb{1}$ is an indicator function that takes 1 when the economy is open (zero otherwise) and XN_t represents the net trade balance (exports minus imports). This last terms takes the country's net export position, when the economy is open and trade is not balanced, and credits (or debits) the household's income. Asymptotically, this terms vanishes either due to a no-Ponzi condition that impedes that the economy continues with a trade deficit indefinitely,¹⁸ or simply because in the long-run the economy converges toward services, which is a closed sector. The inter-temporal household's problem is described as follows:

Household's (Inter-Temporal) Problem

$$\begin{aligned} \max_{\{C_t, K_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \log C_t \text{ s.t. } \quad & i) \quad P_t C_t + K_{t+1} \leq (1 - \delta + R_t)K_t + W_t - \mathbb{1}XN_t \\ & ii) \quad K_{t+1} = (1 - \delta)K_t + X_t \\ & iii) \quad K_0 > 0, \end{aligned} \tag{1.3}$$

where δ reflects the aggregate capital's depreciation rate in the law of motion for capital (restriction *ii*) in (1.3)). I assume interior solutions, so the budget constraint binds with equality and the first-order conditions are sufficient to characterize the optimal solution to the household's problem. The combination of the first order conditions yield the Euler equation

$$\frac{1}{\beta} \frac{P_t}{P_{t-1}} \frac{C_t}{C_{t-1}} = 1 - \delta + R_t \tag{1.4}$$

Firms

There are two constant-return-to-scale technologies with equal factor proportions for the production of consumption and investment goods. As Herrendorf et al. (2014) suggest, it is convenient to impose Cobb-Douglas production functions with the same capital shares in both sectors. I let the aggregate

¹⁸A continued surplus also violates the no-Ponzi condition because it implies another country having a negative trade balance indefinitely.

capital share to vary over time to generalize the aggregate production functions for cases in which the agricultural sector is still important in the economy and the constancy in the aggregate capital income share is not evident, but in the steady state the capital share converges to a constant.¹⁹ For the remainder of the paper, upper case letters reflect aggregate variables whereas lower case letters are sectoral variables unless specified otherwise. The superscripts c and x denote consumption and investment sectors respectively whereas the subscript $i \in \{a, m, s\}$ indicates whether the sector in question belongs to agriculture, manufacturing and services respectively. The production functions of aggregate consumption and investment goods are

$$\begin{aligned} C_t &= A_{ct}(k_t^c)^{\Theta_t}(l_t^c)^{1-\Theta_t} \\ X_t &= A_{xt}(k_t^x)^{\Theta_t}(l_t^x)^{1-\Theta_t} \end{aligned}$$

where A_{ct} (A_{xt}) is the total factor productivity (TFP) in the production of consumption (investment) goods, k_t^c (k_t^x) is the capital used in the production of consumption (investment) goods and l_t^c (l_t^x) is the labor demanded for consumption (investment) goods. Imposing equal capital shares for the consumption and investment sectors implies that one only needs to account for the allocation within the consumption bundle between agriculture, manufacturing and services to explain the structural transformation. I now formally state this proposition.

Proposition 1. *For a closed economy, if the production function of consumption and investment goods are Cobb-Douglas with the same capital shares, accounting for the structural transformation in consumption goods is sufficient for explaining the structural transformation of the entire economy.*

Proof. Define the aggregate capital income shares in the production of consumption and investment goods as the weighted average of the capital income shares in agriculture, manufacturing, and services, namely $\theta_t^c = \frac{1}{l_t^c} \sum_i l_{it}^c \theta_{it}^c$ and $\theta_t^x = \frac{1}{l_t^x} \sum_i l_{it}^x \theta_{it}^x$, $i \in \{a, m, s\}$. Using the assumption of equal capital shares for consumption and investment ($\theta_t^c = \theta_t^x = \Theta_t$) then $\frac{1}{l_t^c} \sum_i l_{it}^c \theta_{it}^c = \frac{1}{l_t^x} \sum_i l_{it}^x \theta_{it}^x$. Recall that the output of agriculture, manufacturing, and services is used as consumption and investment goods but it is produced with

¹⁹Even with the extreme and implausible case of singularity presented by Nordhaus (2015), the capital income share converges to one in the steady state.

the same production technology regardless of the destination of the output. Therefore, $\theta_{it}^c = \theta_{it}^x$ for all i . For the equality of the consumption and investment capital shares to hold, it must be true that the labor shares in consumption and investment are equal, namely $\frac{l_{it}^c}{l_t^c} = \frac{l_{it}^x}{l_t^x} = \frac{l_{it}}{L_t}$ for all i . \square

Proposition 1 is silent on the levels labor demand devoted to consumption and investment goods. l_{it}^c does not have to be equal to l_{it}^x nor the total l_t^c has to be equal to l_t^x , but only the labor shares across sectors within consumption and investment must be equal so in aggregate the capital income share of consumption and investment goods is equal to θ_t , which converges to θ in the long run.²⁰

Note that if one imposes equality in factor proportions for the production of consumption and investment goods, the only difference between these two sectors is driven by differences in their respective TFPs.²¹ The problem of a representative firm in consumption and investment is defined as follows:

Representative Firm's Problem in the Consumption Sector

$$\max_{k_t^c, l_t^c} P_t C_t - W_t l_t^c - R_t k_t^c. \quad (1.5)$$

The first-order conditions yield the equation for the capital-to-labor ratio in the production of consumption goods.

$$\frac{k_t^c}{l_t^c} = \frac{\Theta_t}{1 - \Theta_t} \frac{W_t}{R_t} \quad (1.6)$$

Representative Firm's Problem in the Investment Sector

²⁰The differences in capital income shares between investment and consumption goods is an interesting topic of its own, but comes at the expense of not being able to aggregate these two sectors into a neoclassical production function without further assumptions and additional parameters to account for. In addition, the data from World KLEMS identifies observations across sectors, but does not discriminate on whether the sectoral output was devoted to consumption or investment, imposing additional challenges to the empirical counterpart of the model.

²¹If the productivities in consumption and investment goods are different, they will have effects on the overall use of labor in each sector, but not in the composition within the sector. In the empirical counterpart I assume that both sectors have the same TFP to keep track of the differences in productivity between agriculture, manufacturing and services. Although theoretically it is possible to reconcile Proposition 1 with differences in TFP between consumption and investment, the data does not allow for the possibility of disentangling which output from agriculture, manufacturing or services is devoted to either consumption or investment goods.

$$\max_{k_t^x, l_t^x} X_t - W_t l_t^x - R_t k_t^x, \quad (1.7)$$

and first-order conditions yield a similar for the capital-to-labor ratio in the production of investment goods

$$\frac{k_t^x}{l_t^x} = \frac{\Theta_t}{1 - \Theta_t} \frac{W_t}{R_t}. \quad (1.8)$$

Market Clearing Conditions

The market clearing conditions are straightforward. The inputs used in both sectors need to add up to the total supply of each input and the total output is used between consumption and investment,²² namely

$$K_t = k_{ct} + k_{xt}; \quad L_t = l_{ct} + l_{xt}; \quad Y_t = P_t C_t + X_t. \quad (1.9)$$

For interpreting P_t in the market clearing conditions, Herrendorf et al. (2014, p. 877) suggest that “(...) we can consider an aggregate production function that produces a single good that can be turned into either consumption or investment via a linear technology with marginal rate of transformation equal to P_t ”.

Equilibrium

The right hand side of equations (1.6) and (1.8) are the same, thus if one assumes equal factor proportions and perfect mobility of inputs, the capital-to-labor ratio for consumption and investment goods are the same and equal to the aggregate capital-to-labor ratio $\frac{K_t}{L_t}$. From the first-order conditions one can obtain an expression for the aggregate price of consumption goods in term of investment goods

$$P_t = \frac{A_{xt}}{A_{ct}}. \quad (1.10)$$

The aggregate price for the consumption bundle in terms of the investment

²²I neglect the role of trade since the trade balance vanishes asymptotically and traded goods are in the end nothing but either consumption or investment goods.

goods reflects differences in TFP.²³ Using equations (1.6), (1.8) and (1.10) one gets

$$P_t C_t = A_{xt} \left(\frac{K_t}{L_t} \right)^{\Theta_t} l_{ct},$$

and with the market clearing conditions in equation (1.9) the aggregate production function is

$$Y_t = A_{xt} \left(\frac{K_t}{L_t} \right)^{\Theta_t} l_{ct} + A_{xt} \left(\frac{K_t}{L_t} \right)^{\Theta_t} l_{ct}$$

$$Y_t = A_{xt} K_t^{\Theta_t} L_t^{1-\Theta_t}. \quad (1.11)$$

As Herrendorf et al. (2014) conclude, assuming equal capital shares in the production consumption and investment goods allows the model to aggregate on the production side. This assumption also implies that one only needs to account for the structural transformation of the entire economy by focusing on the household's choices for the *consumption* of goods produced in agriculture, manufacturing and services. Herrendorf et al. (2014) demonstrates that in this setup a Generalized Balanced Growth Path (GBGP) where the constancy of interest rates is the only condition does exist. This is possible when the aggregate capital income share Θ_t has converged to its steady state value of Θ . The next section presents the intra-temporal choice of the households to derive a system of structural transformation equations to account for the observed labor (re)allocation across sectors.

1.3.2 Intra-Temporal Allocations

Proposition 1 argues that it is sufficient to account for the labor allocations between agriculture, manufacturing and services used to produce consumption goods to explain the structural transformation. This section uses this result and focuses on the intra-temporal allocations within the consumption bundle, once the inter-temporal trade-off between consumption and savings

²³If one assumes that the output in the economy is produced with an unique technology regardless of its final destination, and that the only differences are if the firm belongs to agriculture, manufacturing or services, then it follows that P_t is equal to one in each and every period. I use this assumption in the empirical counterpart of the model, but it is not necessary in the exposition of the model.

is optimally solved.

Additional assumptions are required to account for the intra-temporal allocations. Households are indifferent about the type of firm that hires their labor services, even if the job takes place in the countryside as peasants. There is a large number of perfectly competitive firms for the three main sectors in the economy and each firm takes wages and capital rental rates as given and combine capital and labor according to a Cobb-Douglas production function whose input elasticities reflect the time-varying capital intensity of each sector i . The firm produces output according to a constant returns to scale technology and the differences between agriculture, manufacturing and services are with respect to their TFPs and their capital intensities, both of them changing over time differently across sectors.

Households

Each period a household receives instantaneous utility from its consumption bundle. Borrowing from Comin et al. (2015), the CES non-homothetic preferences are described by the implicitly defined function

$$\sum_i \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i - \sigma}{\sigma}} c_{it}^{\frac{\sigma - 1}{\sigma}} = 1, \quad i \in \{a, m, s\}, \quad (1.12)$$

where Ω_i are constant weights for each sector in the economy, $\sum_i \Omega_i = 1$, σ is the elasticity of substitution, ϵ_i is the income elasticity for each sectoral output i , C_t is the aggregate bundle of consumption and c_{it} stands for the consumption from sector i . Multiplying C_t on both sides of equation (1.12) yields a CES non-homothetic aggregator that takes the form

$$C_t = \sum_i \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i}{\sigma}} C_{it}^{\frac{\sigma - 1}{\sigma}}, \quad i \in \{a, m, s\}. \quad (1.13)$$

The key element of equation (1.13) is the parameter ϵ_i , which governs the degree of the non-homotheticity. This parameter alone differentiates the role of income across sectors, and unlike the non-homothetic parameters from Stoney-Geary preferences, the income elasticity does not level-off in the long-run. This feature is particularly relevant for the service sector whose consumption grows more than proportional, especially at later stages

of development.²⁴ The non-homothetic CES aggregator provides a unified framework to study the role of income on the structural transformation process.

Another fundamental parameter is σ , the elasticity of substitution. Ngai and Pissarides (2007) argue that to generate the observed patterns of labor allocation described by Baumol (1967) in which workers are displaced from more productive to less productive sectors, σ must be below the unity. In this context, the elasticity of substitution also governs partially the effect of growing capital intensities on the structural transformation, where workers are displaced from sectors of low capital intensity to sectors of high capital intensity. This displacement is stronger if σ is inferior to one. Given the non-homothetic CES aggregator, the intra-temporal household's problem is as follows:

Household's (Intra-Temporal) Problem

$$\begin{aligned} \max_{C_t, C_{mt}, C_{st}} C_t \quad \text{s.t.} \quad & \text{i) } \sum_i \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i - \sigma}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}} = 1 \\ & \text{and ii) } \sum_i p_{it} c_{it} \leq W_t L_t + R_t K_t - \mathbb{1} X N_t - X_t \end{aligned} \quad (1.14)$$

where X_t reflects the optimal investments. Each period a household chooses optimally the composition of its consumption bundle subject to the implicit CES non-homothetic aggregator and its budget constraint. The first-order conditions yield the expenditure shares for each sector i as

$$\frac{p_{it} c_{it}}{P_t C_t} = \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i - \sigma}{\sigma}} c_{it}^{\frac{\sigma-1}{\sigma}}, \quad (1.15)$$

and multiplying both sides of equation (1.15) by $\frac{p_{it}}{P_t C_t}$ one gets

²⁴The Stoney-Geary preferences do a good job explaining the transition from agriculture to non-agriculture activities (see for instance Gollin, Parente, and Rogerson (2002) and Gollin, Parente, and Rogerson (2007)) since this transition takes place at low levels of development when the economy is starting its modernization process. However, the rise of the service sector takes place at later stages of developments and to understand this fact it is necessary that the income elasticity for services does not level-off. With Stoney-Geary preferences the home production parameters play an important role only early stages but its effect vanishes in the long-run (see the discussion on Stoney-Geary preferences and home production for the service economy in Buera and Kaboski (2009)).

$$c_{it} = \Omega_i C_t^{\epsilon_i} \left(\frac{p_{it}}{P_t} \right)^{-\sigma}. \quad (1.16)$$

Equation (1.16) illustrates both the supply and demand side mechanisms for the structural transformation through the allocation of consumption between agriculture, manufacturing and services. First, the parameter ϵ_i governs the income elasticity and generates long-run Engel curves. If $\epsilon_i < 1$, as long as the household gets richer and affords a bigger consumption bundle, the consumption of good i grows less than proportional. This is the case for agricultural goods. If $\epsilon_i > 1$ the growth in consumption of good i is more than proportional compared to the overall bundle C_t , as the stylized facts suggest to be the case for services. Importantly, the Engel curves generated do not level off at later stages of development.

On the other hand, the parameter σ governs the supply side mechanisms of the structural transformation via price effects. For the empirical relevant case of $\sigma < 1$, when the price of a good drops (relative to the price of the aggregate consumption bundle) due to either increases in TFP or to an increase in capital intensity, the change in prices is accompanied with an increase in quantities demanded less than proportional, suggesting an overall reduction in quantities demanded from sector i . Whereas increases in TFP combined with a price elasticity of substitution below one account for Baumol's (1967) transition of labor from productive sectors (or progressive as he refers) to less productive sectors, changes in capital intensity are an additional supply side driver that reduces labor demand. As Adam Smith (2000, p. 9) conjectured almost 250 years ago, "(...) every body must be sensible how much labour is facilitated and abridged by the application of proper machinery".

Firms

For each sector $i \in \{a, m, s\}$, output is produced with a constant-returns to scale technology

$$y_{it} = A_{it} k_{it}^{\theta_{it}} l_{it}^{1-\theta_{it}}; \quad \theta_{it} \in (0, 1), \quad (1.17)$$

where A_{it} is the firm's TFP, k_{it} and l_{it} are the firm's capital and labor demand

respectively, and θ_{it} is the capital intensity of sector i at period t . Given the constancy in the returns to scale and the zero-profit condition, the capital intensity the production process is reflected in the capital income share. The firm does not have any inter-temporal choices, and each period solves the following problem:

Firm's Problem

$$\max_{k_{it}, l_{it}} p_{it} A_{it} k_{it}^{\theta_{it}} l_{it}^{1-\theta_{it}} - W_t l_{it} - R_t k_{it}, \quad (1.18)$$

where p_{it} is the price of output y_{it} at period t . The first order conditions yield the capital-to-labor ratio and the output price in terms of the time-varying capital intensity parameters, the relative input prices and the firm's TFP

$$\frac{k_{it}}{l_{it}} = \frac{\theta_{it}}{1 - \theta_{it}} \frac{W_t}{R_t}, \quad (1.19)$$

and

$$p_{it} = \frac{R_t^{\theta_{it}} W_t^{1-\theta_{it}}}{A_{it} \theta_{it}^{\theta_{it}} (1 - \theta_{it})^{1-\theta_{it}}}. \quad (1.20)$$

Equation (1.19) demonstrates that in presence of heterogeneous capital intensities, the capital-to-labor ratios will not be the same across sectors. Moreover, these differences change over time if one acknowledges the dynamic component of capital intensities. Equation (3.7) illustrates the inverse relation between TFP and prices across sector, which is a key element in Ngai and Pissarides (2007) to account for the structural transformation. Additionally, one can show using (3.7) that prices are also fundamentally affected by the presence of time-varying capital intensities. In particular, since the ratio $\frac{W_t}{R_t}$ is growing in the balanced growth path, increasing capital income shares have negative effects of prices. The following Lemma formalizes this statement.

Lemma 1. *In the balanced growth path, increasing capital income shares are negative related with output prices.*

Proof. Take logs on both sides of equation (3.7). Differentiating with respect to the capital income share one gets

$$\frac{\partial \log p_{it}}{\partial \theta_{it}} = -\log \left(\frac{W_t}{R_t} \right) - \log \theta_{it} + \log(1 - \theta_{it}).$$

Since the ratio $\frac{W_t}{R_t}$ is assumed to be above one (and growing in the balanced growth path) the first term on the right hand side drives down the price. For the next two components of the right hand side since, at low levels of capital intensity the term $-\log \theta_{it} + \log(1 - \theta_{it})$ is positive and could counterbalance the negative effect of the first component. On the other hand, for high levels of capital intensity the second part of the term dominates (negatively) driving down prices even more. In fact, these two terms cancel each other for a θ_{it} of 0.5. But, even increasing capital income shares around a small neighborhood of low initial levels of capital intensity will have a negative effects asymptotically on prices since the ratio $\frac{W_t}{R_t}$ is growing in the balanced growth path. \square

Market Clearing Conditions: Closed Economy

In a closed economy, the expenditure shares and consumption shares are equivalent. The output produced in autarky must be equal to the consumption and investment for each sector. Additionally, sectoral input demands are equal to the aggregate supplies of capital and labor and the aggregate output, consumption and investment must be equal to the sum of output, consumption goods, and investment goods produced in each sector respectively. Therefore, $\forall i$, in each period t

$$\begin{aligned}
 y_{it} &= c_{it} + x_{it}; \\
 l_t^c &= \sum_i l_{it}^c; \quad l_t^x = \sum_i l_{it}^x; \\
 k_t^c &= \sum_i k_{it}^c; \quad k_t^x = \sum_i k_{it}^x; \\
 Y_t &= \sum_i y_{it}; \quad C_t = \sum_i c_{it}; \quad X_t = \sum_i x_{it}.
 \end{aligned} \tag{1.21}$$

Equilibrium: Closed Economy

Using the household's optimal expenditure shares (equation (1.15)), the firm's optimal price (equation (3.7)), the production technology (equation

(1.17)) and the market clearing conditions (equation (1.21)), one gets the following expression

$$\frac{W_t}{P_t C_t (1 - \theta_{it})} l_{it}^c = \Omega_i^{\frac{1}{\sigma}} C_t^{\frac{\epsilon_i - \sigma}{\sigma}} c_{it}^{\frac{\sigma - 1}{\sigma}}. \quad (1.22)$$

With the assumption of equal production functions for consumption and investment, and the optimal capital-to-labor ratio for sector i in equation (1.19) one gets

$$c_{it} = A_{it} \left(\frac{\theta_{it}}{1 - \theta_{it}} \frac{W_t}{R_t} \right)^{\theta_{it}} l_{it}^c,$$

and plugging this expression in equation (1.22) and solving for the labor demand l_{it}^c one obtains

$$l_{it}^c = \left(\frac{P_t}{W_t} \right)^\sigma \Omega_i C_t^{\epsilon_i} A_{it}^{\sigma - 1} \left(\frac{W_t}{R_t} \right)^{\theta_{it}(\sigma - 1)} (1 - \theta_{it})^\sigma \left(\frac{\theta_{it}}{1 - \theta_{it}} \right)^{\theta_{it}(\sigma - 1)} \quad (1.23)$$

Equation (1.23) reflects consumption component of the *absolute* labor demand across sector predicted by the model and illustrates the three main drivers proposed to account for the structural transformation: Time-varying capital intensities, non-homothetic preferences and heterogeneous TFP growth rates across sectors. The income elasticity of sector i generates long-run Engel curves that do not level off, and as long as the elasticity of substitution is below one the heterogeneity on TFP growth rates pushes labor toward the sector experiencing lower productivity growth. In addition, increasing capital intensities drive labor away from a sector with an elasticity of substitution below one. I now proceed to formalize this statement.

Proposition 2. *In the balanced growth path, the capital income share is negatively related to the labor demand as long as the elasticity of substitution is less than one.*

Proof. Take logs on both sides of equation (1.23) and after differentiating with respect to the sectoral capital income share the following expression is obtained:

$$\frac{\partial \log l_{it}^c}{\partial \theta_{it}} = (\sigma - 1) \left[\log \left(\frac{W_t}{R_t} \right) + \log \theta_{it} - \log(1 - \theta_{it}) \right] - \frac{1}{1 - \theta_{it}}.$$

Notice that only if the elasticity of substitution is below one the first expression of the right hand side is below one ($1 - \sigma$) is negative and the expression resembles the price effect as described by Lemma 1 where the effect of increasing capital income shares is negative. In addition second the term of the right hand side makes the negative effect on labor demand even stronger. \square

Proposition 2 shows that the effect of capital intensity is mediated partially by the price effect together with the elasticity of substitution similar than the effect of the TFP on prices and labor demand, but there is also an additional force that affects negatively the sectoral employment that is independent of the price elasticity. With a price elasticity closer to the unity, time-varying capital intensities still drives employment out as opposed with to the TFP channel that depends solely on the elasticity of substitution.

Equation (1.23) describes the consumption component of absolute levels of labor demand across sectors. In order to derive a system of structural transformation equations I still need to account for the total labor demand for production goods in the economy, l_t^c , to construct sectoral labor shares. Using the market clearing conditions

$$\begin{aligned} l_t^c &= \sum_{j \in \{a, m, s\}} l_{jt}^c \\ &= \left(\frac{P_t}{W_t} \right)^\sigma \sum_{j \in \{a, m, s\}} \Omega_j C_t^{\epsilon_j} A_{jt}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{jt}(\sigma-1)} (1 - \theta_{jt})^\sigma \left(\frac{\theta_{jt}}{1 - \theta_{jt}} \right)^{\theta_{jt}(\sigma-1)}. \end{aligned} \quad (1.24)$$

Recall that Proposition 1 states that accounting for the structural transformation in consumption is sufficient in order to account for the structural transformation in a closed economy. Therefore, since $\frac{l_{it}^c}{l_t^c} = \frac{l_{it}^x}{l_t^x} = \frac{l_{it}}{L_t}$, the ratio of equation (1.23) to the equation to equation (1.24) are the employment shares in a closed economy model of structural transformation

$$\frac{l_{it}}{L_t} = \frac{\Omega_i C_t^{\epsilon_i} A_{it}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{it}(\sigma-1)} \xi_{it}}{\sum_{j \in \{a, m, s\}} \Omega_j C_t^{\epsilon_j} A_{jt}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{jt}(\sigma-1)} \xi_{jt}}, \quad (1.25)$$

where $\xi_{it} = (1 - \theta_{it})^\sigma \left(\frac{\theta_{it}}{1 - \theta_{it}} \right)^{\theta_{it}(\sigma-1)}$.

Equation (1.25) delivers a system of structural transformation equations for agriculture, manufacturing and services in a closed economy where the (re)allocation of labor depends on time-varying capital intensities, Engel curves and heterogeneous TFP growth rates across sectors. Two things are worth highlighting from equation (1.25). First, notice that the term $\left(\frac{P_t}{W_t} \right)^\sigma$ observed in equation (1.24) for absolute labor demands is not part of the labor shares, emphasizing that every element that does not play a differential role across sectors will not affect the structural transformation. This reinforces the convenience of separating inter and intra-temporal trade-offs to account for labor income shares across sectors. Second, and connected with the previous argument, notice that the introduction of capital in a model of structural transformation is only useful as long as different capital income shares are considered across sectors (even if they don't change over time as in Acemoglu and Guerrieri (2008)). Otherwise, (1.25) demonstrates that constant capital income shares for every sector will not have effects on the structural transformation. Following the tradition of Debreu (1959, p. 79), the equilibrium for the closed economy model is defined as follows:

Definition 1: A structural transformation closed economy competitive equilibrium is a collection of exogenous time-paths $\{A_{it}\}_{i \in \{a,m,s\}}$ and $\{\theta_{it}\}_{i \in \{a,m,s\}}$ such that the labor allocations that define the structural transformation in equation (1.25) are consistent with:

- α) *The firm's optimization problem defined in (1.5), (1.7) and (1.18).*
- β) *The household's problem defined in (1.3) and (1.14).*
- γ) *Resource constraints and market clearing conditions defined in (1.9) and (1.21).*

1.3.3 Opening the Economy: The Role of Market Clearing Conditions

The labor demand predictions of equation (1.23) are based upon the notion of autarky in which firms demand labor domestically responding to the household's consumption and saving patterns across sectors given the state of their production technology. However, it is evident that the role of trade across nations is precisely to break the connection between domestic demand and

production, and therefore in an open economy the structural transformation patterns cannot be predicted with domestic labor demands solely. Without loss of generality, the simplest way to consider a structural transformation open economy model is to incorporate the effects of trade directly into the market clearing conditions to discipline the labor demands across sectors.

In an open economy framework the domestic production for any given sector should be equal to the domestic demand plus the net trade balance for goods in that sector. In addition to satisfying the needs for the domestic markets, now a firm belonging to a open sector needs to fulfill orders abroad while exporting. Exports have positive impact on domestic labor demand for that sector. On the other hand, domestic demand of goods can also be fulfilled with imports and openness will have a negative effect on the labor demand of a representative firm in a sector that faces competition from imports.

I assume that manufacturing is the only tradable sector in the economy. The rationale of this assumption is twofold: First, the service sector has been traditionally considered in the literature as a closed sector given the nature of some services in which production and consumption takes place simultaneously.²⁵ Second, Gollin et al. (2007) document that the fundamental element to understand the transition from agricultural to non-agricultural activities is the solution of the “food problem”, namely the state of development so critical that a country uses a large proportion of its resources to the production of food. In particular, according to FAO data, most countries at early stages of development meet their food needs domestically (Gollin et al., 2007, p. 1,234), thus it is reasonable to consider the agricultural sector as closed in order to account for the movement of labor out of agriculture observed in the data. Moreover, the sharp decline in agricultural labor share is a robust stylized fact observed both in early and late starters regardless of the pattern of trade. As Kuznets (1968) argues

With no absolute reduction in world-wide per capita use of agricultural products and the prevalence of declines in the share of agriculture in the labor force, reduced exports or increased imports of agricultural products of country A only shift the question to countries B, C, D, and so forth. How can these countries ad-

²⁵See for instance Uy et al. (2013) and Betts et al. (2013) who consider a structural transformation model for South Korea where services are not tradable.

just to decreased imports from or increased exports to country A, while their own per capita use of agricultural products does not decline and agriculture's share in labor does? This is not to deny that international division of labor in agriculture (and other sectors) and shifts in it are not important in the study of economic growth. The only point here is that it cannot be used (...) to explain trends in the distribution of the labor force and product away from agriculture, observed in so many countries and not offset by opposite movements in any (Kuznets, 1968, p. 27).

In addition, exports of good and other agricultural product are considered as manufacturing output²⁶ that uses agricultural inputs as raw produce.²⁷

The model can be disciplined to account for other tradable sectors, such as some subset of services tradable, but for the sake of simplicity I assume that the balance of trade represents flows of manufacturing goods. Therefore, the manufacturing labor demand has, in addition of a domestic component, a foreign component given by the net position of the balance of trade

$$l_{mt} = l_{mt}^D + l_{mt}^F, \quad (1.26)$$

where l_{mt}^D represents the labor demand predicted in autarky (equation (1.23) for $i = m$) and l_{mt}^F represent the adjustment due to the net trade position due to the presence of foreign markets. The domestic economy shares the same technology and capital income shares for producing output devoted to either domestic demand or exports. If the economy is importing manufactures, then the employment loses in the manufacturing sector would be *as if* the imported output would have been produced with the domestic technology and capital income shares. In that sense, the production technology

²⁶Uy et al. (2013) consider agriculture as an open sector, but in their empirical counterpart they relabel some of the categories that belong to manufacturing – such as food, beverages and tobacco – as agricultural goods. Since I consider agriculture as closed, I kept these categories in manufacturing, as they are labeled originally in the data.

²⁷Think for instance about the case of coffee beans in Colombia. The production of coffee is not bound by domestic consumption, but the output that is not consumed domestically is not immediately exported. After the coffee beans are collected from the trees, they are subject to a process of washing, cleaning and drying and then this raw produce is purchased by middlemen that sell the beans to manufacturing plants in charge of threshing, packaging and labelling with the intention to export. In fact, even for domestic consumption the coffee beans need a manufacturing process, meaning that for this particular example the output of coffee farms is demanded almost in its entirety as an investment good.

(equation (1.17)) and the firm's first order conditions (equation (1.19)) can be used to determine l_{mt}^F as

$$l_{mt}^F = \frac{XN_t}{A_{mt} \left(\frac{\theta_{mt} W_t}{1-\theta_{mt} R_t} \right)^{\theta_{mt}}}, \quad (1.27)$$

where XN_t represents net exports. Equation (1.27) illustrates the positive effect of the balance of trade on manufacturing employment. To account for the manufacturing share in an open economy one can simply observe the net trade position as an exogenous element in order to determine the adjustment needed in the manufacturing labor demand. Notice that the trade adjustment can potentially play an important role at low levels of manufacturing TFP and/or where the capital intensity is low. One can show that besides the observed TFP growth in manufacturing, growing capital intensities decrease as well the quantitative importance of the trade adjustment for the prediction of the labor demand in manufacturing.

Lemma 2. *In the balanced growth path, increasing capital income shares decrease the importance of trade to account for the manufacturing labor demand.*

Proof. Take logs on both sides of equation (1.27) and when differentiating with respect to the sectoral capital income share one gets the following expression:

$$\frac{\partial \log L_{mt}^F}{\partial \theta_{mt}} = -\log \left(\frac{W_t}{R_t} \right) - \log \theta_{mt} + \log(1 - \theta_{mt}) - \frac{1}{1 - \theta_{mt}}.$$

As demonstrated in Proposition 2, this expression is overall negative for increasing capital income shares in the balanced growth path. \square

Three additional considerations need to be addressed regarding the role of trade on prices and trade frictions. First, if a country is exporting manufacturing products the prices are simply described by the firms' first order conditions since the country has a revealed comparative advantage in manufacturing. However, when the country is importing manufacturing products, this does not mean that all the domestic production of manufactures is outsourced since exports and domestic output coexist. Of course there are possibly several specializations within the manufacturing sector that are not

traced in this paper and merit further work, but there is no full specialization in the sense that there will be no domestic employment in manufactures when the balance of trade is negative. For this reason, due to the co-existence of domestic manufactures and imports, the price of manufactures is driven by arbitrage to be equal to the domestic firm's optimal price. Imports compete with domestic manufactures and share the domestic market.²⁸

Second, given that there is only one sector involved in trade, the model necessarily requires the existence of trade imbalances.²⁹ As in Sposi (2015), for each period the income of households is credited or debited based on the country's net exports.

Last, the introduction of trade ignores all sorts of distortions and transportation costs explicitly because the goal is not to determine endogenously the patterns of specialization but simply to discipline the labor income shares under the presence of trade. The model takes the net exports as given after all the trade frictions have played their role on the patterns of specialization and investigates the effect of the trade position on labor shares. In other words, all distortions are implicitly incorporated in NX_t .

In an open economy the expenditure shares and consumption shares are no longer equal in manufacturing due to the existence of net exports in this particular sectors. Recall that these imbalances credits (or debits) the household each period. Therefore, all the remaining market clearing conditions remain *as if* the economy was in autarky. Then, $\forall i, t$

$$\begin{aligned}
y_{at} &= c_{at} + x_{at}; & y_{mt} &= c_{mt} + x_{mt} + NX_t; & y_{st} &= c_{st} + x_{st} \\
l_t^c &= \sum_i l_{it}^c; & l_t^x &= \sum_i l_{it}^x \\
k_t^c &= \sum_i k_{it}^c; & k_t^x &= \sum_i k_{it}^x \\
Y_t &= \sum_i y_{it}; & C_t &= \sum_i c_{it}; & X_t &= \sum_i x_{it}.
\end{aligned} \tag{1.28}$$

²⁸Under the presence of full specialization across sectors one would not even need to consider international prices for imports to account for its labor demand since the sector simply would not exist.

²⁹Reyes-Heroles (2016) documents that due to the decline in trade costs, the surge in net trade imbalances has been notable during the last four decades.

Equilibrium: Open Economy

Equation (1.23) accounts for the labor demand of each sector i in a closed economy. Since manufacturing is the only open sector by assumption, including trade reduces to accounting for the foreign labor demand in manufacturing. Using equation (1.27) for $i = m$ and the open economy market clearing conditions (equation (1.28)), the labor demand in manufacturing is given by

$$l_{mt} = \left(\frac{P_t}{W_t} \right)^\sigma \Omega_m C_t^{\epsilon_m} A_{mt}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{mt}(\sigma-1)} \xi_{it} + \frac{XN_t}{\phi_t}, \quad (1.29)$$

where $\phi_t = A_{mt} \left(\frac{\theta_{mt}}{1-\theta_{mt}} \frac{W_t}{R_t} \right)^{\theta_{mt}}$. The system of structural transformation equations is described by

$$\frac{l_{it}}{L_t} = \frac{\Omega_i C_t^{\epsilon_i} A_{it}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{it}(\sigma-1)} \xi_{it} + O_m \frac{XN_t}{\phi_t}}{\sum_{j \in \{a,m,s\}} \Omega_j C_t^{\epsilon_j} A_{jt}^{\sigma-1} \left(\frac{W_t}{R_t} \right)^{\theta_{jt}(\sigma-1)} \xi_{jt} + \frac{XN_t}{\phi_t}}. \quad (1.30)$$

where O_m is an indicator function that takes 1 for manufacturing ($i = m$) and zero otherwise. For the open economy model the concept of equilibrium is defined as follows:

Definition 2: A structural transformation open economy competitive equilibrium is a collection of exogenous time-paths $\{A_{it}\}_{i \in \{a,m,s\}}$, $\{\theta_{it}\}_{i \in \{a,m,s\}}$, and $\{XN_t\}$ such that the labor allocations that define the structural transformation in equation (1.30) are consistent with:

- α) *The firm's optimization problem defined in (1.5), (1.7) and (1.18).*
- β) *The household's problem defined in (1.3) and (1.14).*
- γ) *Resource constraints and market clearing conditions defined in (1.9) and (1.28).*

1.4 Calibration

To address the plausibility of the theory, I calibrate the model to the development experience of South-Korea between 1970 and 2010 and derive the model's predictions for the employment shares of agriculture, manufacturing and services. For the computation of the aggregate allocations, I use the

inter-temporal optimal choices and the fact that on aggregate the economy is represented by the neoclassical growth model with one sector. I employ a shooting algorithm³⁰ to find the entire path allocations for aggregate consumption, wages and the real interest rate since 1954, the first complete year after the Korean War ended. For the shooting algorithm, a guess for the value of K_{t+1} determines the entire sequence for the aggregate capital. With this sequence, I compute the time-series for $\{C_t, W_t, R_t\}$ as a function of $\{A_t, K_t\}$ and the parameters of the model involved in the inter-temporal optimization problem.

For the intra-temporal optimal allocations, I proceed in two steps. First, to pin down the income and price elasticities, I use parameter estimates based system of relative labor demands across sectors using the data from a panel of countries with comprehensive measures of capital income shares.³¹ Second, I normalize the productivity levels in agriculture, manufacturing and services to 1 in 1970 and calibrate the distribution parameters of the preferences (the non-homothetic CES weights) to match perfectly the labor shares of employment for Korea in 1970. With the observed growth in sectoral labor productivities across sectors, I independently feed in capital income share values for each sector to identify the capital intensities and then compute the model's predictions to generate the time-paths of the employment shares of agriculture, manufacturing and services.

1.4.1 Test of the Theory

The test of the theory is whether the model's prediction follows closely the observed hump-shaped evolution in manufacturing activity for South Korea. The Korean manufacturing employment share displays a well-defined hump-shape during the post-WWII years, and World KLEMS provides comprehensive measures of sectoral capital income shares for the entire period. A period in the model is a year in the data. Most countries that have comprehensive data on capital income shares across sectors are already at later stages of development during the sample period where the manufacturing shares of employment are declining. Thus, the Korean development experience is a well-suited laboratory with all the ingredients necessary to test

³⁰Appendix A.1 describes the shooting algorithm in detail.

³¹These data was already introduced in Section 1.2.

on whether the model is capable to predicting the observed hump-shape in manufacturing.³²

To consider the theory as plausible, the model’s predicted date (or income level) of the peak of the hump should be in the neighborhood observed in data and the model should be able to display the rise in manufacturing followed by substantial decline in its labor share after the peak. In addition, the model should continue to generate the observed decline in agricultural shares and the rise in services. As I will show, the model does a good job predicting the whole hump-shape (rising and declining part) with a manufacturing peak that is fairly close to the data while delivering closely as well the agriculture and services shares. The next subsection explain in detail the parametrization.

1.4.2 Parametrization

Table 3.2 presents the parameter values. The set of values are divided according to whether they are needed to account for aggregate or sectoral allocations. Since the parametrization of the one-sector neoclassical growth model for aggregate variables is standard in the literature, no further comments are need to explain the parameter values. However, the parametrization of the intra-temporal allocations is not common and requires a detailed explanation since it involves four independent steps.

First, I use the model to derive equations for the ratio of labor demand of agriculture and services relative to manufacturing as in Comin et al. (2015) to estimate the income (ϵ_i) and substitution (σ) parameters for the subsample of countries with measures of capital income shares, as described in Section 1.2.³³ This is an important step because as long as capital income shares are changing over time, the introduction of fixed effect estimators will no longer control for them.

Second, I normalize the initial levels for productivity and the aggregate consumption as follows: The productivity levels $A_{i,1970}$ are normalized to 1 as suggested by Duarte and Restuccia (2010). This procedure “shuts-down” the structural transformation mechanism described by Ngai and Pissarides

³²Additionally, the Korean structural transformation process has been documented in detail and has been used as a laboratory to test the role of trade in the structural transformation. Thus far, the mechanisms proposed only generate the rising part of the hump-shape (See for instance Uy et al. (2013) and Betts et al. (2013)).

³³Appendix A.2 explains in detail the estimation procedure to obtain these elasticities.

Parameter	Value	Target/Comment
Aggregate Allocations		
Θ	0.5	Aggregate capital income share in 2010.
β	0.96	Preference discount factor in Connolly and Yi (2015).
n	0.01	Average population growth in Korea (1970-2010).
δ	0.06	Average capital depreciation rate in Korea (1970-2010).
γ	0.02	Long-run growth rate in the United States.
<i>Aggregate Time-paths</i>		
A_{1970}	1	Normalization, consistent with initial levels of sectoral productivities.
C_{1970}	0.98	Consistent with TFP normalization and optimal aggregate allocations.
$\frac{W_{1970}}{R_{1970}}$	2.54	Consistent with TFP normalization and with $\frac{1-\Theta_{1970}}{\Theta_{1970}} \left(\frac{K_{1970}}{Y_{1970}} \right)^{1-\Theta_{1970}}$.
$\{A_t\}$	$\{\cdot\}$	$A_t = (1 + \gamma_{KOR})^t$, where γ_{KOR} is the average GDP per capita growth rate in Korea (1970-2010).
$\{C_t\}$	$\{\cdot\}$	Computed with growth rates of C_t , where $C_t = f(A_t, K_t)$.
$\left\{ \frac{W_t}{R_t} \right\}$	$\{\cdot\}$	Computed with growth rates of W_t and R_t , where $W_t = f(A_t, K_t)$ and $R_t = f(A_t, K_t)$.
$\{XN_t\}$	$\{\cdot\}$	Observed trade imbalance (exports minus imports as a share of GDP).
Sectoral Allocations		
σ	0.68	Estimation of price elasticity.
ϵ_a	0.36	Estimation of income elasticity of agriculture relative to manufacturing.
ϵ_m	1	Homothetic preferences for manufacturing.
ϵ_s	1.27	Estimation of income elasticity of services relative to manufacturing.
Ω_a	0.81	Chosen jointly with Ω_m to match the labor shares for agriculture and manufacturing for South Korea in 1970.
Ω_m	0.11	Chosen jointly with Ω_a to match the labor shares for agriculture and manufacturing in South Korea in 1970.
Ω_s	0.08	$1 - \Omega_a - \Omega_m$.
<i>Sectoral Time-paths</i>		
$A_{i,1970}$	1	Normalization.
$\{A_{i,t}\}$	$\{\cdot\}$	Computed with observed growth rates of labor productivity.
$\{\theta_{i,t}\}$	$\{\cdot\}$	Observed time-paths for capital income shares.

Table 1.2: Parameter values and targets for the calibration to the South Korean development experience, 1970–2010. $i \in \{a, m, s\}$, where a stands for agriculture, m for manufacturing and s for services.

(2007) for the initial period.³⁴ As a consequence of normalizing the sectoral productivity levels, the aggregate TFP of the economy is also normalized to 1. With this normalization one also needs to discipline the initial level for the consumption bundle C_t and the initial wage to interest rate ratio $\frac{W_t}{R_t}$. For C_{1970} , the aggregate resource constraint implies that aggregate output must be equal to the total of consumption and investment goods. Therefore, using the optimal choices for consumption and investment, the implied value for C_{1970} with a normalized aggregate TFP is of 0.98. For the initial ratio $\frac{W_{1970}}{R_{1970}}$ one can use the first-order conditions of the inter-temporal problem to derive an expression for the wage ratio as

³⁴However, recall that price effects due to differences in TFP are based on *growth* rates, not levels, and the structural transformation process will not be affected if different initial levels are chosen, as long as the growth rates are in line with the data.

$$\frac{W_{1970}}{R_{1970}} = \left(\frac{1 - \Theta_{1970}}{\Theta_{1970}} \right) \left(\frac{K_{1970}}{Y_{1970}} \right)^{\frac{1 - \Theta_{1970}}{\Theta_{1970}}},$$

consistent with the TFP normalized to 1. With values for the aggregate capital income share and the capital to output ratio in 1970,³⁵ the initial level of $\frac{W_{1970}}{R_{1970}}$ is 2.54.

Third, for the initial period I use the preference weights (Ω_i) as free parameters to match perfectly the initial labor shares employment South Korea. The preference weights Ω_i only have *level* effects on the labor shares of agriculture, manufacturing and services once the time-paths for the TFP, the consumption bundle and the ratio of wages to real interest rates are normalized for the initial period. The role of the preference weights in the computation of the model prediction's is limited to match perfectly – by construction – the model to the initial labor shares

Last, I use the growth rates obtained from the aggregate variables computed in the shooting algorithm³⁶ to compute time-paths for $\{C_t\}$ and $\{\frac{W_t}{R_t}\}$ starting in 1970. Additionally, I use the observed growth rates in labor productivity and the measures of capital intensity to compute the time-paths for the sectoral $\{A_{it}\}$. With time-varying capital intensities I cannot use the observed growth rates neither from labor productivity measures nor from direct data of sectoral TFPs because the notion of capital intensity has direct implications on these two objects. Whereas the labor productivity – defined as real value added per hour worked – includes the role of capital intensity, the sectoral TFP is constructed as a residual in which the role of time-varying capital intensity is neglected because the input elasticities used in the construction of the *Solow residual* are time-invariant. In order to overcome these measurement challenges, I compute the TFP growth as the labor productivity growth adjusted by capital intensities changing over time.³⁷

1.4.3 Model's Main Prediction: South Korea's Manufacturing Hump-Shape of Economic Activity

Figure 1.10 presents the main prediction of the model. It compares the model's manufacturing labor share to the observed manufacturing labor share in South Korea. Panel 1.10a plots the manufacturing share with respect to time while Panel 1.10b uses the income level as a reference, which is more useful for cross-country comparisons across different stages of development. The model successfully generates the manufacturing hump-shape for the South Korean development experience. In 1970, the manufacturing labor share in Korea was 17 per cent of the total employment. Whereas the observed trend illustrates a continuous rise up to 1990 where the peak of the manufacturing employment share was about 36 per cent, the model's predicted labor share rises to a peak level of 37 per cent for the same period. More important, the model does generate a deindustrialization after the peak in line with the data. After 1990, the observed manufacturing employment shares falls from 36 per cent in 1990 to 26 per cent in 2010 whereas the model predicts a slightly steeper deindustrialization, with an implied fall from 37 per cent in 1990 to 24 per cent in 2010. Overall, the model behaves fairly well in comparison to the data. The model does a good job predicting both the peak level and its timing in the data when time-varying capital intensities are considered as a

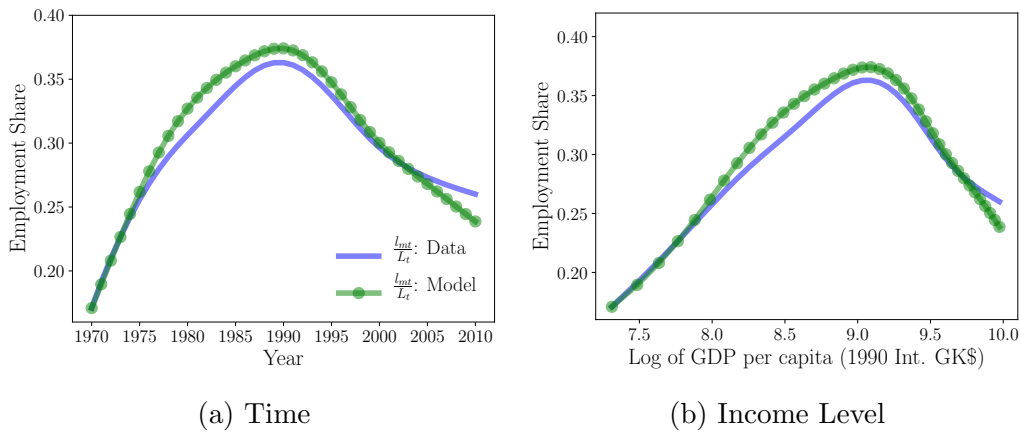


Figure 1.10: Manufacturing labor share in Korea, 1970-2010. Data vs. model.

³⁵These values are taken from Penn World Tables 9.0

³⁶Recall that in the shooting algorithm C_t , W_t and R_t are functions of A_t and K_t .

³⁷Appendix A.3 describes in detail the computation of the Sectoral TFPs.

additional driver of the structural transformation.

Additionally, Panel 1.10b illustrates that when the manufacturing employment share is plotted with respect to the income level the message is virtually the same. The model does generate a manufacturing hump-shape that resembles the data fairly close and predicts correctly the timing of the deindustrialization. The peak of the model and the peak in the data takes place about an income of 9.1 log points, or about 9,000 international (GK) dollars. The model successfully generates the hump-shaped pattern of economic activity in manufacturing for the Korean development experience.

Figure 1.11 plots the predictions of the model for agriculture and services together with the manufacturing hump shape and compares the outcome of the model with the data. The prediction of the manufacturing hump-shape is consistent with the observed decline in agricultural employment share and the rise in services.³⁸ The model predicts a slightly lower decline during the 1980s and early 1990s, but the distance in the prediction closes after the 1990s. The model also generates the rise in services, although the model

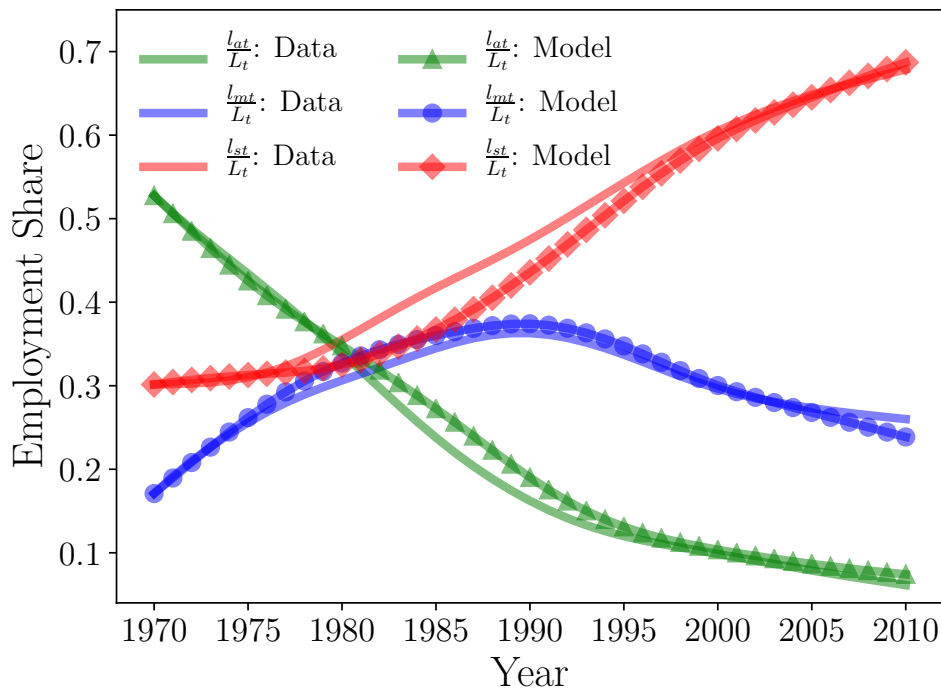


Figure 1.11: Labor shares in Korea over time, 1970-2010. Data vs. model.

³⁸The model does a good job as well when the labor shares of agriculture and services are followed with respect to the income level.

takes longer to start generating the increase in the services' share compared to the data. The performance of the model under-predicts the allocation of labor to the service sector in the 1980s, but the gap between the model and the data closes after the 1990s as well. Whereas the steep rise in services starts in the late 1970s, the model starts to generate a rise only after the early 1980s.³⁹ Nevertheless, the model still generate a rise in services consistent with the Korean development experience.

Figure 1.11 presents the three main stylized facts in the literature of structural transformation: declining agricultural labor shares, hump-shaped manufacturing employment shares, and rising shares in services. The predicted equilibrium allocations of labor hours illustrate that time-varying capital intensities are an important additional driving force of the structural transformation process to account for the core stylized facts of development.

1.4.4 Model's Prediction for an Early Starter: The United States' Structural Transformation

Buera and Kaboski (2009) illustrates the puzzles for the theoretical literature on structural transformation by using the United States as a laboratory. They present long time series for the US value added shares starting from 1870 and show that there is also a hump-shape in the manufacturing sector. However, the challenge for the US is that it is an early starter country and one needs to go before WWII to find the hump in the *employment* manufacturing share, for which unfortunately there is no comprehensive data for factor income shares across sectors to test the capacity of the model to generate the hump-shaped economic activity in manufacturing. Nevertheless, several theoretical models have been tested in light of the United States' development experience in spite of the absence of the hump-shape. For instance, Duarte and Restuccia (2010) show that with a production function whose only input is labor and with Stoney-Geary preferences one can follow the labor shares closely for the United States and several European Countries.

The absence of the hump-shape for the post-WWII development experience in the US makes this country an inferior candidate to test the theory. However, after showing that the model does generate the hump-shape for a

³⁹With long-run Engel curves, it is not surprising that the rise in services starts to dominate at later stages of development.

late starter country like Korea, it is important to show that the model still does a good job when is confronted with the data of an early starter such as the United States. For this purpose, I follow a slightly more parsimonious calibration procedure. Instead of computing the optimal allocations for the inter-temporal trade-off with a shooting algorithm, I use exogenous growth rates for C_t and $\frac{W_t}{R_t}$ to compute the aggregate time series. This procedure yields very similar predictions for the Korean development experience when compared with Figure 1.10a, as shown by Figure A.1 in the appendix. This calibration is more parsimonious because it takes the inter-temporal trade-off allocations as given exploits the the intra-temporal allocations, where the structural transformation takes place.⁴⁰

Figure 1.12 compares the prediction of the model for the United States to the observed labor shares between 1948 and 2010.⁴¹ The labor shares of

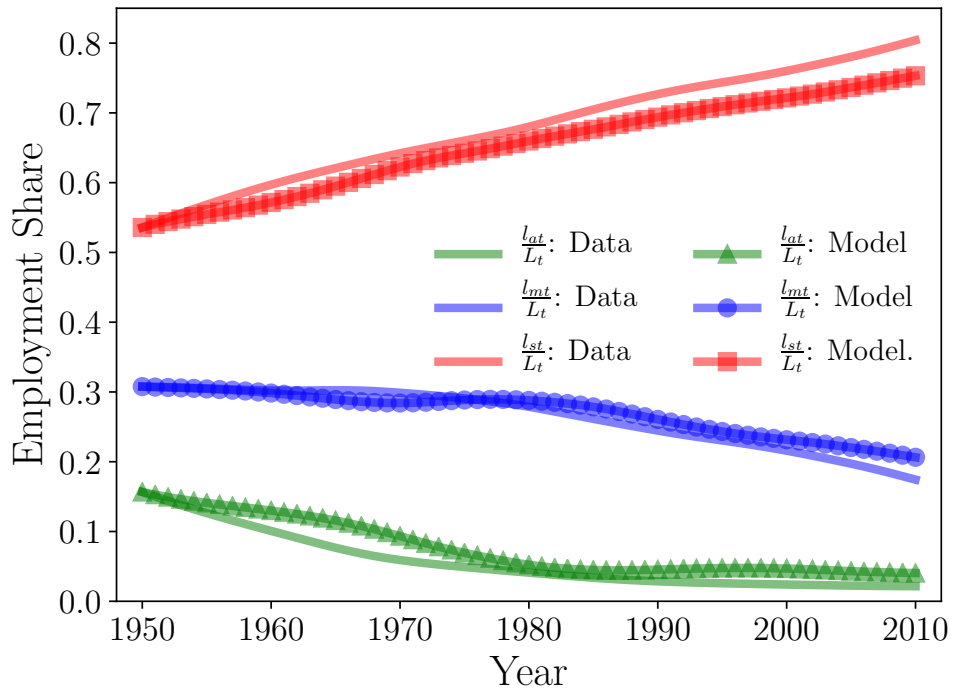


Figure 1.12: Labor shares in the United States over time, 1948-2010. Data vs. model.

⁴⁰One can simply feed the model with exogenous time-paths for C_t and $\frac{W_t}{R_t}$, which is the same as taking the inter-temporal trade-off optimization as given and repeat the parametrization procedure for the intra-temporal allocations.

⁴¹For the United States, the parameters that match perfectly the data for the initial period are $\Omega_a = 0.21$ and $\Omega_m = 0.25$ with an initial aggregate consumption bundle C_{1948}

equilibrium follow closely the observed labor shares in the United States. The decline in agricultural labor shares falls from 16 per cent in 1948 to 2 per cent in 2010. The model predicts a decline down to 4 per cent, following the data closely throughout the period. The decline in manufacturing starts at a higher level, from 31 per cent in 1948 down to 17 per cent in 2010. The model's predicted decline similar, and follows even closer the manufacturing share, with a small gap opening during the last years of the sample, with a prediction of the manufacturing labor of 21 per cent in 2010. Last, the model slightly under predicts the rise in services. Whereas the observed labor shares in services rise from 54 per cent up to 80 per cent, the predicted rise in services is only up to 75 per cent of the labor force, and the gap starts to open during the early 1950s. Overall, the model behaves reasonably well for the United States, which is a late starter country whose manufacturing share is already at the downward part of the hump-shape during the post-WWII years. A model of structural transformation with time-varying capital intensities – in addition to Engel curves, heterogeneous TFP growth rates and trade – does account for the main stylized facts of the structural transformation for early and late starters.

1.5 Alternative Hypotheses and Numerical Experiments

What is the role of time-varying capital intensities on the structural transformation? As showed in the previous section, time-varying capital intensities are the key missing ingredient to generate the hump-shaped pattern followed by the manufacturing employment share. This section discusses some of the competing hypotheses discussed in the literature as fundamental drivers of the structural transformation in comparison with time-varying capital intensities to illustrate that accounting for the changes in the bias toward capital in the production function is necessary to generate the manufacturing hump-shape. Nevertheless, I show that the extant supply and demand side mechanisms proposed in the literature are critical as well to follow closely the observed labor shares. Time-varying capital intensities are necessary, but

of 1.5 and a wage to capital rental ratio $\frac{W_{1948}}{R_{1948}}$ of 10.84.

not sufficient to explain the evolution of economic activity in manufacturing.

In addition, I use the model to shed some light on the experiences of other countries that in spite of having well-defined hump-shape during the post-WWII years in their manufacturing employment share, data on capital income shares across sectors are not available. For these countries, I use the model as a measuring device to generate the implied time-paths of capital income shares consistent with their structural transformation to see whether their manufacturing humps are related to a bias toward capital in the production function in the manufacturing sector, similar to the Korean case. Additionally, I use the predicted time series of capital income shares to see whether they are consistent with the aggregate constancy of the capital income share.

1.5.1 Alternative Hypotheses

Heterogeneous Time-Invariant Capital Intensities

To discuss the role of time-varying capital intensities I consider a model for the structural transformation *à la* Acemoglu and Guerrieri (2008) with differences in capital intensities across sectors but constant over time. Figure 1.13 plots the predicted manufacturing employment share under this scenario and compares it to the predictions with time-varying capital intensities. Panel 1.13a uses the average of the observed capital income shares for each sector as a measure of its “constant” capital intensity while Panel 1.13b uses the initial observation of the capital income share time series to measure this constancy. For both cases, the model does generate the rise in the manufacturing employment share but not the observed decline after the peak. The combined effect of Engel curves, heterogeneous TFP growth rates and trade does play an important role for the rise in manufacturing employment shares, but in absence of time-varying capital intensities, the model fails to generate the deindustrialization observed after the peak.

When average capital income shares are used, the model over predicts the manufacturing peak to reach a share of the labor force of 39 per cent, although the observed peak is only 3 percentage points lower. The model does generate the rise in manufacturing fairly closely in absence of time-varying

capital intensities. However, Panel 1.13a shows that for 2010 the manufacturing employment share was above 36 per cent, which is a value higher than the historical maximum share of manufacturing in Korea, observed in 1991. The predicted deindustrialization with constant capital intensities is about 3 percentage points since the 1990s, which is a drop in the manufacturing share of economic activity that hardly can be called a deindustrialization.

When the initial capital income shares are used to account for the constancy in capital intensity, the model slightly under-predicts the peak of the manufacturing employment share, but it is still fairly close. Nevertheless, even with lower levels displayed at the peak, the model cannot follow the deindustrialization path observed in the data. Whereas the peak of the prediction in Panel 1.13b is above 34 per cent, the predicted manufacturing employment share in 2010 was above 31 per cent, which again, is a modest deindustrialization compared to the data. Not even with a lower prediction for the manufacturing peak the model is capable to predict a close value for the manufacturing employment share for 2010 in absence of time-varying capital intensities.

As an additional exercise to highlight the importance of time-varying capital intensities, Figure 1.14 plots the predictions of the model for the United States with constant capital income shares in the same spirit as Acemoglu and Guerrieri (2008). The Figure suggests that in absence of time-varying capital intensities the models performance is not as good as when this element is considered explicitly. In particular, notice that the model does not

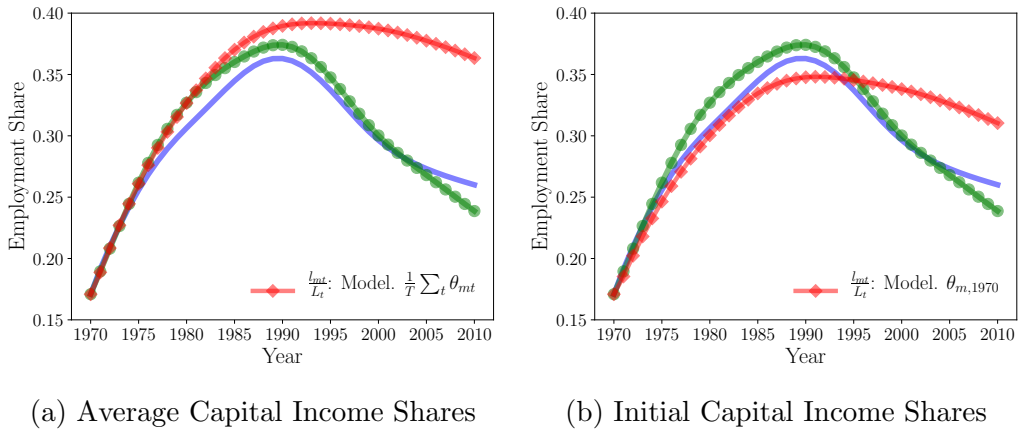


Figure 1.13: Manufacturing labor share in Korea, 1970-2010. Data vs. model with constant capital intensities *à la* Acemoglu and Guerrieri (2008).

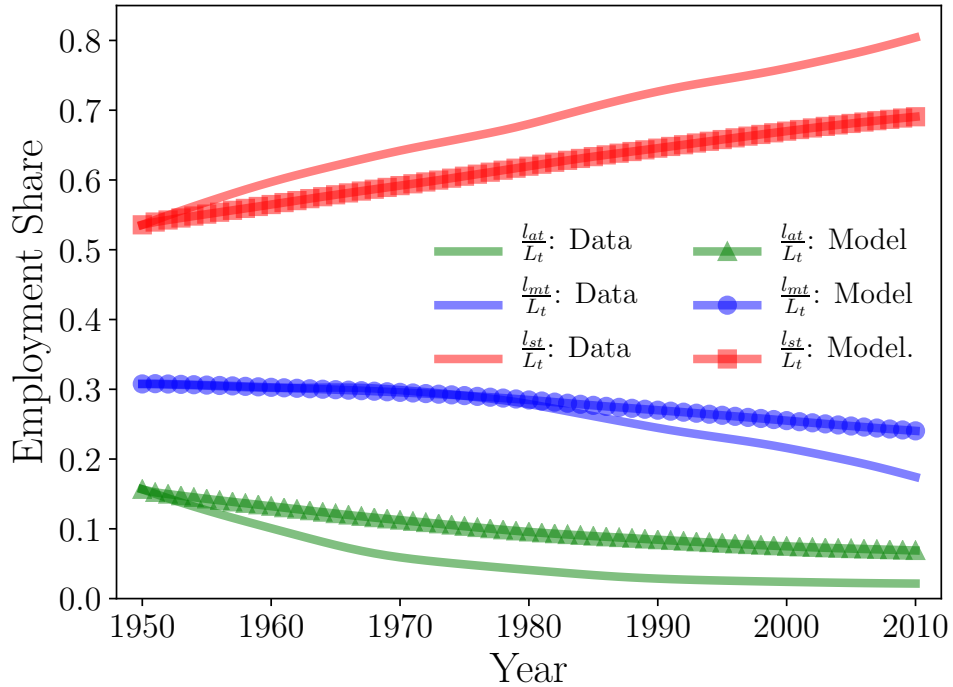


Figure 1.14: Labor shares in the United States, 1948-2010. Data vs. model with constant capital intensities *à la* Acemoglu and Guerrieri (2008).

predict as closely the deindustrialization observed at later stages of development compared to Figure 1.12. Figure 1.14 uses the average of capital income shares to address the constancy of the capital intensity across sectors, but the message with initial capital income shares is virtually the same. Time-varying capital intensities are a critical additional driver to generate the observed deindustrialization at later stages of development.

Figures 1.13 and 1.14 suggest that in addition to the traditional drivers of the structural transformation, time-varying capital intensities are fundamental to account for the deindustrialization observed at later stages of development, and should be considered as an essential ingredient in a theory of structural transformation that aims to be consistent with the Kuznets facts by following closely the evolution of manufacturing activity as long as economies develop.

Trade vs. Time-Varying Capital Intensities

In their concluding remarks, Uy et al. (2013, p. 681) suggest that additional trade features in their model such as the role of China as a competitor could help to understand the declining part of the hump-shape. In their words “[their model] does not explain the declining portion of the hump(...). However, in our view, the key missing ingredient from the calibrated model is China (...). China experienced manufacturing productivity growth and lower trade costs that enabled it to essentially take market share in manufacturing from Korea.”

If a proper treatment of trade, instead of time-varying capital intensities, is the missing ingredient to account for the Korean manufacturing hump-shape, a natural question that the model can answer is as follows: In absence of time-varying capital intensities, what would be the implied balance of trade in Korea to account perfectly for the observed deindustrialization? Figure 1.15 considers the heterogeneity in capital intensities *à la* Acemoglu and Guerrieri (2008)) and illustrates the implied balance of trade necessary to account for the manufacturing hump in Korea.

Panel 1.15a uses the average capital income shares as a measure of the time invariant differences of capital intensity across sectors while Panel 1.15b uses the initial observations of the capital shares in agriculture, manufacturing, and services. Notice that the model predicts in both cases an implausible large balance of trade deficit for South Korea in absence of time-varying capital intensities as opposed to the observed balance of trade surplus in the data. This exercise suggests that it is the growing bias toward capital in the production of manufacturing output rather than trade the missing ingredient to generate the observed deindustrialization in Korea, although it is important to emphasize that the treatment of trade in this paper is embedded in the market clearing conditions assuming that only manufacturing goods are traded and it plays not role in determining the patterns of trade endogenously. Moreover, it is not clear whether one should consider trade and time-varying capital intensities as separable phenomena. As Parente and Prescott (1994, p. 319) conjecture, “() greater trade openness contributes to development because it weakens the forces of resistance to technology adoption”. This excersice simply shows that the counterfactual for trade *in absence* of time-varying capital intensities delivers implausibly large trade

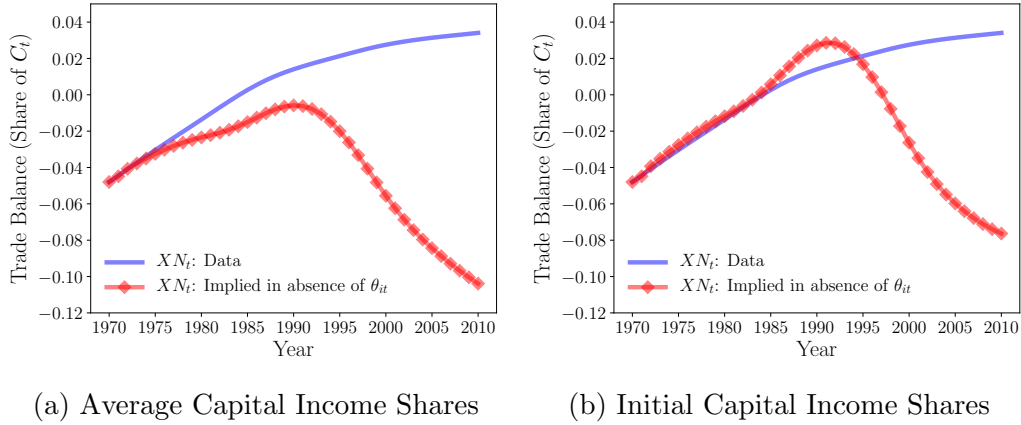


Figure 1.15: Implied trade to account for the observed deindustrialization in Korea, 1970-2010. Data vs. model with constant capital intensities *à la* Acemoglu and Guerrieri (2008).

deficits.

The role of trade on manufacturing has also been considered as a primary candidate to understand the observed deindustrialization in the United States. For instance, Autor, Dorn, and Hanson (2013) suggest that import competitions from China have played a sizable role in explaining the decline in the US manufacturing employment. In that sense, it is natural to repeat the counterfactual exercise carried out for Korea to shed some light on this debate for the United States. Figure 1.16 illustrates that without time-varying capital intensities, the trade deficit in the United States would need to be substantially stronger. For instance, the US trade deficit in 2010 in absence of time-varying capital intensities would need to double its size in order to account for the observed deindustrialization. This counterfactual is not necessarily inconsistent with the findings of Autor et al. (2013) but it does suggest that trade *alone* is not the primary driver of the deindustrialization in the United States.

Notice that Panels 1.16a and 1.16b are virtually the same in spite using averages vs. initial values to account the time invariant value capital income shares consistent with Acemoglu and Guerrieri (2008). As a validation exercise, Figures A.2 and A.3 from Appendix A.5 illustrate that indeed the implied paths for the balance of trade do generate the observed manufacturing employment shares in Korea and the United States respectively.

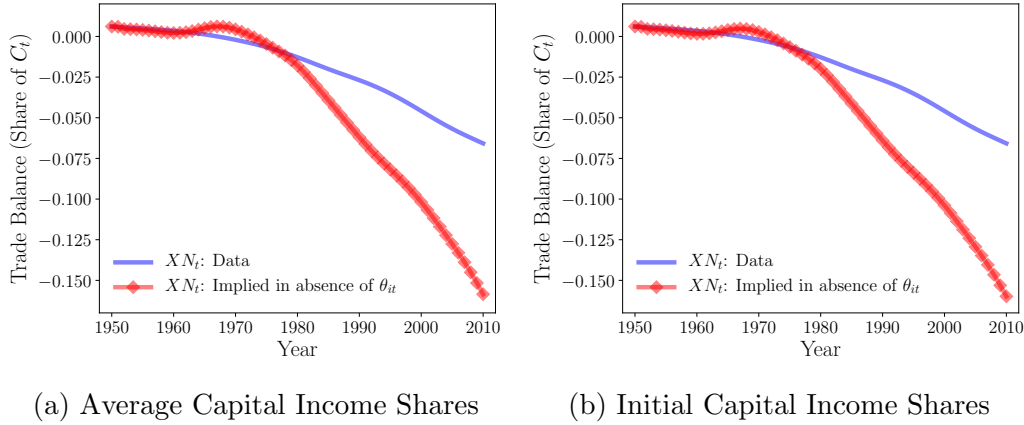


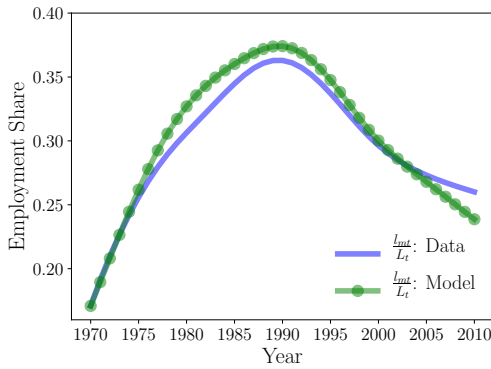
Figure 1.16: Implied trade to account for the observed deindustrialization in the United States, 1950-2010. Data vs. model with constant capital intensities *à la* Acemoglu and Guerrieri (2008)

Capital Intensity Over Time: Necessary but not Sufficient Condition

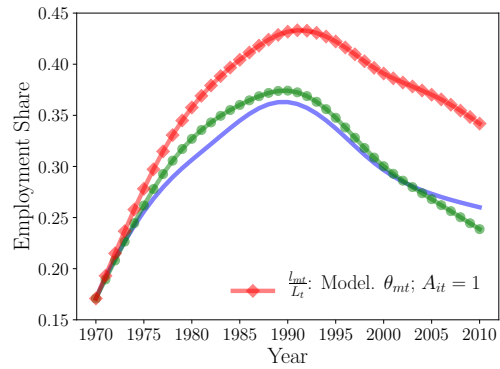
Are time-varying capital intensities a sufficient condition to generate the observed labor allocations across sectors? Figure 1.17 illustrates the performance of the model under difference scenarios. Recall that the equilibrium allocations of labor hours across sectors are the result of four main drivers: Time-varying capital intensities, Long-run Engel curves (Comin et al., 2015), TFP heterogeneous growth rates across sectors (Ngai & Pissarides, 2007) and trade. Therefore, the natural question that arises is related to the performance of the model with time-varying capital intensities in absence of these drivers. In addition, recall that the model considers trade in a simplistic manner through the market clearing conditions, so it would be important to address the sensibility of the model with respect to trade.

Panel 1.17a provides the benchmark prediction for which time-varying capital intensities operate together with long-run Engel curves, heterogeneous TFP growth rates and trade. Panel 1.17b shuts down the mechanism described by Ngai and Pissarides (2007). This scenario does not suggest the absence of aggregate TFP growth but only that this process is the same for each and every sector in the economy and therefore it does not have implications on the structural transformation.⁴² Notice that the model over

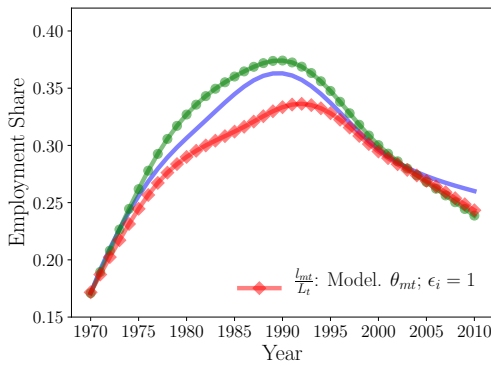
⁴²Putting it differently, in this counterfactual scenario the labor productivity compensates the changes in capital intensity so that there are no differences in the relative TFP across sectors.



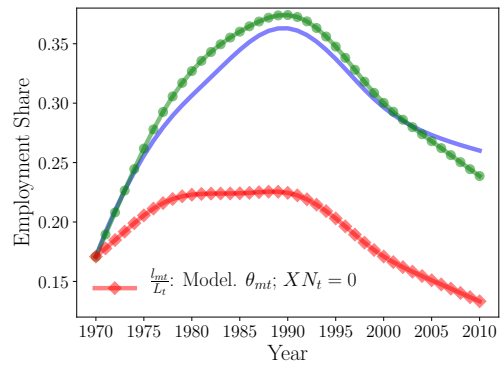
(a) Benchmark



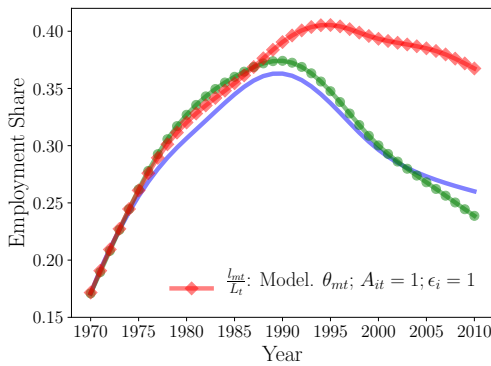
(b) No TFP Heterogeneity



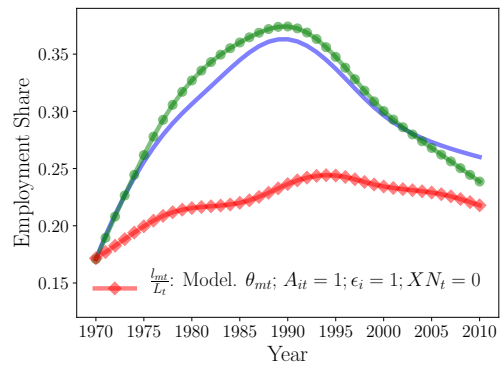
(c) No Engel Curves



(d) No Trade



(e) No Engel Curves, No TFP Heterogeneity.



(f) No Engel Curves, No TFP Heterogeneity, No Trade.

Figure 1.17: Manufacturing labor share in Korea, 1970-2010. Data vs. model with time-varying capital intensities under alternative hypotheses.

predicts the labor participation of the manufacturing sector but importantly, without this mechanism the model still generates a hump-shape. While the TFP differences are fundamental to account for the “Baumol’s cost disease”, in which labor moves from more productive to less productive sectors when the elasticity of substitution is below one, the hump-shape does not depend on differences in TFP growth rates across sectors. The reason for the over prediction is because the labor push toward services from the manufacturing sector driven purely by differences in TFP growth rates is neglected with the imposition of homogeneous sectoral growth rates of technology.

Panel 1.17c imposes homothetic preferences. The model under predicts the role of manufacturing in the structural change but again, the hump-shape is not driven by the *implicitly additive isoelastic non-homothetic CES* crafted by Comin et al. (2015). The non-homotheticity is a fundamental mechanism to account for the decline in agriculture at early stages of development and the rise of services at later stages of development. In fact, the primary reason for the under prediction of the manufacturing sector are the poor performance in these two sectors. Nevertheless, with time-varying capital intensities in absence of non-homothetic preferences the model still generates the manufacturing hump-shape.

Panel 1.17d shuts down the net exports channel and reduces the model to a closed economy setting, which has been a fruitful approach to document the structural transformation for countries that started their transformation early, such as the United States and Great Britain. Notice that trade does matter fundamentally in order to understand the manufacturing employment in South Korea. However, it is not due to trade in the market clearing conditions that the model generates the hump-shape. As Uy et al. (2013) illustrate, trade is an important mechanism to understand the rise of the hump, but time-varying capital intensities provides the additional force needed to generate the decline of the employment share. Time-varying capital intensities in absence of trade generate a manufacturing peak at a significantly lower level compared to the data, but that peak is around the same time, and more importantly it is followed by an important decline in the manufacturing employment share unlike open economy settings that neglect time-varying capital intensities, where the success in generating the rise is not followed by a steep decline in manufacturing labor shares similar to the pattern observed in Figure 1.13.

Panel 1.17e excludes both Engel curves and the heterogeneity in TFP growth rates and shows that the model with time-varying capital intensities and trade, in spite of not using two of the main drivers of the structural transformation proposed in the literature, still generates a hump-shape for the Korean manufacturing sector, although its peak is observed at a much higher level. Although the predicted labor shares predicted differ abysmally from the data, the prediction is still hump-shaped.

Panel 1.17f constrains the model even further by shutting down the trade mechanism as well. Notice that even when time-varying capital intensities are the only explanation for the manufacturing hump-shape, the model still generates a rise and a decline for industrial employment that is not observed in without this mechanism. Of course, the predicted labor shares differ substantially from the data in absence of all the additional mechanisms but the hump-shape is displayed even for this drastic scenario.

The main message of Figures 1.13 and 1.17 is that Engel curves, heterogeneous TFP growth rates and trade are fundamental forces to address the development experience in Korea, but none of them – on their own or combined – generate the manufacturing hump-shape in absence of time-varying capital intensities. Accounting for the changes in capital intensity in the production functions of each sector is necessary but not sufficient to generate to generate the hump-shaped evolution of manufacturing activity that reasonable resembles the labor shares patterns observed in the data.

1.5.2 Numerical Experiments: Implied Capital Income Shares for Other Countries

Figure 1.18 plots the data on employment shares and capital income shares in manufacturing for South Korea with independent ordinate axes. The negative correlation between capital income shares and employment shares in manufacturing shows that the hump-shaped evolution in manufacturing coincides with movements in the capital intensity in the opposite direction.⁴³ More importantly, the pattern of deindustrialization observed after the man-

⁴³Even though the time series of capital income shares look like the mirror image of the employment share in manufacturing, recall that the axis are independent and one cannot compare their levels directly. Moreover, time-varying capital intensities alone cannot generate the observe path of employment shares, as demonstrated in the previous section.

ufacturing peak coincides with a period where the capital intensities in manufacturing rise sharply and substantially. Table A.2 from Appendix A.6 shows that this is consistent with the development experience of South Korea where the industrialization moved rapidly from labor intensive industries to capital intensive industries. As Gereffi (1990) argues, Korea pursued an outward oriented industrialization relying first on light industries that were labor intensive, and later on heavier manufacturing processes, that were further removed from their factor endowments. At later stages of industrialization East-Asian countries in general relied more on tech-intensive rather than labor intensive exports, and Figure 1.18 suggest that this transition is responsible in great deal for the hump-shaped pattern observed in South Korea.

Is this pattern similar for other episodes of hump-shaped manufacturing employment shares? The first-best approach to answer this question would be simply to look for the measures of capital income shares directly, compare them with the manufacturing share of employment, and use this information and measures of labor productivity to calibrate the model directly with time-varying capital intensities. Unfortunately, with the exception of Korea, for most of the countries with well-defined manufacturing employment shares during the post-WWII, there are no comprehensive measures of capital in-

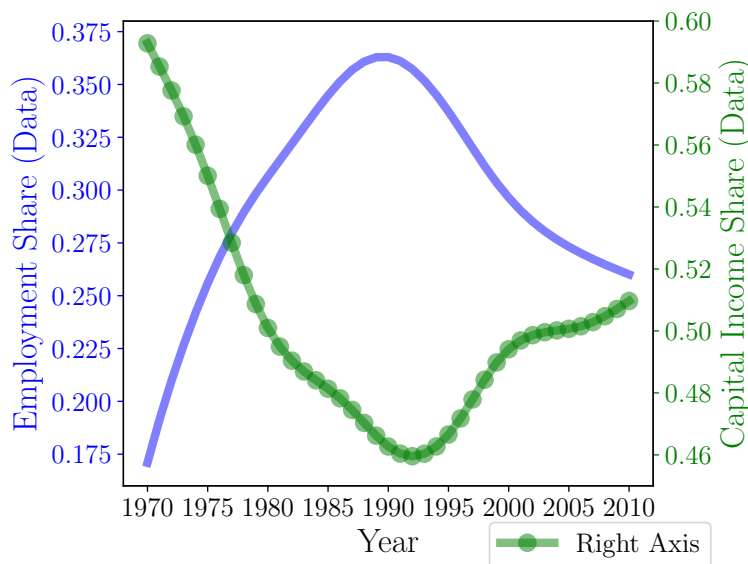


Figure 1.18: Employment shares and capital income shares in manufacturing for South Korea during the period 1970-2010.

come shares across sectors.

A second-best alternative is to use the model of structural transformation presented in this paper, which allows for time-varying capital intensities, to recover the implied capital income shares needed to account for the hump-shaped evolution of manufacturing activity as well as for the decline in agriculture and the rise in services. For the sake of parsimony, I use exogenous growth rates to compute the time series $\{C_t\}$ and $\{\frac{W_t}{R_t}\}$ that are feed in the model to avoid the computation of the inter-temporal trade-off as shown before in the U.S. calibration. Even though it is straightforward to derive these time series endogenously from the model, one would need to account for the starting date of the transitional dynamics on an individual basis and make assumptions about the long-run steady state in each country individually, and for the case of Korea it is clear that the hump-shape does not depend on the computation of these aggregate time series.

Figures 1.19 and 1.20 use the intra-temporal allocations of the structural transformation model to recover the implied time-paths of capital income shares for Argentina and Japan respectively. In absence of information for capital income shares, I need to impose values for $\Omega_i, i \in \{a, m, s, \}$ instead of calibrating them for each country individually. Following Duarte and Restuccia (2010) I used the values obtained in the calibration for the US after normalizing productivity levels to one. This procedure has a direct effect on the implied *levels* of the capital income shares time-paths because the initial labor shares of employment are targeted with the first values of the series. Choosing different values for $\Omega_i, i \in \{a, m, s, \}$ would yield different

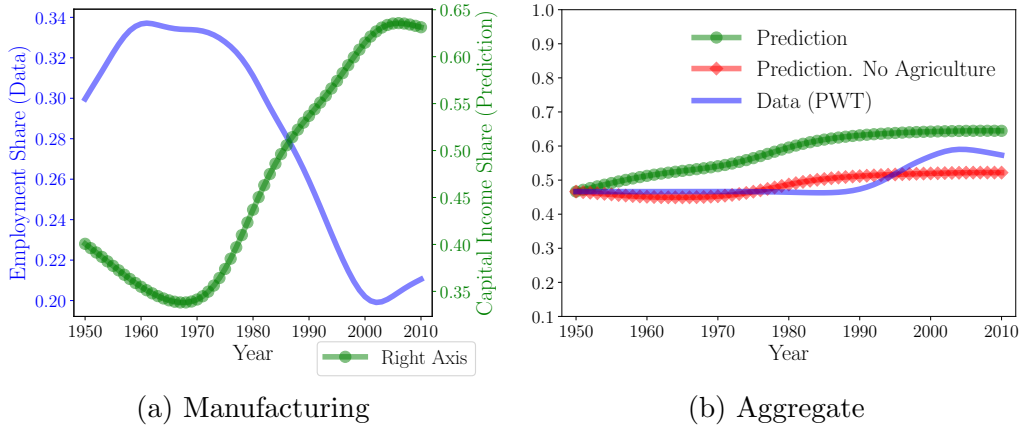


Figure 1.19: Argentina. Implied capital income shares

starting levels of the capital income share time-paths. Thus, the object of interest is the variation observed in capital income shares, rather than their levels displayed. Panels 1.19a and 1.20a illustrate that, similar to the Korean case, the capital income shares do exhibit an upward movement that coincides with periods of deindustrialization, suggesting that for these countries time-varying capital intensities can potentially help to explain as well their hump-shaped evolutions in manufacturing activity.

Panels 1.19b and 1.20b use the implied capital income shares to generate weighted averages as I did in for Korea and the United States in section 1.2 to address whether the predicted capital income shares are consistent with the Kaldor Facts. Recall that the levels of these predictions should not be interpreted. For this reason, I normalize the levels of the weighted averages to match the initial observation of the capital income shares observed in Penn World Tables to compare the *variation* of these two time series. Whereas the prediction with agriculture, manufacturing and services seems to reject the constancy of the aggregate capital income share, once I consider the caveats of Gollin (2002) and exclude agriculture to compute the weighted averages, the predictions are remarkably flat and close to the observed capital income shares in Penn World Tables. This suggests that the predicted variation for the capital income shares are reasonable and that the Kaldor facts seem to hold only after substantial declines in agricultural participation even if capital income shares are properly measured in the agricultural sector. Appendix A.7 repeats this exercise for Brazil, Costa Rica, Spain, France, Italy, Mexico,

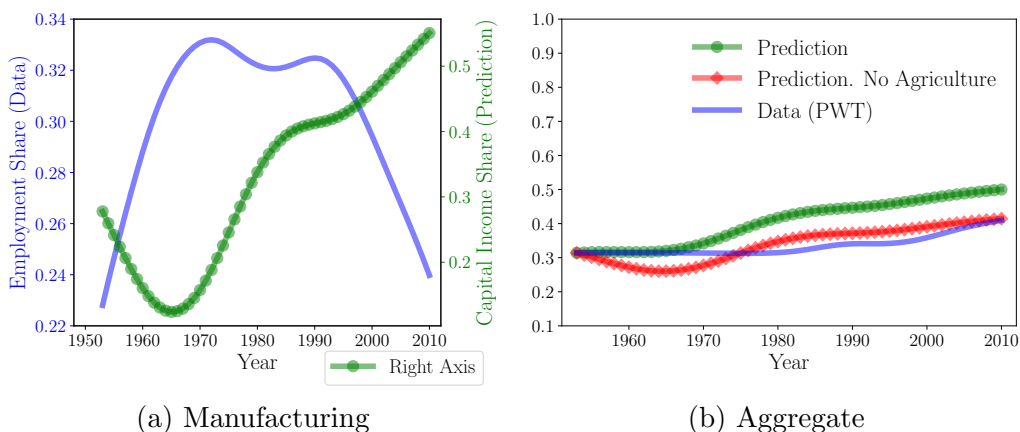
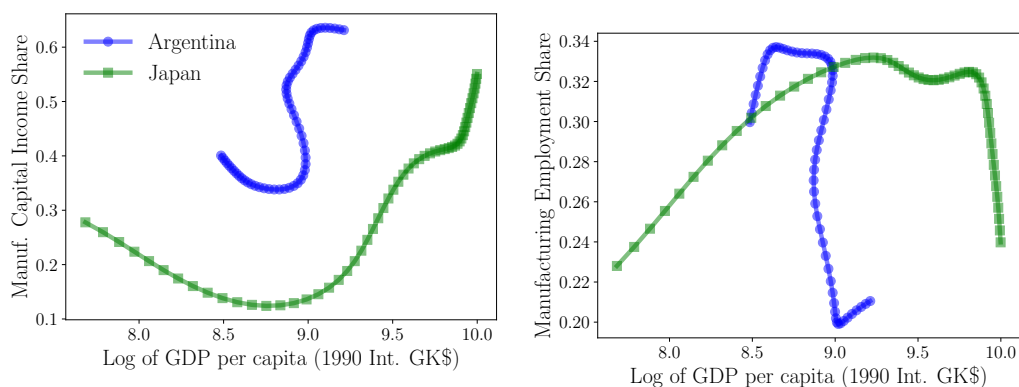


Figure 1.20: Japan. Implied capital income shares

Malaysia, Peru, Taiwan and South Africa.⁴⁴ The results are similar.

In spite of their similar patterns *over time* suggested by Figures 1.19 and 1.20, it is important to emphasize Argentina and Japan are good examples of *divergent* patterns of structural transformation for late starter countries. To illustrate this point, Figure 1.21 shows the predicted manufacturing capital income shares (Panel 1.21a) and the observed employment shares (Panel 1.21b) with respect to the income level. Panel 1.21b clearly demonstrates the point addressed by Rodrik (2015): Whereas Japan followed a pattern of deindustrialization similar to other advanced economies and started to deindustrialize after reaching an income per capita above 9,000 international dollars of 1990, Argentina experienced a premature deindustrialization starting its deployment of labor out of manufacturing at an income per capita level slightly above 5,000 international dollars of 1990.

Panel 1.21a suggest that to understand this process of premature deindustrialization not only in Argentina but in several Latin American countries (See for instance Figure A.4 from Appendix A.7 for the Brazilian case) the process of time-varying capital intensities is critical. The numerical experiments suggests that overtime, the growth in the capital income shares in



(a) Argentina and Japan. Implied capital income shares

(b) Manufacturing Employment Shares

Figure 1.21: Argentina and Japan. Divergent patterns of deindustrialization. Implied capital income shares and observed employment shares are trended using the Hodrick–Prescott filter with a smoothing parameter of $\lambda = 100$.

⁴⁴The data on implied time-paths for capital income shares in agriculture, manufacturing and services for these countries are available at <https://sites.google.com/site/luisfelipesaenz/research>.

manufacturing after 1990 observed both in the United States and Korea seem to be in line with the implied manufacturing capital income shares for Japan and Argentina.

What is the main driver of a premature deindustrialization? Alvarez-Cuadrado and Poschke (2011, p. 130) argue in favor of common technological trends over time. In their words “The importance of time periods (...) suggests the presence of common trends in technology, most plausibly in innovation and the diffusion of technology. However, a country’s current stage in structural transformation also matter.” Similarly, one can think about the presence of common trends in the bias toward capital in the production of manufacturing output, as suggested by the data. After all, the combination of inputs to produce a manufacture is nothing but a “recipe” subject to diffusion across nations. The implied capital income shares needed to obtain the observed deindustrialization suggest that, in line with Rodrik (2015), openness is critical to address the premature deindustrialization, but primarily due to its role in the diffusion and adoption of “recipes” that bias the production toward capital. My conjecture is that the premature deindustrialization is largely due to a bias toward capital in manufacturing taking place at different stages of development. Japan and Argentina experienced similar evolutions in their manufacturing employment share over time, but these processes took place at different stages of development. Since Argentina started to structurally transform later, it was more likely for them to experience a premature deindustrialization in a world that is more integrated and shares more knowledge about labor-saving technologies in manufacturing.

1.6 Conclusion

Motivated by the evidence on capital intensity changing over time in manufacturing, this paper argues that the time dimension of capital intensities across sectors is critical to understand the patterns of structural transformation, and puts forth a theory whereby time-varying capital intensities account for the hump-shaped evolution in manufacturing. Extant drivers of the structural transformation are fundamental to account for the structural transformation in several dimensions, but only with the introduction of time-varying capital intensities the theoretical model generates time-paths for the

manufacturing employment share that follow closely the data. Time-varying capital intensities are the additional “labor push” needed to generate the movement of labor out of manufacturing and explain the declining part of the hump.

This paper presents evidence suggesting that capital intensities across sectors do change over time. This fact has been largely overlooked in the literature of structural transformation. I show that capital intensities changing over time and across sectors are consistent with a roughly constant aggregate capital income share at the aggregate level, which suggest that the Kaldor facts are not inconsistent with time-varying capital intensities at the sector level. In fact, the evidence presented here suggests that the bias toward capital in the production of manufacturing output is accompanied by capital income shares falling in the service sector as a whole.

Using the development experience of South Korea as a laboratory to test the theory, I find that time-varying capital intensities are necessary but insufficient for a complete understanding of the labor (re)allocations across sectors. A model of the structural transformation that considers time-varying capital intensities in addition to long-run Engel curves, heterogeneous TFP growth rates and trade does captures well the Kuznets facts.

This paper suggests that changes in the capital intensity over time are fundamental to understand the development process, and are a plausible candidate to explain the divergent patterns of structural transformation observed in developing countries. This paper considers such changes exogenously and addresses their consequences. Given their importance for development, a theory of capital intensity and its differences over time and across sector is needed. Such a theory needs to reconcile the bias toward capital in manufacturing with the growing labor income share observed in the service sector.

CHAPTER 2

THE RICARDIAN EFFECT: WHERE CAPITAL REPLACES LABOR. EVIDENCE FROM COLOMBIA

“It is not easy, I think, to conceive that under any circumstance, an increase in capital should not be followed by an increased demand for labour; the most that can be said is, that the demand will be in a diminishing ratio.”

— David Ricardo. 1821

2.1 Introduction

In 1821, for the third edition of his 1817 masterpiece entitled *On the Principles of Political Economy and Taxation*, David Ricardo decided to include a whole new chapter to his bestseller in which he wrote a *mea culpa* regarding his previous ideas with respect to the role of machines. Ricardo confessed that before writing “On the Machinery”, the 31st chapter of his classic, he was not aware of any conflict between the interests of the laboring class and the arrival of machines to the production process. In Ricardo’s own words:

(...)I have been of opinion, that such an application of machinery to any branch of production, as should have the effect of saving labour, was a general good, accompanied only with that portion of inconvenience which in most cases attends the removal of capital and labour from one employment to another.(Ricardo, 1821, pp. 466-67)

David Ricardo devoted a whole new chapter in his *Principles* to reveal his change of opinion. His new vision was that the application of machinery

could reduce labor demand (Ricardo (1821), Samuelson (1989)).¹ Regardless of the virtuosity (or lack of it) of introducing machines for producing goods, David Ricardo introduced a concept to the economic jargon: *The Ricardian Effect*. In short, the *The Ricardian Effect* is the replacement of labor in the production process when new capital units are introduced.

Sympathetic with Ricardo's new chapter, Samuelson (1988) introduced a "simple classical model"² in which the invention of robots reduces the demand for labor permanently, as Ricardo predicted. Contrary to the opinion of several followers of Ricardo, Samuelson considered chapter 31st as the best single chapter of Ricardo's book. He provided a dramatic example to illustrate that the invention of robots capable of replacing the entire human labor in the production of corn will yield Ricardo's prediction: human jobs are replaced by machines. An interesting implication explained in detail by Samuelson (1988) is that if robots are relative cheaper compared to labor, even by just a small fraction, no labor will be demanded at all. Samuelson crafted this overdramatic example of robots replacing humans as a way of vindicating Ricardo's reasoning as logically feasible, at a time when his new chapter was in doubt and was considered as a logical fallacy (Samuelson, 1988). Lord Keynes also contributed in this debate coining a term to describe the unemployment created by the introduction of machines: *Technological Unemployment*. According to Keynes (1930, pp. 196),

We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come - namely, technological unemployment. This means unemployment due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor.

The debate regarding the complementarity/substitutability between labor and capital goods in the production process today is well and alive. Burke and Rumberger (1987) compile a series of papers that address the impacts of technology on work and education in the United States and Australia.

¹The interest reader should consult directly Ricardo (1821) to understand the evolution of his ideas with respect to the role of machines. The discussion of his arguments is beyond the scope of this article, mainly because a preliminary discussion of the value labor theory is imperative in order to address Ricardo's concerns related with the distribution of income.

²As Paul Samuelson called it himself.

The principal questions that are addressed in the collection of papers are related with the job creation/destruction due to the increased use of new technologies, and with what kinds of jobs will be created and what kinds will be destroyed. They conclude that new technologies, especially those associated with micro-electronics, are capable of further routinizing and simplifying tasks into repetitive and machine operated-monitored functions, but also new technologies enhance the decision role of employees and potentialize the skills and education of the labor force.

Knights and Willmott (1988) consider that as long as economies are expanding, the substitution of capital for labour due to the dramatic advance in the use of new technologies is not reflected in unemployment figures instantaneously, but with the continuum arrival of new technologies, labor demand suffers, specially during times of recessions where the technological expansion is still supported by governments.

Krusell, Ohanian, Ríos-Rull, and Violante (2000) illustrate that changes in observed inputs of production can explain most of the variations in the labor skill premium from 1963 to 1991 in the United States. They identify the following puzzle: The supply of skilled labor increased significantly during this period but at the same time the skill premium, defined as the wage of skilled labor relative to that of unskilled labor, grew considerably since 1980. They argue that with a neoclassical production function whose technology is capital-skill complementary, the puzzle is explained in terms of input variations. In short, with the development of better and cheaper capital equipment the wages of unskilled workers are (relatively) driven down since unskilled labor is competing not only with skilled employees, but with persistently cheaper and better machines.

Krusell et al. (2000) found that the substitution elasticity between unskilled labor and equipment is 1.67 whereas for skilled labor and equipment is 0.67. They also found that the skill premium is driven by changes in observed factor quantities. The supply of skilled labor puts a downward pressure to the premium, while the capital skill complementarity effect puts an upward pressure which ultimately dominates. Hanson (2001) considers an exogenous growth model in which machines are complement to human labor when they become more productive, but also machines are substitutes for human labor by taking over jobs. The conclusion of this modeling exercise is that in spite of the complementary effects due to increases in productivity,

in the end the substitution effects are dominant.

Acemoglu (2002) contributes to this debate by addressing the direction and bias of technical change, since in most situations technical change is not neutral: it benefits some factors of production more than others. He develops a workhorse to understand why technical change can be skill biased, and why new technologies introduced during the late eighteenth and early nineteenth centuries were unskilled biased. This framework provides analytically the conditions for capital and labor to be gross complements or gross substitutes based on the idea that firms can invest resources to develop technologies that complement a particular factor. Acemoglu (2002) provides an explicit micro-foundation to the complementarity/substitutability nature of technology and production inputs.

More recently, Acemoglu and Autor (2011) proposed a framework called “A Ricardian Model of the Labor Market” in which they explicitly incorporate a distinction between Workers skills and job tasks, and they allow the assignment of skills and tasks to depend on labor supplies, technologies, and task demands. They consider that the distinction between skills and tasks is critical to understand how the set of tasks that workers perform responds to changes in supplies or technology. According to Acemoglu and Autor (2011), a task is a unit of work activity that produces output while a skill is the worker’s endowment of capabilities to perform various tasks. They argue that “(...) an explicit distinction between skills and tasks (...) will enable the model to allow for certain tasks to become mechanized.” (Acemoglu & Autor, 2011, pp. 1119) Therefore, in the task-based approach, tasks are applied to produce output, and skills have an influence in output through its relation with tasks.

Acemoglu and Autor (2011) consider that the task-based framework can be used to understand the displacement of labor out of tasks they previously performed in the workplace when technology (embodied in capital) is used to perform these tasks. The introduction of the concept of tasks in the production function thus allows me to paraphrase the Ricardian Effect within this framework: The Ricardian Effect is the mechanization of tasks when capital is introduced in the production function making some workers redundant since their tasks can be performed cheaper by machines.³

³It calls my attention that Acemoglu and Autor (2011) coined their approach as “Ricardian” without references to Ricardo’s Chapter 31st, where the discussion of the relation

Roberts and Skoufias (1997) can be considered as the first attempt to estimate input demand equations for labor using Colombian data for the period 1981-1987. They divide the labor force between skilled and non-skilled labor measuring the latter as a weighted sum of employees considered as skilled workers, local technicians, and foreign technicians.⁴ They find that the demand for skilled workers is less elastic than the demand for unskilled workers, while the output response for skilled labor is greater compared to unskilled labor. However, a serious limitation of this paper is that there is no capital demand equation to estimate capital input demands, since their definition of capital is a binary variable that takes 1 if the plant is owned by a corporation and 0 if owned by a proprietorship or partnership as if the latter plants were not demanding new technologies incorporated in their demands of capital stock.

Fabrizio, Rose, and Wolfram (2007) also consider demand inputs of labor, materials and fuel for the US energy plants, but the plant's stock of capital available in the industry is not considered explicitly. They measure capital input by a plant's capacity and vintage, combining the establishment's capacity in megawatts with information of unit retirements to define plant-epochs. Any time the capacity of the plant is significantly changed, they assume a new plant-epoch specific effect. Instead of defining categorical variables to measure capital, this paper considers explicitly the capital demand equation exploiting the information of the physical quantities of capital stock that are available in the EAM.

The purpose of this article is to provide quantitative evidence of the so-called Ricardian Effect using a unique plant-level longitudinal dataset for Colombian manufacturing establishments for the period 1982-1998. The data requirements needed for establishing a relationship between different inputs of production are very stringent. It must include at least information of labor and capital at the plant level, which is the relevant unit of analysis, and it must vary across time since this relationship is dynamic. This is precisely

between machines and workers is taken explicitly. Instead, they extend the concept of comparative advantages using workers (instead of countries) as the unit of analysis given the differences across skills and tasks of the employees.

⁴Unfortunately these data is not available for the whole 1982-1998 period in the 'Plant-Level Price Indices for Output and Materials' database used in this paper. See section 2.2 for more details related to the data used in this paper.

the information available in the Annual Manufacturing Survey (EAM⁵) in Colombia. Moreover, the variable that measures the labor demand of the plants in the EAM is disaggregated between production and non-production workers, and therefore it is possible to disentangle the effects of capital into the demand of *workers* (production workers) and *managers* (non-production workers).

This paper uses this decomposition of labor force to test whether (i) there is supporting evidence of the Ricardian Effect in Colombia; (ii) whether this effect varies between two qualitatively different types of labor (managers vs. workers); and (iii) whether this effect changed under a period of “market oriented reforms” whose purpose was, among several others, to reduce distortions in the factor markets. Any evidence of the replacement of labor force when new units of capital are introduced in the production process should be stronger on workers, whose tasks can be more considered as routine.⁶

Colombia is a very interesting case of study mainly for two reasons. First, the information at disposal is based on a uniquely rich and representative data for Colombian manufacturing plants, derived from yearly plant censuses over the period 1982-1998 with detailed information of physical quantities of inputs. It is the most complete source of product-level information in a nationally representative plant database in any country (Kugler & Verhoogen, 2012). Second, the Colombian experience can be considered as a “natural experiment” of exogenous shocks to the relative prices of inputs, since during the early 1990s, the country underwent countrywide market oriented reforms, and thus the data provides a clean base for comparison between pre-reform and Post-Reform periods (Eslava, Haltiwanger, Kugler, & Kugler, 2004).

This paper is a relevant contribution for three reasons: First, up to my knowledge, no previous attempt has been made to provide quantitative evidence of the Ricardian Effect, mostly due to the stringent data requirements imposed by the nature of the question. I have not found yet any attempt to understand the effects of capital demand on managers and workers demand where the unit of observation is a manufacturing plant. Second, this paper is an empirical contribution to the “task-based approach” framework

⁵Acronyms in Spanish for “Encuesta Anual Manufacturera”.

⁶This is consistent with Acemoglu and Autor (2011, pp.1076), who state that “Routine tasks are characteristic of many middle skilled cognitive and manual jobs (...) Because the core job tasks of these occupations follow precise, well-understood procedures, they can be (and increasingly are) codified in computer software and performed by machines.”

developed by Acemoglu and Autor (2011) where the effects of capital demand on labor differ depending on the tasks performed by the employees. This article provides some sense of the orders of magnitude of the effects of capital demand on labor of different qualities based on plant-level data on a country that experienced structural changes after a “market oriented reform” process. Third, this paper can be considered as a contribution to the literature unleashed by Hamermesh (1993) who concluded that demand estimates for heterogeneous group of labor based on micro-data were almost absent in the empirical literature. Several papers have faced this challenge, and this paper in particular considers explicitly the demand of managers and workers, and its relation with capital demand with data at the plant level, which is precisely the unit of observation where input demand decisions take place.

As Fabrizio et al. (2007) illustrate an important challenge to estimate input demands is the measurement of input costs. Usually, the level of disaggregation for wages and other costs are not at the plant level. In this paper I exploited the detailed information for material prices at the plant to produce relative costs for input together with the time series for wages and capital costs. This approximation can be considered as a second best approach to measure input costs given the lack of information on payroll and capital expenditures at the plant level for the manufacturing census in Colombia for the period 1982-1998.

In order to estimate input demands, I addressed the endogeneity problem with output using demand shocks that vary across sectors as an instrument. Output estimates are likely to be downward biased due to the simultaneity with input decisions, but demand shocks are more likely to be correlated with output. The *planned* decisions of inputs and output are taken simultaneously, but the response to random demand (unplanned) shocks are more likely to be correlated with output, since react producing immediately with the inputs at disposal, and the latter effects on input demands are mediated only through output decisions. This is particularly evident for plants that are below its production capacity. Regarding input costs Roberts and Skoufias (1997) argue that elasticities estimated with micro-data are less likely than aggregate studies to suffer from simultaneous bias. In particular, they consider that since the supply of labor to a single plant can be viewed as perfectly elastic, the endogeneity of input costs at the plant level is not a problem. Based

on the IV estimates, I simulated input demands for capital managers and workers after a continuous drop in the capital input cost due to the arrival of vintage and cheaper technology embodied in the capital stock.

Among the principal results, after estimating input demands for capital, managers, and workers instrumenting output with demand shocks, I found that the output elasticities for the three inputs are in the range of 0.58 to 0.65, while the price elasticities for capital, managers, and workers are -0.28, -0.32, and -0.21 respectively. Output elasticities were in fact underestimated with OLS estimations. These numbers are not only statistically significant but of great economic importance since they imply that in fact input demands respond to price changes in a sizable way. Additionally, compared to the pre-reform period, the reaction for input demands with respect to input prices during the post-reform era is stronger. The market oriented reforms in Colombia turned input demands to be more elastic with respect to prices. This can be considered as suggestive evidence that the goal of making factor markets more competitive at least is reflected in labor and capital markets with more elastic demands.

Based on a simulated arrival of cheaper capital goods, these input demand coefficients are used to predict that, on average, when a plant increases its capital stock by about 67 per cent, it will reduce its payroll by one manager and 4 workers. Capital replaces labor, and this replacement is stronger for employees that perform routine tasks in the work place. This replacement was also significantly stronger during the post-reform years since reforms turned input demands more elastic with respect to prices. In fact, the input demand simulations suggest that after the arrival of cheaper capital goods, a plant will increase its capital stock about 21 per cent during the pre-reform period, compared to an increase of 111 percent based on post-reform elasticities. On the other hand, for pre-reform periods a plant will demand one less manager and two less workers, while for post-reform periods the cut will be of 2 managers and 5 workers. After performing several robustness checks, I found that these effects are not driven by plant's observable characteristics.

The rest of the paper is organized as follows: Section 2.2 describes the data and provides a brief description of the Colombian context in light of the evidence. Section 2.3 illustrates the empirical strategy pursued in this research. Section 2.4 presents the main results of the paper. Section 2.5 performs some robustness checks and section 2.6 provides some concluding

remarks.

2.2 Data

The database comes from the project “Plant-Level Price Indices for Output and Materials” created under a technical cooperation between the Colombian National Administrative Department of Statistics (DANE hereafter for its acronym in Spanish) and John Haltiwanger from Maryland University. This database have the same coverage period and most of the information that was used in Eslava et al. (2004). The information gathered is taken directly from the Colombian Annual Manufacturing Survey (EAM hereafter for its acronym in Spanish).

The EAM is an unbalanced panel that has information since 1982 of any industrial establishment in Colombia that employs ten or more employees, or that its annual output is worth more than 65 million Colombian pesos (around 35 thousand dollars) at the reference year. These reports are adjusted each year with the producers price index created by the Colombian Central Bank. The dataset of Haltiwanger’s project contains information for each establishment of the manufacturing sector for the following variables: production, capital (buildings, structures, machinery, and equipment), employees (production and non-production personnel), hours worked (average hours worked per employee times number of employees per sector per year), materials (intermediate consumption), and energy consumption. Production, capital and materials are in constant thousands of pesos of 1982, whilst energy is in Kw per hour.

Eslava et al. (2004) and the technical document that accompanies the “Plant-Level Price Indices for Output and Materials” database provide detailed documentation of the construction of the variables. However, since the measurement of capital, managers, and workers is critical for my purposes, I will explain briefly the construction of these variables that is contained in both documents.

2.2.1 Capital

The capital stock is constructed recursively based on the following formula:

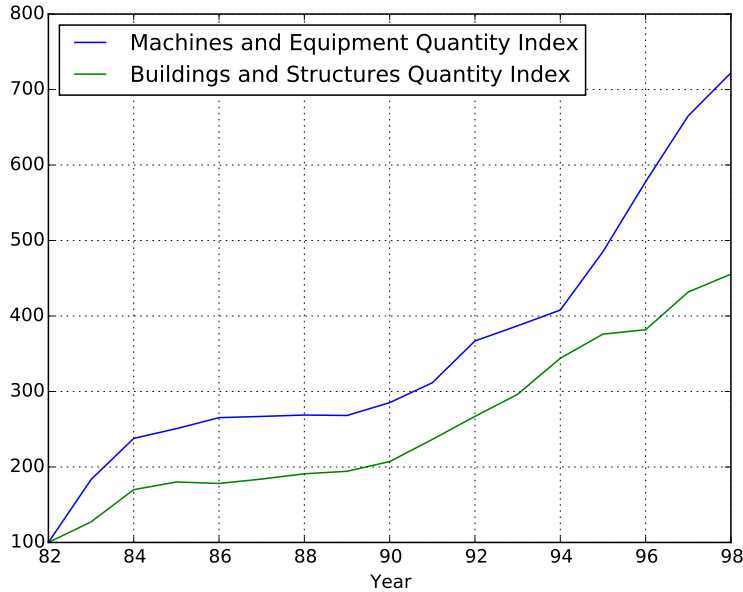


Figure 2.1: Input quantities. Index for machines and equipment, and for buildings and structures: Both lines represent averages per year for the plants of the manufacturing sector. 1982 = 100. Source: EAM.

$$K_{it} = (1 - \delta)K_{it-1} + \frac{I_{it}}{D_t}$$

where K_{it} are the units of physical capital for plant i in year t , K_{it-1} are units of physical capital for plant i in year $t - 1$, δ is the depreciation rate, I_{it} is the gross investment for plant i in year t , and D_t is the gross capital deflator for year t .⁷ The capital stock series only includes equipment, machinery, buildings, and structures. With the information on fixed assets reported by each plant together with depreciation rates and inflation reported to adjust fixed asset values, gross investment series for each plant are generated to compute the capital series (Eslava et al., 2004).

Figure 2.1 illustrates the average per year of the components of the capital for the plants of the manufacturing sector. The components of capital are the buildings and structures, and the machinery and equipment reported by the plant at any given year. The sum of these two components compose the

⁷See Eslava et al. (2004) and the technical document of the construction of variables of the “Plant-Level Price Indices for Output and Materials” for the details regarding the depreciation rates, deflators, the generation of the gross investment series for each plant, and the assumptions for the initial capital stocks.

capital of each plant. Samuelson (1988) considers that the ideas exposed in his Ricardo's chapter 31st should be extended beyond the concept of machines and include the entire capital stock held by the unit of production. Therefore, I consider that the Ricardian effect should be understood in terms of the capital stock, not only on the subset of capital reported as machines.⁸ The average capital for the manufacturing sector has increased since 1982 for both of its components. The capital growth was slower before 1991, and notice that it was rather flat during the period 1984-1990, and only after 1991 it recovered its pace of growth. During the period 1982-1998 the Buildings and Structure Quantity Index had a four fold increment while the Machines and Equipment Quantity Index multiplied by more than 7 times.

In the Colombian context, 1991 is a year that deserves special attention. After the infamous murder of Luis Carlos Galán, the virtual winner for the 1990 presidential elections, Cesar Gaviria won the presidency for the period (1990-1994). President Gaviria was a technocrat who worked in Galán's campaign as Chief of Staff. During his tenure several episodes marked dramatically the modern history of the country: Pablo Escobar was killed and his entire drug cartel was dismantled after years of terror; the most emblematic left-wing guerrilla group, the M-19, signed an armistice with the Colombian Government, and a new constitution in 1991 created a whole new legal environment in every level of the State. Additionally, during the early nineties the Colombian economy underwent extensive structural reforms whose purpose were to enhance the role of productivity and undermine the role of demand of factors, with special emphasis on artificially imperfect competitive markets (Eslava et al., 2004). In particular, dismissal costs on labor were reduced dramatically, the average tariffs fell significantly, capital markets and banking legislation were modernized, and restrictions on FDI were removed (Eslava et al., 2004). In spite of all the plant heterogeneity across the manufacturing sector that Figure 2.1 is incapable to capture, it is illustrative that the average capital has increased more dramatically precisely during this "post-reform" environment.

⁸Moreover, if I decide to consider the components of the capital series individually, I would need prices for each of these variables to estimate input demands. This is not feasible for me with the data sources that I have at disposal, but further research on this area would be enlightening to understand the effect of each of the components of the capital on labor demand.

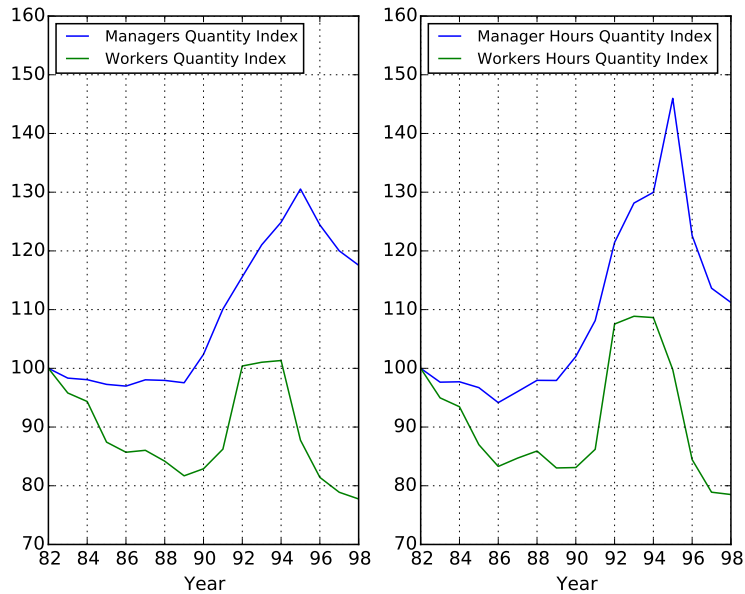


Figure 2.2: Input quantities. Index for managers and workers based on number of employees (left panel), and for manager hours and worker hours based on number of employees times hours worked (right panel): Each line represent averages per year for the plants of the manufacturing sector. 1982 = 100. Source: EAM.

2.2.2 Labor

The EAM divides the labor force between production and non-production workers based the qualitative differences of the tasks performed at the workplace. Appendix B.1 illustrates the taxonomy used by the EAM to classify both production and non-production personnel. Workers are presumed to perform more routine tasks than managers, since they are directly involved in the production process, whereas managers are in charge of the decisions to run the plant. From Appendix B.1 it is clear that there is a class of tasks labeled as managers that involve more skills and are less prone to routine, and this family of tasks is not found in the category of workers. However, Appendix B.1 also illustrates that the task-based distinction is not as clear as the separation between water and oil since there are some tasks labeled as managers that can be thought of as routine. Nevertheless, I consider that the distinction made by the EAM is a good approximation (with some measurement error) to disentangle the labor force between managers and workers based on what they *do* at their workplace.

The left panel of Figure 2.2 plots the evolution for the average number of managers and workers while the right panel plots the average number of manager hours and worker hours employed. On average, both panels illustrate that the demand of workers has been consistently below relative to the demand of managers, but with a wider gap during the post-reform period. The Index for workers fell from its 100 base in 1982 to almost 80 in 1990. It rose back to 100 during the next two years but after 1994 it fell again to levels even below 80. For worker hours the message is similar, although this index was above 100 at its 1994 peak. On the other hand, the average number of employees labeled as managers was more or less steady until 1990, then it reached a peak of 130 in 1995, and later it fell again, but still above its initial 100 base. When manager hours are considered, the amplitude is bigger but the message is the same.

The comparison between the left and right panels of Figure 2.2 should not be interpreted as an illustration between the extensive and intensive margins for the demand of managers and workers. The EAM does not have hours discriminated between managers and workers. In fact, the total hours worked are not observed at the plant level. Following Eslava et al. (2004), I am computing the total hours per worker from a given plant with the average number of hours worked at the plant's industrial sector at the three-digit level.⁹ This measure of hours varies across sectors and years, not across plants within a sector in a given period. The average hours per week worked throughout the sample is 38, which is close to usual 40 hour schedule per week observed in Colombia.

Since I am not capable of discriminating between the hours worked between managers and employees, I am assuming that all the payroll of a given plant shares the same working schedule. This is not an unreasonable assumption. It is just saying that in order to operate, the plant needs both managers and workers to be present at the workplace at the same time. However, this approach is not capable of discriminating between the extensive or intensive use of the labor force. It is just rescaling the labor force by the number of hours employed in the sector where the plant belongs. A proper discussion between extensive *vis à vis* intensive employment of managers and workers and its relation with the stock of capital demands data on manager and

⁹The sectors in the EAM are classified using the United Nations International Standard Industrial Classification (ISIC) of All Economic Activities, Revision 2.

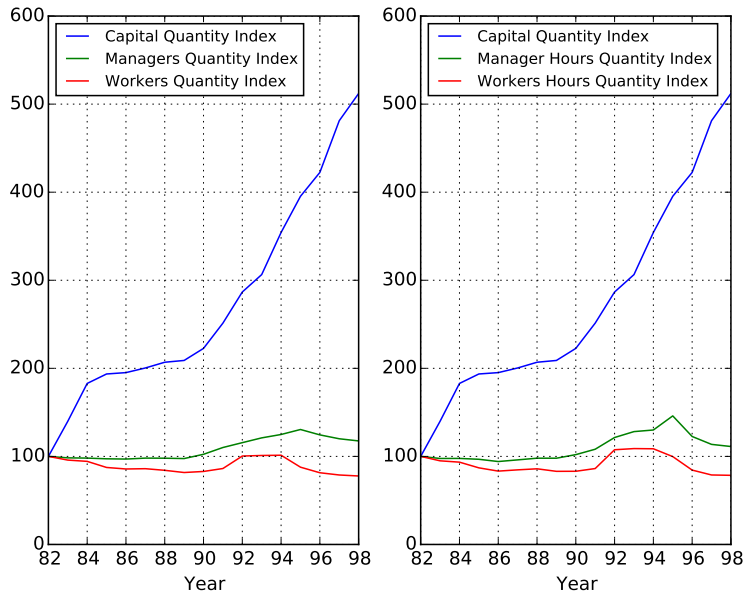


Figure 2.3: Input quantities. Index for managers and workers based on number of employees (left panel), and for manager hours and worker hours based on number of employees times hours worked (right panel): Index for capital (machines, equipment, buildings, and structures) in both panels. Each line represent averages per year for the plants of the manufacturing sector. 1982 = 100. Source: EAM.

worker hours separately.

Figure 2.3 plots both Figure 2.1 and Figure 2.2 in a single graph to get a visual illustration of the evolution of the demand of capital and labor. Compared to the capital demand, the evolution of the labor demand looks almost like a flat line, even when hours worked are considered. Figure 2.3 suggest that the manufacturing sector in Colombia was not an important engine for job creation; its expansion is more reflected in capital inputs, and the differences between workers and managers are not sizable compared to the capital demand, on average.

It is not clear from Figure 2.3 that the pattern of capital and labor demand is not just an average that is not reflecting the sectors of the manufacturing industry when they are analyzed on a case-by-case basis. Figure 2.4 replicates the exercise of Figure 2.3 for each of the three digit level sectors, and it establishes that the pattern observed in Figure 2.3 is roughly consistent with the experience observed in every industrial sector but one: *Petroleum*

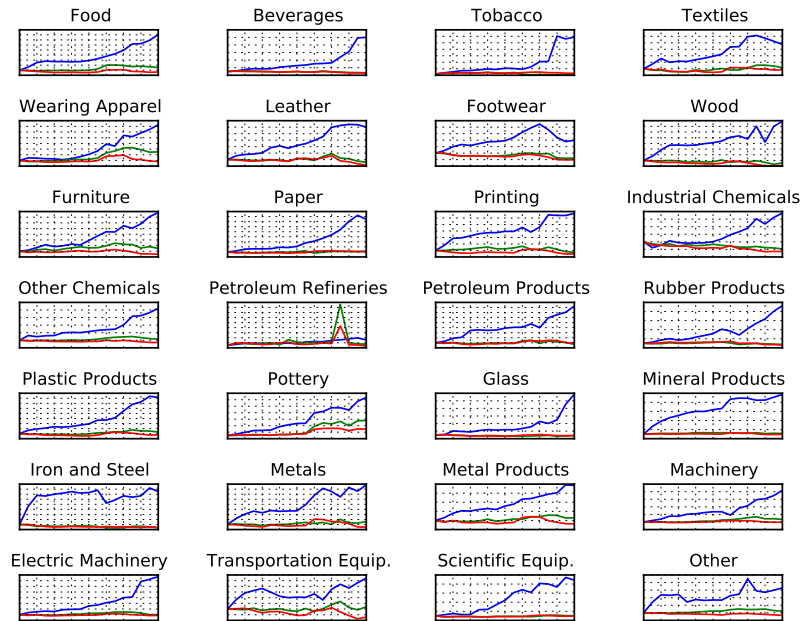


Figure 2.4: Input quantities. Index for managers [green line] and workers [red line] based on number of employees, and index for capital (machines, equipment, buildings, and structures) [blue line]: Each line represent averages per year per sector (three digit level) for the plants of the manufacturing sector. 1982 = 100. Source: EAM.

Refineries. Sáenz (2010) documents that the Petroleum Refineries sector is an outlier in terms of investments in Research and Development, and Bucheli and Sáenz (2014) argue that historically the petroleum sector in Colombia has faced high technological barriers that were critical to the early establishment of oil multinationals in order to surpass these limitations. Therefore, it is not surprise that for the period 1982-1998 the capital stock in this sector was already at a high level, and thus its growth for the last two decades of the twentieth century is not impressive relative to its labor demand.

2.2.3 Input Costs

In order to estimate input demands I need information on relative prices of inputs. Unfortunately, the EAM only contains prices at the plant level for output, materials and energy. Therefore, I used alternative sources of

information related to wages and capital cost. The webpage of the Colombia's Central Bank provides the historical series for the Producer Price Index (PPI) since 1970 under several classifications. In particular, under the category: "PPI by use or destination of good" the subcategory of capital goods is available. The Capital Cost Index then is measured as the capital goods' PPI relative to the manufacturing PPI, normalized to a base of 100 for 1982.¹⁰

Regarding labor costs, Urrutia and Ruiz (2010) present real wage series for several sectors and periods in Colombia. They provide the real wages discriminated by economic activity for the period 1980-2006. I constructed the Industrial Wage Index as the industrial wages from Urrutia and Ruiz (2010) multiplied by the consumer price index (CPI) and divided by the manufacturing PPI, normalized to a base of 100 for 1982. I also used the series of minimum wage deduced from the Colombian National Government Decrees to construct the Minimum wage Index as the nominal minimum wage divided by the manufacturing PPI, normalized to take 100 for 1982.¹¹ I am assuming that the relevant cost for the demand of managers and workers is captured by the Industrial Wage Index and the Minimum Wage Index respectively. This assumption has two caveats. First, it is possible that the Industrial Wage Index is capturing part of the disbursements of the plants to pay workers so this index could be underestimating the relative costs paid for managers. Second, it might be also that some workers get paid below the minimum wage in informal settings, although this is less likely due to the requirements that a plant must fulfill to be considered in the EAM. It is necessary to recall this possible biases when interpreting the price effects on input demands, but the important contribution of this exercise is to get two different proxies for the costs of managers and worker.

¹⁰There is an extensive literature related with computations of capital costs in Colombia, but i) they consider the capital cost mostly in terms of the opportunity cost, ii) these calculations do not vary across plants or sectors in the manufacturing industry, and iii) the PPI of capital goods is already a major component of the capital costs in the algorithm. For the purposes of this document, using the PPI solely to construct relative costs of inputs is an approach more clean and tractable compared to using of any of the algorithms available. See Diéz, Gaitán, and Valderrama (2011) for a short literature review and summary of the methodologies related with the computation of capital costs in Colombia. In particular see the discussion in Diéz et al. (2011) regarding the lack of consensus to estimate capital costs.

¹¹The minimum wage is available since 1984. To complete the series backwards up to 1982 I will use the growth in the real wage for the industry for those two years to have the base for 1982 for the three series.

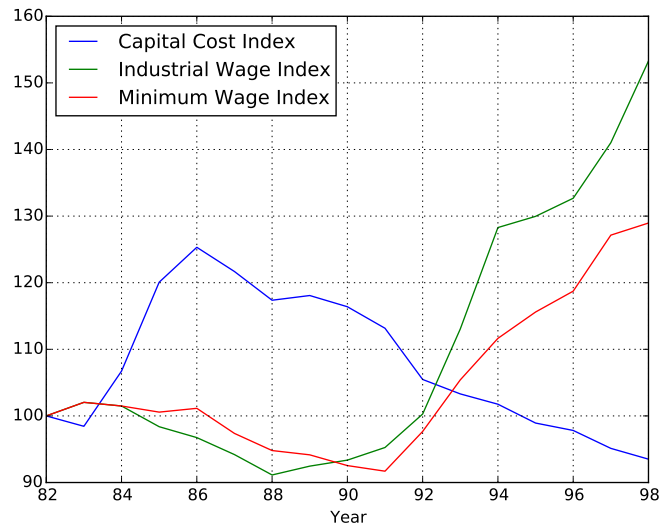


Figure 2.5: Input prices: Capital and labor: The Capital Cost Index is measured as the capital goods' Producer Price Index (PPI) relative to the manufacturing PPI, normalized to a base of 100 for 1982. The Industrial Wage Index is computed as the real industrial wage multiplied by the consumer price index (CPI) and divided by the manufacturing PPI, normalized to a base of 100 for 1982. The Minimum Wage Index is computed as the nominal minimum wage divided by the manufacturing PPI, normalized to take 100 for 1982. The growth rates of the Industrial Wage Index were used to complete the series of the Minimum Wage Index for 1982 and 1983, since the minimum wage decrees started in 1984. Sources: Colombia's Central Bank, Colombian National Government Decrees, and Urrutia and Ruiz (2010).

Figure 2.5 illustrates the indexes of the costs of capital, managers, and workers relative to the manufacturing PPI for the period 1982-1990. The three series plotted in Figure 2.5 can be considered as second best alternatives to the non-existent data on capital and labor costs that each plant of the manufacturing is disbursing during the period 1982-1998. From 1982 to 1986 the cost of capital relative to the other manufacturing costs was grew about 25 per cent, but from 1986 to 1990, the capital cost index decreased a few points (around 115). During the pre-reform period the capital cost reduction gained momentum and it ended in 1998 below the 100 base of 1990. This is consistent the fact that after the reform process, the average tariffs fell, the banking sector was modernized, and the prevailing sectorial restrictions to Foreign Direct Investment were removed (Eslava et al., 2004; Edwards &

Steiner, 2008).

The labor costs relative to the manufacturing PPI fell during the pre-reform period, but since 1991 they rose consistently. Moreover, during the post-reform period the gap between industrial wages and minimum wages is opened. This increment can be explained not only through the fall in capital costs (since its a relative cost), but also through the fact that in spite of the policies oriented to enhance the flexibility on hiring labor force as well as the reduction in hiring costs, the reform period introduced also mechanisms to provide better protection of the worker's rights, and protection to the union activity (Edwards & Steiner, 2008). Additionally, in 1993 a national reform increased by 13.5 per cent the contributions of payroll to social security, where 75 per cent of these contributions were paid directly by employers (Eslava et al., 2004).

Figures 2.2 and 2.5 can be used to paraphrase Krusell et al.'s (2000) puzzle within the Colombian context: While the cost of managers has increased more than the cost of workers, the demand of managers has increased more relatively. Krusell et al. (2000) would suggest that the reason is to be found in the complementarities between skilled workers, presumably managers, and capital. I argue that capital and managers are less substitutes than workers and managers, or that the Ricardian Effect is stronger for workers than for managers. It is a similar message, but based on different premises.

2.2.4 Descriptive Statistics

Table 2.1 presents the principal descriptive statistics. Capital, total employment hours, materials, energy, output, and demand shocks¹² are in logs, and the cost indexes are normalized to a base of 100 for 1982. For the period 1982-1998, the number of observations for all variables oscillates between 90 and 100 thousand, although the indexes for capital, managers, and workers are repeated observations of the same sector (or plant) invariant number per year in the panel. The average of capital is 8.44 with a standard deviation of 2.12. Its range is from -2.3 to 17.44 log points. The average number of managers is 20, and the standard deviation is 54, which indicates an important concentration in the right tail since the range goes from 0 to 1,882. The av-

¹²In section 2.3 I will describe in detail the construction of the demand shocks.

Variable	Mean	(Std. Dev.)	Min.	Max.	N
Capital	8.44	(2.12)	-2.3	17.44	96,232
Managers	20.04	(54.55)	0	1,882	100,112
Workers	52.12	(121.65)	0	5,229	100,112
Total Emp. Hours	10.96	(1.17)	6.68	17.81	99,102
Materials	9.89	(1.89)	-1.11	17.79	90,938
Energy	11.42	(1.93)	0	20.29	99,476
Capital Cost Index	108.27	(10.07)	93.51	125.32	100,114
Industrial Wage Index	108.83	(18.84)	91.13	153.28	100,114
Minimum Wage Index	104.32	(11.21)	91.7	128.96	100,114
Materials Price Index	767.47	(962.82)	34.52	58847.97	91,540
Energy Price Index	8,394.5	(1,344,645.04)	-10,872.46	373,056,000	100,114
Output	10.68	(1.78)	-1.87	18.46	100,114
Demand Shocks	5.12	(2.65)	-1.62	32.08	100,114

Table 2.1: Descriptive statistics. 1982-1998: Capital, total employment hours, materials, energy, output, and demand shocks are in logs, while indexes are normalized to a base of 100 for 1982.

average number of workers is 52, with a standard deviation of 122, showing the same concentration pattern since the range goes from 0 to 5,229 workers. For the whole period, the industrial sector in Colombia demanded, on average, more managers than workers, but the standard deviation suggest an important degree of variability in the sample. The log average of total employment hours is close to 11, which is about 60 thousand labor hours (employees times hours worked), with a standard deviation of 1.2. The averages for materials and energy are 9.9 and 11.4 respectively.

Regarding cost indexes, the descriptive statistics of Table 2.1 for capital cost and wages simply reflect the message of Figure 2.5 since they are nothing but time series. However, for materials and energy costs, the data has information that varies across plants. The average index for materials is 767 while for energy is 8,394. There is an important degree of dispersion in the data for these two inputs. The standard deviation for the materials price index is 962.82 while for energy is 1,344,645. This excessive volatility in energy prices is possibly explained from the fact that energy consumption is measured in Kw per hour and the bill of Kw per year, reported directly in the EAM, and the energy prices per plant can be considered on its own a measure of capital utilization. Prices of materials (and output) are constructed with Tornqvist indices where weighed average for growth in prices of materials (or products) generated by the plant are used.¹³

¹³See Eslava et al. (2004) and the technical document of the “Plant-Level Price Indices

Variable	Mean	(Std. Dev.)	Min.	Max.	N
<i>Panel A. Pre-reform Period. 1982-1990</i>					
Capital	8.21	(2.05)	-2.3	17.22	53,034
Managers	18.23	(51.93)	0	1,553	55,298
Workers	51.96	(122.48)	0	5,229	55,298
Total Emp. Hours	10.97	(1.1)	6.95	16.13	55,055
Materials	9.60	(1.85)	-1.11	17.5	51,741
Energy	11.3	(1.88)	0	20.29	54,762
Capital Cost Index	113.98	(9)	98.44	125.32	55,298
Industrial Wage Index	96.49	(3.83)	91.13	102.04	55,298
Minimum Wage Index	98.09	(3.42)	92.54	102.04	55,298
Materials Price Index	307.29	(343.94)	40.69	23,109.16	52,280
Energy Price Index	7,506.85	(1,586,504.62)	0.06	373,056,000	55,298
Output	10.49	(1.67)	5.15	18.05	55,298
Demand Shocks	5.08	(2.6)	0.07	31.76	55,298
<i>Panel B. Post-Reform Period. 1991-1998</i>					
Capital	8.75	(2.18)	-2.13	17.44	43,198
Managers	22.28	(57.53)	0	1,882	44,814
Workers	52.31	(120.62)	0	2,849	44,814
Total Emp. Hours	10.95	(1.25)	6.68	17.81	44,047
Materials	10.25	(1.88)	0.21	17.79	39,197
Energy	11.55	(1.99)	0	20.19	44,714
Capital Cost Index	101.23	(6.05)	93.51	113.16	44,816
Industrial Wage Index	124.06	(18.84)	95.26	153.28	44,816
Minimum Wage Index	112.02	(12.62)	91.7	128.96	44,816
Materials Price Index	1,380.27	(1,160.36)	34.52	58,847.97	39,260
Energy Price Index	9,489.76	(966,109.47)	-10,872.46	201,600,000	44,816
Output	10.9	(1.88)	-1.87	18.46	44,816
Demand Shocks	5.18	(2.72)	-1.62	32.08	44,816

Table 2.2: Descriptive statistics. Panel A: Pre-reform period (1982-1990). Panel B: Post-reform period (1991-1999): Capital, total employment hours, materials, energy, output, and demand shocks are in logs, while indexes are normalized to a base of 100 for 1982.

Last, Table 2.1 shows that for the full sample, the average output per plant was about 10.7 with a standard deviation of 1.8 with a minimum of 1.87 and a maximum 18.46 log points. The “Plant-Level Price Indices for Output and Materials” also provides data on demand shocks with different sectorial elasticity computed in Eslava et al. (2004). The average demand shock is of 5.1 log points, with a standard deviation of 2.6. The range for this shocks goes from 0.1 to 31.8.

In order to provide a first snapshot of the differences between pre and Post-Reform periods in the sample, Panels A and B of Table 2.2 splits the sample for Output and Materials” project for more details on plant level prices.

between 1982-1990 (Pre-Reform Period), and 1991-1998 (Post-Reform Period) and provide the main descriptive statistics for each period. The capital increased from 8.2 to 8.8 log points. In 1982 thousand pesos, this is a difference of about 2,633, on average, for the period after the reforms. The average number of managers in the Pre-Reform Period is 18 while for in the Post-Reform period is 22, a substantial difference of 5 workers per plant, *on average*. The number of workers on the other hand remain virtually the same around 55 per plant on average. The output increased in the post-reform period on average about half log point, or 18,000 thousand pesos of 1982. Table 2.2 delivers the following stylized fact: During the post-reform era, the plants on average increased its production and its demand of capital and managers, while the demand of workers remained stagnant. It is also noticeable that the number of observations between pre and Post-Reform periods was reduced in about 10,000 observations. Even though there are 9 years in the Pre-reform Period and only 8 years for the Post-Reform Period, Table 2.2 suggests that some plants did not survive the new competitive environment imposed by the market oriented reforms.

2.3 Empirical Strategy

In order to test whether the transition from cost-of-service regulation to market oriented environments for many US electric generating plants had an impact on cost minimization, Fabrizio et al. (2007) estimate input demands based on a cost-minimization optimization from a Cobb-Douglas production technology to obtain a system of input demand equations that ultimately depend on quantities and prices. As Fabrizio et al. (2007) did, I derive input demand equations based on the Cobb-Douglas production technology as illustrated in equation (2.1):

$$Y_{it} = A_{it} \prod_{j=1}^n X_{ijt}^{\alpha_j}, \quad (2.1)$$

where Y_{it} is the production of plant i in year t , X_{ijt} is the demand of plant i for input j in year t . The inputs of production considered are: capital, managers, workers, energy, and materials ($n = 5$). Unfortunately, The EAM does not contain information of the skill level of the labor force at the plant level that

allows me to build the bridge proposed by Acemoglu and Autor (2011) from skills to tasks to production. In other words, I am not considering a General Equilibrium framework that considers the decisions of the households to react to the Ricardian Effect by improving their skill level, or to migrate to other sectors in the economy (for instance services). Therefore, as in Krusell et al. (2000), I will focus on the production abstracting from the household sector with the five-input production function presented in equation (2.1):

A given plant i at year t takes the input costs as exogenous parameters in their optimization process, yielding the following FOC:

$$\frac{\partial Y_{it}}{\partial X_{ijt}} : A_{it} \alpha_j X_{ijt}^{\alpha_j - 1} \prod_{k \neq j, k=1}^{n-1} X_{ikt}^{\alpha_k} = C_{ijt}, \quad (2.2)$$

where C_{ijt} is the cost of input X_{ijt} relative to inputs X_{i-jt} . Equation (2.2) can be rewritten to include directly the production level, as shown in equation (2.3):

$$\alpha_j \frac{Y_{it}}{X_{ijt}} = C_{ijt}. \quad (2.3)$$

Notice that the effects of TFP (A_{it}) are captured directly in equation (2.3) in the level of production Y_{it} . After taking logs on both sides of equation (2.3), I get the following input demand equation in terms of prices and quantities.

$$\log X_{ijt} = \beta_0 + \log Y_{it} - \log C_{ijt}, \quad (2.4)$$

where $\beta_0 = \log(\alpha_j)$. From equation (2.4) I can derive an econometric model to estimate demand equations for each input exploiting the idiosyncrasy of the observations given the level of disaggregation provided by the EAM, as illustrated in equation (2.5):

$$\log X_{ijt} = \beta_0 + \beta_1 \log Y_{it} - \beta_2 \log C_{ijt} + \gamma_i + \delta_t + \varepsilon_{ijt}, \quad (2.5)$$

where γ_i stands for plant fixed effects, δ_t measures the time fixed effects, and ε_{ijt} is an idiosyncratic error term. Additionally, since I am interested in the effects of the “market oriented reforms”, which can be thought of as exogenous sources of variation to the relative prices of inputs, equation (2.6) includes the interaction between the relative costs, $\log C_{ijt}$, and the binary

variable PR that takes 1 for the 1991-1998 period, and 0 otherwise.¹⁴

$$\log X_{ijt} = \beta_0 + \beta_1 \log Y_{it} - \beta_2 \log C_{ijt} - \beta_3(\log C_{ijt} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt}. \quad (2.6)$$

On the right hand side of equation (2.6), notice that all regressors can be considered as exogenous but one: $\log Y_{it}$, the level of production.¹⁵ Roberts and Skoufias (1997) argue that the *planned* decisions of inputs and output are taken simultaneously, but the response to random demand shocks are more likely to be correlated with output, since plants respond to unplanned positive random shocks by producing more with the inputs at disposal, and the later effect on input demands are mediated only through output decisions. This is particularly true if plants are *not* operating at its full capacity, since they can produce more output instantaneously with the same level of inputs.¹⁶ Moreover, demand shocks with different sectoral elasticity are more likely to be perceived as industry-specific shocks to be responded with production, than economy-wide shocks to be responded with either price changes and/or cost restructuring that will have direct impacts (not mediated through production) on input demand. The effects of demand shocks on inputs therefore will only take place through the output channel (through the second stage).

Fabrizio et al. (2007) instrument plant output with a nonlinear function of state demand. They argue that state-level electricity demand is likely to be highly correlated with output, and less with inputs and that their approach is particularly effective for capturing the response to demand fluctuations in real time. In the same spirit, I argue that for the manufacturing sector in Colombia it is more likely that plants react to positive demand shocks by increasing their production rather than for instance, by hiring more workers or buying more machines. In order to address this endogeneity issue I propose to use the estimated demand shocks with different sector elasticities estimated in Eslava et al. (2004) and available in the “Plant-Level Price Indices for Output and Materials” dataset as a plausible instrument for the

¹⁴Notice that the level effects of the reform process are already captured by δ_t , the time fixed effects.

¹⁵Roberts and Skoufias (1997) argue that input cost elasticities estimated with micro-data are not suffering from simultaneous bias, since from the point of view of a single plant, the supply of inputs is perfectly elastic.

¹⁶However, I consider that this strategy is weak for the estimation of energy demand since this particular input is closely related with capacity utilization.

production level.¹⁷ Eslava et al. (2004) estimate demand shocks to capture the demand component of profitability with the log residual of the following inverse-demand:

$$P_{it} = Y_{jt}^{-\rho} D_{jt}.$$

With prices and production disaggregated at the plant level, it is possible to obtain estimates of plant-level demand shock. Importantly, the estimates for inverse elasticities of demand ($-\rho$) vary across sectors, providing an additional variation at this level of disaggregation.¹⁸

Equation 2.7 illustrates the first stage regression where demand shocks are used to address the endogeneity of the production level:

$$\log Y_{it} = \theta_0 + \theta_1 \log D_{it} + \theta_2 \log C_{ijt} + \theta_3 (\log C_{ijt} \times PR) + \eta_i + \phi_t + \nu_{ijt}, \quad (2.7)$$

where $\log D_{it}$ is the demand shock faced by plant i on period t , η_i stand for plant fixed effects, ϕ_t represents time fixed effects, and ν_{ijt} is the idiosyncratic error term of the first stage. The relevance conditions implies that $\hat{\theta}_1$ must be statistically, and economically significant. I cannot test whether $\log D_{it}$ is completely orthogonal to ε_{ijt} , but the intuition described above illustrates that the relationship between between inputs and demand shocks is to be found in the first stage, not in the error term of equation (2.6).

Considering each input individually, equation (2.6), either estimated directly or with Instrumental Variables, is nothing but a system of equations that can be used to understand the effects of changes in the relative prices on more than one input. In particular, it can be used to trace the effects of a simulated reduction in relative price of capital due to technological innovations on the demand on capital, managers, and workers. Consider the following system of equations:

¹⁷Fabrizio et al. (2007) also addressed the endogenous nature of the relation between inputs and output, but they consider as an instrument the state-level electricity demand as a instrument for plant-output, arguing that this demand is likely to be highly correlated with the amount of output a plant will be called to produce, but uncorrelated, with inputs use and efficiency.

¹⁸See Eslava et al. (2004) for more details of the estimation of demand shocks.

$$\begin{aligned}
\log X_{i1t} &= \beta_0^1 + \beta_1^1 \log Y_{it} - \beta_2^1 \log C_{i1t} - \beta_3^1 (\log C_{i1t} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt} \\
\log X_{i2t} &= \beta_0^2 + \beta_1^2 \log Y_{it} - \beta_2^2 \log C_{i2t} - \beta_3^2 (\log C_{i2t} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt} \\
\log X_{i3t} &= \beta_0^3 + \beta_1^3 \log Y_{it} - \beta_2^3 \log C_{i3t} - \beta_3^3 (\log C_{i3t} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt} \\
\log X_{i4t} &= \beta_0^4 + \beta_1^4 \log Y_{it} - \beta_2^4 \log C_{i4t} - \beta_3^4 (\log C_{i4t} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt} \\
\log X_{i5t} &= \beta_0^5 + \beta_1^5 \log Y_{it} - \beta_2^5 \log C_{i5t} - \beta_3^5 (\log C_{i5t} \times PR) + \gamma_i + \delta_t + \varepsilon_{ijt}
\end{aligned} \tag{2.8}$$

where $J = [1, 2, 3, 4, 5]$ is indexing capital, managers, workers, materials, and energy respectively. For instance, the term $\beta_2^1 \log C_{i1t}$ represent the coefficient for relative capital costs ($j = 1$) on the capital demand equation. After estimating the system of equations (2.8) with instrumental variables, I will use the coefficients β_2^j , and β_3^j to simulate capital, managers, and workers demand after a reduction on capital relative costs due to a technological increase. Krusell et al. (2000) argue that technological changes can be understood as declines in the relative price of capital equipment; they illustrate the effects of this price on demand of skilled and non-skilled workers. Therefore, the purpose of this simulation is to test whether capital demand stimulated by technological innovations that reduce the relative price of capital come together with reductions of labor demand, given the labor-saving nature of technology embodied in capital. Also, this simulation provides a testing ground to illustrate whether this effect varies between managers and workers, and whether the replacement of labor was stronger during the post-reform years in Colombia. Appendix B.2 explains in detail the algorithm that I used to simulate input demands.

2.4 Results

2.4.1 Input Demands: Capital, Managers, and Workers. OLS Estimates

Table 2.3 presents the OLS estimation of equation 2.6 for capital demand. Column 1 of Table 2.3 takes as regressors the level of production and the Capital Cost Index from Figure 2.5. The elasticity of the production level

	(1)	(2)	(3)	(4)	(5)	(6)
Output	0.899*** (0.019)	0.905*** (0.020)	0.903*** (0.020)	0.333*** (0.021)	0.235*** (0.016)	0.236*** (0.016)
Capital Cost Index	-0.987*** (0.171)					
Relative Capital Cost Index		-0.568*** (0.077)	-0.438** (0.151)	-1.044*** (0.054)	-0.130* (0.051)	-0.0212 (0.042)
Relative Capital Cost Index x <i>PR</i>						-0.190* (0.073)
Constant	3.433*** (0.732)	-1.872*** (0.240)	-1.892*** (0.281)	3.747*** (0.248)	5.234*** (0.186)	5.343*** (0.191)
Plant Fixed Effects	No	No	No	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	No	Yes	Yes
Observations	96,232	88,066	88,066	88,066	88,066	88,066
Adjusted R^2	0.572	0.576	0.577	0.134	0.209	0.210
Number of id				11,156	11,156	11,156

Table 2.3: Capital demand. OLS estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Capital Cost Index is calculated as the ratio of The Capital Cost Index to the sum of the Industrial Wage Index, the Minimum Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998).

is 0.9 with the expected sign and significant at the 1 per cent level, and the elasticity of the Capital Cost Index is -0.99, also with the expected sign and significant at the 1 per cent level. All standard errors in Table 2.3 are clustered at the three-digit sector level. Although the signs of the coefficients are correct, the magnitudes are close to 1, indicating the presence of unitary elasticities with respect to costs and production. A problem with the estimation of Column 1 is that Capital Cost Index is a time series and it could be capturing other time-dependent information relevant to understand input demand, such as the business cycle. To address this issue, Column 2 of Table 2.3 considers a Relative Capital Costs Index which is constructed as follows:

$$RCCI_{it} = \frac{CCI_t}{MWI_t + IWI_t + MPI_{it}}, \quad (2.9)$$

where $RCCI_{it}$ stands for Relative Capital Costs Index for plant i in year t , CCI_t is the Capital Cost Index in year t , MWI_t is the Minimum Wage Index at t , IWI_t is the Industrial Wage Index at t , and MPI_{it} represents the

Managers Price Index for plant i at year t . The Relative Capital Costs Index exploits the variability of the material prices reported at the plant level in the EAM to construct a measure of relative costs that varies across plants and years.

It would be ideal to have data for each of the components of $RCCI_{it}$ disaggregated at the plant level, but the EAM does not provide such information. As a second best alternative, $RCCI_{it}$ captures part of the distance from capital costs to other plant costs. This measure has potentially some measurement error since there can be changes in $RCCI_{it}$ due to changes in the prices of materials that are not related whatsoever with capital costs. Nevertheless, even if this is the case, this measure is still a *relative* price that captures the distance between the price of capital with other costs. *Ceteris paribus* on other costs, a plant with higher material costs compared to a plant with lower material costs can be considered as plant with relatively lower capital costs. I decided to exclude the prices of energy from $RCCI_{it}$ since Table 2.1 shows that these prices display an abnormal volatility.

Column 2 of Table 2.3 illustrate that the Relative Capital Costs Index coefficient is -0.57, with the expected sign and statistically significant at the 1 per cent, but the elasticity of the production is still 0.9. Column 3 of Table 2.3 replicates the exercise in Column 2 but additionally it controls for time fixed effects. The coefficient for production is virtually the same, while the coefficient for the relative capital cost falls (in absolute value) to -0.44, significant at the 5 per cent level. To capture idiosyncratic elements that influence input demands, Column 4 of Table 2.3 includes plant, but not fixed effects. With plant effects the coefficient for production drops about a third, statistically significant at the one per cent level, but the relative cost's elasticity is above 1 in absolute value. Columns 3 and 4 of Table 2.3 demonstrate the utmost importance of including both time and fixed effects to reduce the estimate biases due to idiosyncratic elements that have an influence on input demands, so naturally, Column 5 of Table 2.3 includes both in the regression. The coefficient for production dropped even more to 0.24, significant at the 1 percent, while the Relative Capital Costs Index's coefficient is again below the unitary elasticity with a coefficient of -0.13, significant at the 10 per cent level. These coefficients display signs and magnitudes well below the unity, but recall from Section 2.3 that under OLS there still remains an endogeneity issue due to the inclusion of $\log Y_{it}$ as an explanatory variable. Last, to

	(1)	(2)	(3)	(4)
Output	0.569*** (0.020)	0.577*** (0.020)	0.279*** (0.010)	0.280*** (0.010)
Industrial Wage Index	-0.00136 (0.151)			
Relative Industrial Wage Index		-0.129 (0.119)	-0.137* (0.052)	-0.0652 (0.042)
Relative Industrial Wage Index x <i>PR</i>				-0.110 (0.062)
Constant	-4.109*** (0.618)	-4.331*** (0.298)	-1.195*** (0.150)	-1.121*** (0.142)
Plant Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes
Observations	93,650	85,828	85,828	85,828
Adjusted R^2	0.572	0.579	0.135	0.135
Number of id			10,932	10,932

Table 2.4: Managers demand. OLS estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Industrial Wage Index is calculated as the ratio of The Industrial Wage Index to the sum of the Capital Cost Index, the Minimum Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998).

understand the role of market oriented reforms on relative prices, Column 6 of Table 2.3 includes the interaction of Relative Capital Costs Index and the binary variable PR that takes 1 for the post-reform era. While the coefficient for production is virtually the same, Column 6 of Table 2.3 states that the relative costs only had an impact on capital demand during the post-reform years, since the elasticity of the interaction term is -0.19 significant at the 1 per cent level, while the elasticity of the Relative Capital Costs Index is not significantly different from zero (both in the statistical and economic sense of the term).

Table 2.4 illustrate the OLS estimation of equation 2.6 for managers demand. Column 1 of Table 2.4 uses the Industrial Wage Index plotted in Figure 2.5 to measure the costs in the payroll related with managers. The production coefficient is 0.57 with the expected sign and significant at the 1 per cent level. The coefficient for the Industrial Wage has the expected sign,

but it is not statistically different from zero. Like capital costs, the problem with the Industrial Wage Index is that it does not vary across plants. Since this problem is symmetric to the Capital Cost Index, the solution is symmetric as well.¹⁹ I constructed a Relative Industrial Wage Index in the following way:

$$RIWI_{it} = \frac{IWI_t}{MWI_t + CCI_t + MPI_{it}}, \quad (2.10)$$

where $RIWI_{it}$ stands for Relative Industrial Wage Index for plant i in year t . The rest of the terms are defined in the same way as in equation (2.9). Again, this relative wage exploits the variability available for material prices at the plant level.

Column 2 of Table 2.4 uses this relative cost. The coefficient of the production is not altered, but the coefficient of the Relative Industrial Wage Index is -0.13, with the expected sign although still not significant. Table 2.3 demonstrated the importance of including both time and fixed effects, so Column 3 of Table 2.4 controls for both effects. The elasticity of production falls to 0.28 with a positive sign and significant at the one per cent level, and the coefficient for the Relative Industrial Wage Index remains with the expected sign and almost the same magnitude (-0.14), but now it is statistically significant at the ten per cent level. Last, Column 4 of Table 2.4 includes the interaction of Relative Industrial Wage Index and PR . The coefficient for production is 0.28, significant at the one per cent level, but now the relative price of managerial labor force is not significant, despite of the stronger magnitude of the effect during the post-reform. However, none of the coefficients of Table 2.4 should be interpreted as causal relationships due to the already discussed endogeneity problems that arise with the inclusion of production as a regressor.

Table 2.5 presents the OLS estimations of equation (2.6) for workers demand. Column 1 of Table 2.5 uses the Minimum Wage Index to measure the costs of workers. The elasticity of the production level is of 0.47, with the expected sign and significant at the one per cent level. The coefficient of the

¹⁹Fabrizio et al. (2007) also face a challenge in the measurement of input prices. They do not observe firm or plant wages for the US electric generating plants. Instead, they use state-level average wages from the Bureau of Labor Statistics. With respect to capital costs, Fabrizio et al. (2007) measure the capital input by plant capacity and vintage. They combine the plant's capacity in megawatts with information of unit retirements to define plant-epochs, but they do not measure the stock of capital or the capital costs.

	(1)	(2)	(3)	(4)
Output	0.465*** (0.016)	0.469*** (0.017)	0.313*** (0.012)	0.313*** (0.012)
Minimum Wage Index	-1.205*** (0.066)			
Relative Minimum Wage Index		-0.448*** (0.085)	-0.0424 (0.039)	-0.0141 (0.042)
Relative Minimum Wage Index X <i>PR</i>				-0.0455 (0.048)
Constant	3.773*** (0.376)	-2.362*** (0.202)	-0.0416 (0.154)	-0.0126 (0.163)
Plant Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes
Observations	97,788	89,473	89,473	89,473
Adjusted R^2	0.508	0.509	0.161	0.161
Number of id			11,316	11,316

Table 2.5: Workers demand. OLS estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998).

minimum wage is -1.21, statistically significant at the 1 per cent level, an elasticity that implies that the demand of workers reacts more than proportional to changes in minimum wage. As in the case for capital and managers demand, I will construct a relative measure of worker costs that exploits the variability of the material prices at the plant level to overcome the challenges of measuring worker costs with a time series. Using the same procedure that I used to compute relative costs for capital and industrial wages, equation (2.11) illustrates the Relative Minimum Wage Index:

$$RMWI_{it} = \frac{MWI_t}{IWI_t + CCI_t + MPI_{it}}, \quad (2.11)$$

where $RMWI_{it}$ is the Relative Industrial Wage Index for plant i in year t , and all the other terms are known from equations (2.9) and (2.10).

Column 2 of Table 2.5 use the Relative Industrial Wage Index as a regressor. The production elasticity remains virtually unchanged, but the relative price coefficient drops in absolute value to 0.45, with the expected sign, and

significant at the one per cent level. The claim of an elastic demand of workers with respect to the minimum wage is not sustained once the material prices are exploited to introduce variation to the metric used for workers costs. Column 3 of Table 2.5 controls for time and plant effects. The coefficient of production is 0.313, significant at the one percent level, but the coefficient for worker costs is not different from zero. Column 4 illustrates that when the interaction between the Relative Minimum Wage Index and PR is considered the coefficients for prices are still not different from zero, although Columns 3 and 4 display the expected signs.

Overall, the picture delivered by the OLS estimations is that production is a robust predictor of capital, managers, and workers. An ten percent production increase will be translated into a 2.4 per cent increment of capital demand, a 2.8 per cent increase managers demand, and a 0.31 per cent increase in workers demand, but the price effects are not robust for these three inputs. In particular, these estimation suggest that industrial wages were not relevant during the pre and post-reform periods to understand the demand for managers, and also that the relative minimum wage is orthogonal to the demand of workers.²⁰ However, this thought experiment is flawed in its premise since the coefficients of production are potentially biased due to the possible presence of shocks affecting both input demands and production simultaneously.

2.4.2 Input Demands: Capital, Managers, and Workers. IV Estimates

Table 2.6 illustrates the IV estimation of equations (2.6) for demands of Capital, Managers, and Workers. All Columns of Table 2.6 include time and fixed effects. Columns 1 and 2 of Table 2.6 provide estimates for Capital Demand. Column 1 shows that the coefficient of production is 0.58, significant at the one per cent level. With respect to capital demand, the coefficient for production was underestimated; it is more than twice the coefficient obtained with OLS. (See Column 3 of Table 2.3).The coefficient for relative prices is

²⁰Estimates for energy and material are available upon request. Overall, these estimations illustrated that the production effects are stronger for the demand of energy and materials, and that the price effects are negative and significant, although the price effect on materials was economically irrelevant.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.583*** (0.053)	0.583*** (0.052)	0.638*** (0.049)	0.639*** (0.049)	0.650*** (0.046)	0.650*** (0.046)
Relative Capital Cost Index	-0.285*** (0.055)	-0.106* (0.047)				
Relative Capital Cost Index x PR		-0.311*** (0.083)				
Relative Industrial Wage Index			-0.322*** (0.078)	-0.171** (0.063)		
Relative Industrial Wage Index x PR				-0.231** (0.071)		
Relative Minimum Wage Index					-0.207*** (0.056)	-0.109* (0.046)
Relative Minimum Wage Index X PR						-0.157* (0.061)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.767*** (0.074)	0.767*** (0.074)	0.787*** (0.078)	0.787*** (0.078)	0.792*** (0.078)	0.792*** (0.078)
Relative Capital Cost Index	0.890*** (0.127)	0.681*** (0.092)				
Relative Capital Cost Index x PR		0.363** (0.106)				
Relative Industrial Wage Index			0.967*** (0.140)	0.764*** (0.103)		
Relative Industrial Wage Index x PR				0.307** (0.105)		
Relative Minimum Wage Index					0.963*** (0.143)	0.765*** (0.110)
Relative Minimum Wage Index X PR						0.316** (0.101)
Constant	7.525*** (0.419)	7.294*** (0.404)	7.511*** (0.423)	7.291*** (0.411)	7.465*** (0.435)	7.249*** (0.422)
Observations	86,552	86,552	84,331	84,331	87,923	87,923
Number of id	9,642	9,642	9,435	9,435	9,766	9,766
Adjusted R^2	0.247	0.249	0.260	0.261	0.259	0.260
F	88.35	96.37	77.02	110.2	71.46	84.55

Table 2.6: Input demands: Capital, managers, and workers. IV estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects.

-0.285, significant at the one per cent level. In absolute value it is about twice the size of the coefficient illustrated in Table 2.3. This first exercise illustrates that the role of production and prices was underestimated. Panel B of Column 1 presents the first stage of this exercise. Demand Shocks with elasticities that vary across sector are positively and strongly correlated with

output. The coefficient is 0.77, significant at the one per cent level. The instrumented variable is exactly identified with this unique instrument, and the F-test for the first stage is 88.3, rejecting the hypothesis that all the regressors of the first stage are equal to zero. Notice that Panel B of Table 2.3 demonstrates that the relation discussed above for the First Stage of column 1 is robust in all 6 columns.

Column 2 of Table 2.6 includes the binary variable interaction (PR) to understand the role of market oriented reforms on capital demand. In both periods the effect of relative prices is negative and statistically significant, but the effect on the post-period reform is stronger. For pre-reform years the coefficient is -0.11, statistically significant at the 10 per cent level, while for post-reform years the coefficient of relative prices is -0.311, significant at the three per cent level. The market oriented reforms made the demand for capital more elastic with respect to capital relative prices.

Regarding managers demand, Columns 3 and 4 of Table 2.6 show that the elasticity of production is 0.64, significant at the one per cent level. The effect of managers demand was also underestimated, since this coefficient is more than twice the OLS coefficient for production in the equation for managers demand. The coefficient for relative industrial wages is -0.32, significant at the one per cent level, which illustrates an underestimation as well of the role of industrial wages for managers demand. Column 4 of Table 2.6 includes the interaction between prices and PR . In both periods, the price effects are negative. During the pre-reform years, the coefficient is -0.17, significant at the 5 per cent level, and for post-reform years again the effect is stronger, with a coefficient of -0.23, significant at the 5 per cent level. Compared with the results from Table 2.4, these coefficient not only are stronger, but now they are statistically different from zero, which stress the importance of addressing the endogeneity for production in order to interpret quantities and price effects on input demand.

Last, Columns 5 and 6 of Table 2.6 present the IV estimation for workers demand. The elasticity with respect to output on workers demand is of 0.65, statistically significant at the 1 per cent level, which amounts to about two times the elasticity calculated in Column 3 and 4 of Table 2.5. Column 5 of Table 2.6 states that the elasticity of workers demand respect to relative minimum wages is of -0.21, significant at the 1 per cent level compared to the OLS estimation provided in Column 3 of Table 2.5 which states that this

price is not relevant to understand the plant's decision to demand workers, a result that was surprising given the intense debate about minimum wage schemes and industrial jobs. When comparing pre and post-reform periods, Column 6 of Table 2.6 presents the estimation of the interaction of relative prices with PR . The minimum wage effect on worker's demand was stronger during post reform years (-0.16, statistically significant at the ten per cent level) than during the pre-reform period (-0.11, at the ten per cent level). This is consistent with the introduction of payroll taxes in 1993, two years after the market oriented reforms were implemented. Again, notice that this results contrast the message provided in Table 2.5, where the price effects during pre and post-reform years were not different from zero.

As a sum up, Table 2.6 shows that the OLS exercise was consistently underestimating the output effects by a factor of two. The output elasticities for the three inputs are in the range of 0.58 to 0.65. Moreover, the OLS approach was denying the statistical relevance of price effects on input demands. The IV price elasticities for capital, managers, and workers are -0.28, -0.32, and -0.21 respectively, significant at the one percent level. This numbers are not only statistically significant but of great economic importance since they imply that in fact input demands respond to price changes in a sizable way. Moreover, Table 2.6 illustrates that compared to the pre-reform period, the reaction for input demands with respect to input prices during the post-reform era was stronger. The market oriented reforms in Colombia turned input demands to be more elastic with respect to prices. This can be considered as suggestive evidences that the goal of making factor markets more competitive at least is reflected in labor and capital markets in more elastic demands. Prices have a bigger role in factor (re)allocation after the reforms of 1991.

2.4.3 Simulation

Table 2.6 provided the elasticities for input demands for three of the five inputs used in the production function as displayed in the system of equations (2.8). However, this exercise is still silent, at least explicitly, with regard to the Ricardian Effect. Krusell et al. (2000) associate the arrival of vintage capital with falls in the relative prices of new equipment. The algorithm

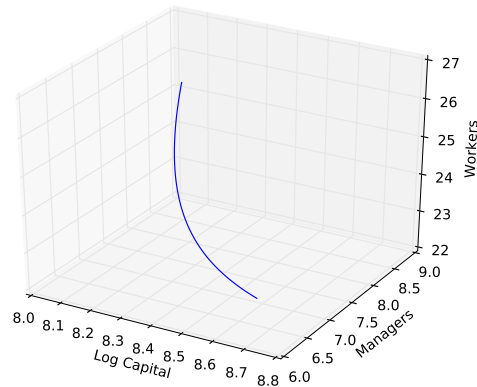


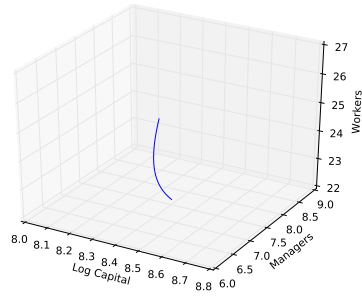
Figure 2.6: Demand Predictions for Capital, Managers, and Workers: Predictions are based on the IV elasticities from Table 2.6. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level.

described in Appendix B.2 provides a testing ground for the consequences of a continuous fall in the price of capital goods that follows the spirit of Krusell et al. (2000): The direct impact of technological process is a sustained reduction in the price of capital equipment that diminishes the relative costs of capital goods. This algorithm computes the predicted demands for capital, managers, and workers, based on the IV coefficients provided in Table 2.6 and on the simulated sequence of relative costs derived by the fall in the price of capital goods.

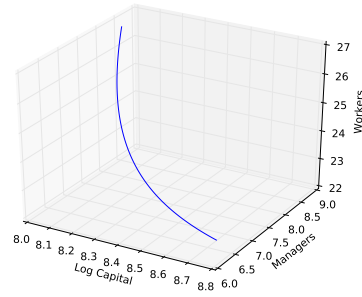
More concretely, the Industry Wage Index, the Minimum Wage Index and the Materials Price Index are set to their 1982 levels in equations (2.9), (2.10), and (2.11) while the Capital Cost Index starts at three times its 1982 level, falling down continuously to 50 per cent its 1982 level. Figure 2.5 illustrates that these numbers are above and below the bounds of the Capital Cost Index alone, but the whole relative cost sequence derived does not generate implausible numbers since the other components of the Index remained constant in the simulation.²¹

Figure 2.6 plots the predicted demands for capital (in logs), managers, and workers after a drop in the price of capital goods. Other things equal, Figure 2.6 shows that when the relative capital cost is at its highest level, the

²¹See Appendix B.2 for more details of the simulation algorithm.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure 2.7: Demand Predictions for Capital, Managers, and Workers. Pre and Post-Reform Elasticities: Predictions are based on the IV elasticities from Table 2.6. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level.

prediction for capital demand is of 8.1 log points (3,330 thousand pesos of 1982). At this level, an establishment will demand 8 managers and 26 workers. When the relative capital cost falls to its lowest level, it is predicted that on average the capital demand will increase to 8.6 log points (5,547 thousand pesos of 1982). Figure 2.6 also predicts that this plant will demand 7 managers and 22 workers. In other words, the arrival of cheaper capital goods creates a strong incentive to introduce more capital units in the plant, and to reduce the labor force: On average, when capital stock is increased about 67 per cent, a plant will reduce its payroll by one manager and 4 workers. Capital replaces labor, and this replacement is stronger for employees that perform routine tasks in the work place. David Ricardo was right indeed.

Figure 2.7 exploits the interaction between relative input prices and the binary variable for the post-reform years to simulate input demands for pre and post-reform periods. For the upper bound of the simulated capital cost level, Figure 2.7a²² predicts that the capital demanded during pre-reform years is of 8.3 log points (4,032 thousand pesos of 1982) while Figure 2.7b predicts that for the post-reform years the capital demand is 7.97 log points (2,890 thousand pesos of 1982). When technical progress drives the price of capital goods to the lowest level in the simulation, Figure 2.7a argues that the capital input for pre-reform years is 8.5 log points (4,877 thousand pesos),

²²Figures 2.6 and 2.7 have the same values in the x, y and z axis to produce straightforward comparisons.

while Figure 2.7b shows that the capital stock will rise up to 8.7 log points (6,102 thousand pesos) in the post-reform era.

Regarding labor input, Figure 2.7a predicts demands for managers and workers of 8 and 25 respectively during the pre-reform years when capital costs are three times their 1982 level, other things equal, and of 7 and 23 (respectively) when the capital cost is at 50 per cent of its 1982 level. For the post-reform era, Figure 2.7b states that the predicted demand of managers and workers is of 9 and 26 employees respectively for high capital costs; these numbers fall to 7 and 22 (respectively) when capital costs reach the lower bound of the simulation.

While for pre-reform years the input demand elasticities from Table 2.6 predict that the arrival of cheaper capital input will increase a plant's capital stock about 21 per cent, the post-reform predictions state that the capital stock will increase 111 per cent. On the other hand, the pre-reform elasticities imply that with cheaper capital goods a plant will cut from its payroll one manager and two workers while post-reform input demands predict that the cut will be of 2 managers and 5 workers. Input demand elasticities are more responsive with respect to prices in the aftermath of the reform process of 1991. The replacement of labor is significantly stronger during the post-reform years.

2.5 Robustness Checks

The Ricardian Effect so far has been discussed in terms of input demand predictions for an average plant, and besides the control for time invariant characteristics at the plant level, no other explicit efforts have been made to control for other observable characteristics that may change over time. In particular, with the reports of production and total number of employees in the panel it is possible to account for the following time variant observable characteristics at the plant level: survival, exit, incumbent, exit and exit plant, as well as the plant's size.

The definition for each category is as follows: (i) Survival Plant: An establishment that reported production in t and in $t + 1$. (ii) Exit Plant: An establishment that reported production in t but not in $t + 1$. (iii) Incumbent Plant: An establishment that reported production in t and in $t - 1$.

(iv) Entry Plant: An establishment that reported production in t *but not* in $t - 1$.

Notice that both exit and entry plants are the complement set of plants in the data for survival and incumbent plants respectively. Also notice that by construction, observations for 1998 (the last year in the sample) are lost when the comparison for survivals and exit plants is established while observations for 1982 are lost the comparisons of incumbent and entry plants.

Regarding a plant's size, I used the total number of employees (managers plus workers) to create the following categories: (i) Small Plant: An establishment that reported a total number of employees below the percentile 33 of the sample (below 17 employees). (ii) Medium Plant: An establishment that reported a total number of employees between the percentiles 33 and 66 of the sample (between 17 and 44 employees). (iii) Large Plant: An establishment that reported a total number of employees above the percentile 66 of the sample (above 44 employees).

There are important reasons to consider these time variant observables categories besides the fact that its computation is trivial. For instance, Hopenhayn (1992) delivers the concept of stationary equilibrium that is based on a long run relationship that accounts for entry, exit, and the size of establishments. He considers that an important component of firm dynamics are exit and entry rates, since there are high and low turnover industries. In a seminal paper, Lucas (1978) links the draw of managerial abilities to the size of firms, although the definition of size is based upon the number of workers solely since the "span of control" of the firm's size is in the hands of one single manager.²³ Jovanovic and Lach (1989) emphasize on the role of learning in order to understand the S-path followed by innovation, where learning is related with the incumbent/exit status of the plant. For instance, early entrants have clear advantages in terms of experience and higher revenues per output in earlier stages, but late entrants can gain from the experience and lessons from the "learning-by-doing" process of earlier entrants and reduce their operating costs.

From an empirical perspective, Eslava, Haltiwanger, Kugler, and Kugler (2013) present evidence that suggest that the connection between productivity and survival in the aftermath of the reform period is stronger: The

²³How many workers the talent of the manager is able to control

Type of Plant	(1) Baseline	(2) Survivor	(3) Exit	(4) Incumbent	(5) Entry	(6) Small	(7) Medium	(8) Large
<i>Panel A. Higher Bound for Relative Capital Cost</i>								
Capital	3,330	3,356	3,356	3,940	702	780	2,882	17,452
Pre-Reform	4,033	4,060	4,060	4,696	987	940	3,378	19,818
Post-Reform	2,891	2,746	2,746	3,462	710	693	2,431	15,974
Managers	8	9	9	9	4	3	6	31
Pre-Reform	8	8	8	9	4	3	6	31
Post-Reform	9	9	9	9	4	3	6	31
Workers	26	27	27	27	12	9	20	90
Pre-Reform	25	26	26	26	11	8	20	88
Post-Reform	26	28	28	28	12	9	20	91
<i>Panel B. Lower Bound for Relative Capital Cost</i>								
Capital	5,548	6,199	6,198	6,327	1,782	1,421	3,274	33,910
Pre-Reform	4,877	5,420	5,420	5,616	1,434	1,259	2,930	31,135
Post-Reform	6,102	7,139	7,139	6,908	1,766	1,536	3,687	36,260
Managers	7	7	7	7	3	2	5	25
Pre-Reform	7	7	7	8	3	2	5	25
Post-Reform	7	7	7	7	3	2	5	25
Workers	23	24	24	24	10	8	19	79
Pre-Reform	23	25	25	24	11	8	19	79
Post-Reform	22	24	24	23	10	8	19	78
Number of Obs.	100,114	85,576	9,028	85,576	8,624	35,183	31,267	33,664

Table 2.7: Input demand predictions. Robustness checks: Capital predictions are in thousands of pesos of 1982. Panel A illustrates the input demand predictions for the higher bound of the Capital Cost Index (three times its 1982 level). Panel B illustrates the input demand predictions for the lower bound of the Capital Cost Index (50 percent its 1982 level).

effect of productivity on survival is more important for sectors that faced the largest tariff reductions. The list of references continues, and a complete review of the research done in this subject is beyond the scope of this section, but this snapshot of the literature is sufficient to illustrate the importance of the categories mentioned above.

In order to account for these characteristics, I created a binary variable for each of them to create subsamples for plants that fulfill each of the categories mentioned above. After this procedure, I estimated equation (2.6) for all the subsamples and then I used the Algorithm described in Appendix B.2 to simulate input demand predictions. Table 2.7 presents a short summary of the main message derived from these exercises. The complete set of figures and tables are in Appendix B.3. First, notice that the coefficients for output are statistically significant in all specifications, while price coefficients are not statistically significant in all subsamples, in particular where the small number of observations (like the case of entry and exit plants) blow up the standard errors. Interestingly, some price effects that are not statistically significant recover their explanatory power once pre and post-reform effects

are included, which is consistent with the idea that market oriented reforms enhanced the elasticities of input demands. Additionally, figures from Appendix B.3 illustrate that the message in all subsamples (except pre-reform periods for entry, small and medium plants) is similar: Capital replaces labor, and this replacement is i) stronger for workers compared to managers, and ii) stronger during the post-reform years.

Table 2.7 illustrates that when plants increase its plant stock after a sustained reduction in prices of capital goods their demand reductions for managers and workers are more or less consistent throughout the samples and in line with the message from Figures 2.6 and 2.7. Nonetheless, there are three challenging cases for this general pattern that deserve special attention: Entry, small, and medium plants. My answers are as follows: For entry plants, it is likely that this plants enter the market with vintage capital. Therefore, the "Ricardian Effect" is already discounted in their entry process decision, and any evidence of The Ricardian Effect will be expected in later years, where the plant is not anymore part of this subsample. For small plants, the similarities for labor demand after the decrease in the price of capital is just a matter of scale. The predicted fall in labor input does not add up to a unit to consider a reduction in the extensive margin for the input demand. Last, the positive slope in the prediction for managers arises from a positive, but not statistically significant, price effect in the capital demand during the pre-reform periods. Notice that this slope is not translated into more demand for managers in the predictions displayed in Table 2.7 again because the predicted effect does not add up to the unit.

An interesting case arises when large plants are considered. As expected, the scale of the Ricardian Effect is bigger for larger plants. However, Column 8 of Table 2.7 demonstrates that the *relative* changes for large plants are not drastically different from the other subsamples. These exercises suggest that the Ricardian Effect is not driven by the size of the plants.

2.6 Conclusion

In this paper, the ideas of the controversial chapter 31st of David Ricardo's master piece were tested using a unique plant level longitudinal database for the manufacturing sector in Colombia. After estimating input demand

equations for capital, managers, and workers instrumenting output with demand shocks, I found that output elasticities are close to 0.6 while price elasticities for capital, managers, and workers are -0.28, -0.32, and -0.21 respectively. Moreover, these elasticities are more strong for the pre-reform period in Colombia, where several artificial distortions in input markets were lifted and as a consequence these markets became more competitive. In other words, the relative prices during the post-reform era play a prominent role in factor (re)allocation in the manufacturing sector.

Based on a simulated fall in the cost of capital goods, the coefficients derived from the input demand estimates were used to simulate demands for capital, managers, and workers. When a plant increases its capital stock due to cheaper vintage capital units, it will reduce its payroll by one manager and 4 workers on average. This replacement effect is stronger during the post-reform era, where the factor markets were more competitive. As Samuelson (1989) claimed, “Ricardo was Right!”

This paper is a positive analysis of the Ricardian Effect. Notice that no welfare consequences are addressed here. However, a class of interesting questions with welfare consequences arise from the evidence regarding labor replacement when new units of capital are demanded. Does the Ricardian Effect overall have overall positive or negative consequences for society? This remains an open question subject to further research, but here I would like to provide a few research areas where a proper understanding of the Ricardian Effect could shed some light to understand the welfare consequences of capital demand and new technologies in input markets.

First, the influential books of Stiglitz (2012) and Piketty (2014) considered that the role of capital on inequality is of the utmost importance. In fact, the driver of inequality is to be found in capital rents. It would be interesting to understand to what extent the rise in capital earnings and its impact on inequality is driven by the replacement of the labor force (mapping labor replacement with labor shares of income), and to integrate the household’s decisions to acquire skills through education as a response to the Ricardian Effect in order to perform tasks less subject to replacement. A first natural step is to build the bridge between skills to tasks to output within a general equilibrium framework that maps the Ricardian Effect and the household’s reaction to income inequality.

Second, this paper estimated the Ricardian Effect only for the manufac-

turing sector in a developing country. Duarte and Restuccia (2010) illustrate that the labor share in manufacturing sectors display an inverted U shape over time. It is possible that the Ricardian Effect provides an explanation for the slippery side of the labor share in manufacturing industries, but it is important to understand whether there is evidence of labor replacement in services. In particular, it would be interesting to consider whether the Ricardian Effect is an important mechanism of sectoral transformation in which labor is moving from one sector to another.

Last, a proper estimation of the dynamics of integration of the labor force in the manufacturing sector, taking into account the differences between managers and workers, could provide some light to the policy debate related with job creation through corporate tax stimulus towards investment in capital, a debate widely spread in the Colombian context.

CHAPTER 3

WHY IS EUROPE FALLING BEHIND? STRUCTURAL TRANSFORMATION AND SERVICES' PRODUCTIVITY DIFFERENCES BETWEEN EUROPE AND THE U.S.

Joint work with Cesare Buiatti and Joao Duarte

3.1 Introduction

Labor productivity in Europe has been falling behind the United States since the beginning of the 1990s, reversing a previously observed pattern of convergence between these two economies. Figure 3.1 illustrates how this process of catch up came to a halt and later reversed for some European countries while the converge stopped for others. Average annual labor productivity growth (measured as GDP per hour of work) in the U.S. accelerated from 1.3% in the 1970–1990 period to 1.7 % from 1995 to 2006 while the European countries on average experienced a labor productivity growth slowdown between these two time periods from 2.9% to 1.5%. The divergence is a combination of the U.S. taking off together with a European slowdown. In other words, the picture is glimmer for Europe either in relative or in absolute terms for most of its countries.

From 1970 to 2009, both the European economies and the U.S. underwent large scale sectoral (re)allocations of labor in a process commonly known as structural change, as defined by Kuznets (1957); Herrendorf et al. (2014) and many others. With Europe and the U.S. at their later stages of structural transformation (the so-called post-industrial society for advanced nations), labor reallocated further away both from agriculture and manufacturing toward services. As Duarte and Restuccia (2010) suggest, through the lenses of structural transformation it is possible to conclude that the service sector is responsible for most cases of relative stagnation and even declines in aggregate productivity observed at later stages of economic development since

no other country experienced the productivity gains in the service sector witnessed in the U.S.

We believe that to understand the relative under-performance of Europe *vis-à-vis* the U.S. it is crucial to break down the service sector. The service economy is the predominant (and growing) sector for the vast majority of advanced nations and its lack of labor productivity gains is an increasing cause of concern for their long-run economic growth. In this paper, we use the lenses of structural transformation following the spirit of Duarte and Restuccia (2010) and decompose the service sector into sub-sectors comparable across Europe and the U.S. to investigate how changes in labor allocation and productivity within services help explain the service sector’s labor productivity.

First, we use the World KLEMS database put forth by Jorgenson (2012)

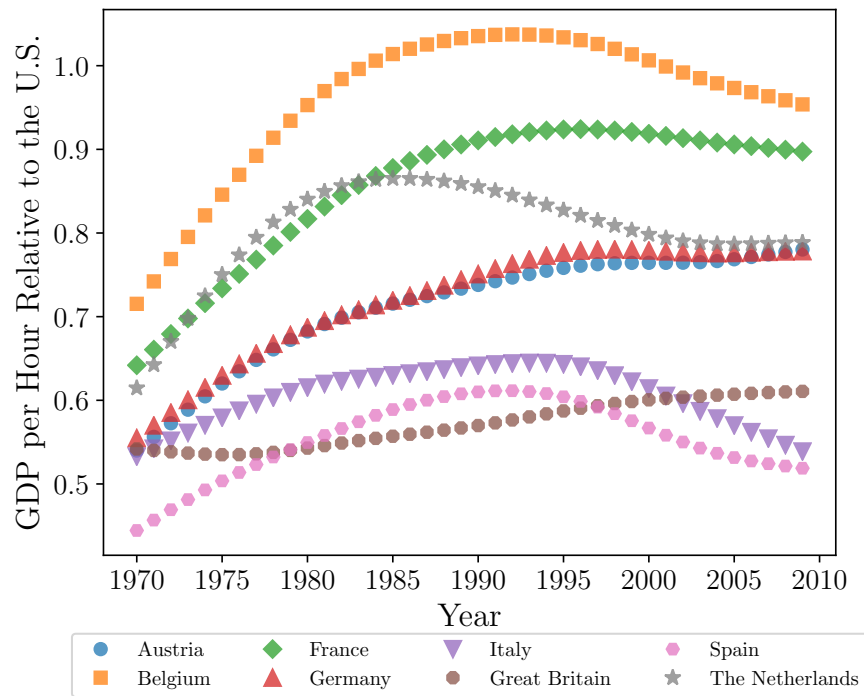


Figure 3.1: Aggregate labor productivity for the European countries relative to the U.S. To construct PPP compatible measures of aggregate labor productivity we used the income per capita measures from The Maddison-Project (2013) to calculate measures of GDP per capita in 1970 relative to the U.S., and then we complete the time path with the growth rates of real value added per hour from the World KLEMS data from Jorgenson (2012).

and we decompose services into 11 comparable sub-sectors between Europe and the U.S.¹ Second, we develop a structural change model that combines the CES nonhomothetic preferences crafted by Comin et al. (2015) with production functions whose unique input is labor as in Duarte and Restuccia (2010) disaggregating services into 11 sub-sectors comparable between Europe and the U.S. Third, we calibrate the model to account for the the U.S. development experience and use the model to measure comparable labor productivity levels for the disaggregated service sector for all European countries in our sample. Our simulations show that the model is quantitatively able to reproduce the labor allocation in all sectors for all countries in our sample. Last, we perform counterfactual exercises to identify what kind of services have been dragging down most of the aggregate service labor productivity in Europe.

Our quantitative experiment suggests substantial differences in sectoral labor productivity of services across countries. The European countries are in generally more productive than the U.S. in communications and health services. However, and more importantly given their large labor shares, the European countries are less productive in wholesale and retail trade and business services, with a relative labor productivity in 1970 average of approximately 50% and 60% of that of the U.S., respectively.

Led by the counterfactual exercises, we identify wholesale and retail trade and business services as the two sectors that are responsible for most of the lack of catch-up in labor productivity of services between Europe and the U.S. In particular, we find that if Europe would have had the same gains in labor productivity as the U.S. in wholesale and retail trade and business services *alone* since 1990, it would have had higher levels of aggregate labor productivity. In fact, if Europe had caught up with its labor productivity of wholesale and retail trade and business services by 2009 with respect to the U.S., the aggregate labor productivity in Europe would have closed more than 50% of the gap with respect to the U.S. labor productivity.

This paper is related primarily to the literature of structural transformation that dates back to the works of (Kuznets, 1957) who documented the sweeping changes across the different industries in the process of economic development. More recent contributions to structural change build upon the

¹We classify these sectors according to the ISIC Rev. 3 at one digit level.

works of (Kongsamut et al., 2001) and (Ngai & Pissarides, 2007) who emphasized the role of income and sector-biased productivity channels respectively as the drivers of structural transformation. Several attempts have been made to incorporate both mechanisms in a single framework, such as (Buera & Kaboski, 2009), (Duarte & Restuccia, 2010), and (Ferreira & Silva, 2014) among many others.² Our paper complements (Buera & Kaboski, 2012) explanation of the rise of the service sectors by showing that a large increase in the labor share of services has also in fact been driven by business to business services.

Our paper also talks to a vast literature that studies cross-country productivity differences and productivity determinants, generally with empirical methodologies. A few examples are (Baily & Solow, 2001), (Nicoletti & Scarpetta, 2003), (Dew-Becker & Gordon, 2012), and (Cette, Lopez, & Mairesse, 2016). More closely related to our research question, (Inklaar, Timmer, & Ark, 2008) provide some insights on what factors might be behind the differences in productivity between Europe and the U.S. They find that the most important factors are lower growth contributions from investment in information and communication technology in Europe, the relatively small share of technology-producing industries in Europe, and slower multi-factor productivity growth. In particular, they find that the latter effect is more notorious in the service sector. We complement their analysis by showing which service sectors are particularly responsible for the observed differences in productivity growth.

The rest of the paper is organized as follows: Section 3.2 develops a our theoretical framework that extends the structural transformation model of (Comin et al., 2015) to include service sub-sectors. Section 3.3 presents our calibration strategy, discusses the test of our theory and presents the parametrization of the model. Section 3.4 presents the results of the calibration. Section 3.5 presents our numerical experiments that identify which sectors are responsible for the widening of the gap in labor productivity between Europe and the U.S. Finally, Section ?? concludes the paper.

²For a detailed survey of the literature of structural change see (Matsuyama, 2008) and (Herrendorf et al., 2014)

3.2 A Model of Structural Transformation

This section presents a model of structural transformation with agriculture, manufacturing and 11 different services where the process of structural transformation depends on income and price effects. We chose the number of sectors in the model to account for the same sectors explored in the previous sector, but the model is flexible to any arbitrary number of sectors. The model borrows the production structure from Duarte and Restuccia (2010) and the preferences from Comin et al. (2015). There are, however, important elements worth to emphasize. First, the model does not has capital (as in Duarte and Restuccia (2010)), which means that there are no investment sector in this economy and that the model has no dynamic component. Therefore, the structural transformation, namely the reallocation of labor over time across sector, is taken as a sequence of static optimal allocations. Second, the absence of capital implies that all the production is devoted to consumption, placing a special emphasis on the role of preferences for the structural transformation. By combining these two frameworks, Engel curves and heterogeneous labor productivity growth rates are sufficient to account for the structural transformation.

We first describe the firm's and household's optimization problem together with the market clearing conditions, and then we perform general equilibrium analysis in order to derive a system of equations that define the optimal allocation of labor across sectors. Since our goal is to address the differences in productivity within services, our model represents a closed economy where domestic production is used in its entirety to satisfy domestic production in each sector.

3.2.1 Environment

In our model economy there is an infinitely lived stand-in household of measure L that supplies labor inelastically.³ Their only endowment is time and labor moves freely across sectors. Moreover, labor is the only input in the economy since firms produce output with labor times its productivity.

³Alternative, one can think of a household of measure one with an endowment of L hours each period. In this case, it is trivial the definition of the measure in spite of allowing growth of the labor force because the structural transformation is a sequence of static choices.

Households

The households has preferences over their consumption stream over time, but since we are not defining inter-temporal problems in our model (*i.e.* there are no savings), there is no need to formalize the structure of preferences toward the inter-temporal substitution of consumption. Following Comin et al. (2015), the representative household has preferences over the consumption of commodities (or services) produced in different sectors represented by

$$\sum_i^I \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma - 1}{\sigma}} = 1, \quad (3.1)$$

where C is the aggregate consumption⁴, c_i is the consumption from output produced in sector i , $\sigma \in (0, 1)$ is the price elasticity of substitution, $\epsilon_i \geq 1$ is the income elasticity for good i and $\Omega_i > 0$ are constant weights for each good i , $\sum_i \Omega_i = 1$. Notice that there are no time subscripts since the model is static. In addition, there are three main reasons⁵ that support the use of this particular non-homothetic CES preference structure to explain the structural transformation in our model of 13 sectors. First, it naturally extends for any arbitrary number of sectors, which is not a feature by other types of preferences such as in Boppart (2014), Herrendorf, Rogerson, and Valentinyi (2013) and Duarte and Restuccia (2010) among many others. Second, it gives rise to heterogeneous sectoral log-linear Engel curves that are consistent with the empirical evidence (Aguilar & Bils, 2015; Comin et al., 2015). Last, the income effects on the relative consumption of sectoral goods and services do not level off as income rises, contrary to structural transformation demand-side theories that rely on Stone-Geary preferences, which is crucial to account for the rise of services in the long-run. Therefore, these preferences allow the demand channel to have a strong role at later stages of development. The household's problem is defined as follows:

Household's Problem

⁴In the empirical counterpart of the model C is considered as income per capita since there are no savings in our model.

⁵There is greater detail in the exposition of other useful features of the non-homothetic preferences in (Comin et al., 2015). In our paper, we highlight the most useful ones for our particular purpose of decomposing extensively the service sector.

$$\begin{aligned}
\max_{c_i} C \quad \text{s.t.} \quad & \text{i) } \sum_i^I \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1 \\
& \text{ii) } \sum_i p_i c_i \leq WL \\
& \text{iii) } c_i \geq 0,
\end{aligned} \tag{3.2}$$

where W is the wage of the household, WL reflects the total disposable income and p_i is the price of output c_i . We assume interior solutions, so the First-Order Conditions are sufficient. The optimal consumption of goods for each sector i is

$$c_i = \Omega_i \left(\frac{p_i}{P} \right)^{-\sigma} C^{\epsilon_i}, \tag{3.3}$$

and the optimal value added share of sector i is described by

$$\frac{p_i c_i}{PC} = \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}}, \tag{3.4}$$

where P is the aggregate price index. Notice that the parameters ϵ_i and σ describe the income and price mechanisms of the structural transformation. Whereas ϵ_i measures the sensitivity for changes in consumption of goods from sector i with respect of changes in income, namely the Engel curve for sector i , σ reflects how sensitive the quantities demanded are toward changes in prices. For the empirical relevant case of $\sigma < 1$, where all goods are gross complements, the price effect illustrates the so-called Baumol's cost disease in which, in this context, labor is continuously allocated toward less productive sectors in the long-run.

Firms

In each periods, there are 13 different goods produced in agriculture, manufacturing and evenen types of services, as described in the previous section. Let I be the set of goods produced every period. There is a large number of competitive firms in each sector i that use technology of production linear in labor described by

$$y_i = A_i l_i \quad \forall i \in I, \tag{3.5}$$

where y_i represents the output produced by a representative firm of sector i , A_i reflects the labor productivity of the firm and l_i is the labor input demanded by the firm, measured in labor hours. The firm in this model economy hires labor at the prevailing wage W – that is the same for each sector i since labor is perfectly mobile – and produces output with the combination of labor hours and an idiosyncratic labor productivity level for each representative firm. The firm’s problem is described as follows:

Firms’ Problem

$$\max_{l_i} \{p_i A_i l_i - W l_i\} \quad \forall i \in I. \quad (3.6)$$

Again, if one assumes interior solutions the First-Order Conditions are sufficient to describe the optimal allocations of the firm. The optimal price is described by

$$p_i = \frac{W}{A_i} \quad \forall i \in I. \quad (3.7)$$

Equation (3.7) shows that increases in sectoral labor productivity will reduce the price of a good produced in sector i , and increases in wages have a positive impact on prices. However, notice that wages do not change the relative prices in the economy since by assumption all sectors in the economy pay the same rental rate of labor, thus it is only through heterogeneous dynamics of the labor productivity across sectors that one gets changes in relative prices. Given the irrelevance of wages for our understanding of relative prices in the model, we consider labor as the *numéraire* in our model economy and normalize its price – the wage rate W – to one. The sectoral price then is simply described as $p_i = \frac{1}{A_i} \quad \forall i \in I$, and it is the inverse of sectoral labor productivity, as in (Duarte & Restuccia, 2010). Given the simplicity of the production technology, one can think that A_i aggregates several factors that separately affect the price of commodities, such as other inputs of production and the quality of the labor. In this sense, A_i can be considered as the measure of our ignorance. In the empirical section we will address this issue by disentangling the effects on the labor productivity coming solely from TFP *vis-á-vis* the effects through production inputs, but for now one can think of these factors as components embedded in A_i .

Equilibrium Conditions

Market Clearing Conditions

As mentioned before, in this model economy in autarky all the production is devoted to consumption since there are no savings or investments. Therefore, for each sector i

$$y_i = c_i \quad \forall i \in I. \quad (3.8)$$

In addition, aggregate output and labor supply are nothing but the sum of sectoral outputs and labor demands respectively, namely

$$\begin{aligned} Y &= \sum_i y_i, \\ L &= \sum_i l_i. \end{aligned} \quad (3.9)$$

General Equilibrium

Combining equations (3.4), (3.5), (3.7) and the market clearing conditions in (3.8) one gets

$$\frac{Wl_i}{PC} = \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} (A_i l_i)^{\frac{\sigma - 1}{\sigma}},$$

and after some algebra, we reach an expression for the sectorial labor demand

$$l_i = \left(\frac{P}{W} \right)^{\sigma} \Omega_i C^{\epsilon_i} A_i^{\sigma - 1}. \quad (3.10)$$

Equation (3.10) illustrates the two main drivers of the structural transformation in our model. First, the parameter ϵ_i defines the Engel curve for sector i , and shows how this non-homotheticity affects the labor demand for each sector linking it directly the sector output's income elasticity. Second, the parameter σ shows the relation of the price elasticity of substitution on the labor demand. As long as this parameter is smaller than one, increases in productivity will reduce the labor hours demanded in a given sector. Equation (3.10) predicts *absolute* levels of labor demand, and shows that aggregate prices and wages⁶ also affect the labor demand in absolute terms, but they

⁶Although we are normalizing the wages in this model economy, we leave them without normalization to illustrate that as long as labor is freely mobile, wages will not have an

are not going to affect the relative labor demand, *i.e.* the structural transformation. Using the aggregate market clearing conditions in equation (3.9), the equation that defines the structural transformation is given by

$$\frac{l_i}{L} = \frac{\Omega_i C^{\epsilon_i} A_i^{\sigma-1}}{\sum_j^I \Omega_j C^{\epsilon_j} A_j^{\sigma-1}} \quad (3.11)$$

The labor share of sector i is affected by both income effects and substitution effects: as aggregate consumption rises one to one with aggregate income, the labor share of sector i will rise if the income elasticity of demand of good i is higher relative to all other sectors and will fall if the elasticity is small relative to all other sectors. On the other hand, as labor productivity grows, the labor share of sector i will diminish relative to other sector with slower rates of labor productivity growth. Now we have all the elements necessary to proceed with our Equilibrium Definition:

Definition: A Structural Transformation Competitive Equilibrium is a collection of exogenous labor productivity paths $\{A_{it}\}$ and optimal allocations $\{c_{it}, l_{it}\}$ such that for each period t and for each sector i , the labor shares defined in equation (3.11) are consistent with:

- α) *The household's problem defined in (3.2).*
- β) *The firm's optimization problem defined in (3.6).*
- γ) *Resource constraints and market clearing conditions defined in (3.9) and (3.8).*

3.3 Calibration

We calibrate our model to the development experience of the United States from 1970 to 2009 in order to assess the plausibility of our theory. The parametrization involves estimating several Engel curves and one price elasticity of substitution based on an econometric model derived from our theory for each of the 13 sectors⁷ and calibrating the time-invariant CES weights to

impact on the structural transformation.

⁷We use a panel data for the US and the major European economies in our analysis to exploit the variation of sectors across countries and over time. This procedure assumes that preferences do not change systematically across countries during our sample period, and therefore we could exploit the variation at this level of aggregation to pin down the Engel curves for the US.

match perfectly the initial labor shares for each sector after normalizing the labor productivity levels in 1970. Then, we feed in exogenous time paths of sectoral labor productivities to generate the sectorial labor share time paths predicted by our model.

3.3.1 Test of the Theory

There are three sets of predictions that we consider as tests of whether our theory can successfully account for the structural transformation. First, the labor-share time paths generated by our model for the US economy should be roughly close to their empirical counterparts in the data. Second, after recovering the initial productivity levels for each of the European economies, the model should be capable of generating labor shares roughly close as well for most sectors in the European countries. Third, the predicted aggregate labor productivity – namely the sum of sectorial labor productivities weighted by their participation in the labor force – should reproduce fairly close the relative aggregate labor productivity between the US and Europe displayed in Figure 3.1. Now we proceed to explain in detail the parametrization of our model.

3.3.2 Parametrization

Estimation of Engel Curves and the Price Elasticity of Substitution

Consider the model’s prediction for the *absolute* labor demand of a sector i , as described by equation (3.10). One can define a system of labor demand for each sector i relative to manufacturing (sector m) to derive the following system of relative labor demands

$$\frac{l_i}{l_m} = \frac{\Omega_i}{\Omega_m} C^{\epsilon_i - \epsilon_m} \left(\frac{A_i}{A_m} \right)^{\sigma - 1}.$$

Taking logs on both sides one gets

$$\log \left(\frac{l_i}{l_m} \right) = \log \left(\frac{\Omega_i}{\Omega_m} \right) + (\epsilon_i - \epsilon_m) \log C + (\sigma - 1) \log \left(\frac{A_i}{A_m} \right). \quad (3.12)$$

From equation (3.12) we can derive the following econometric model to estimate the income and price elasticities

$$\log\left(\frac{l_i}{l_m}\right) = (1-\sigma) \log\left(\frac{A_{mt}}{A_{it}}\right) + (\epsilon_i - \epsilon_m) \log C_t + \zeta_i^c + \nu_{it}^c \quad \text{for } i \neq m, \quad (3.13)$$

where i denotes any sector – except manufacturing – in country c and time t . We control for fixed-effects ζ_i^c to capture time-invariant characteristics that can potentially influence our estimates. $\nu_{im,t}^c$ are the error term of the econometric specification.

Estimating equation (3.13) imposes $i - 1$ cross-equation restrictions for estimating one single price elasticity of substitution for the entire economy. Given the simplicity of our production function, we decided to estimate equation (3.13) with prices predicted directly by the inverse of the productivity rather than with observed prices directly, because the econometric model derived from our theoretical framework is not suited for controlling for differences in technology parameters that do have a direct influence on prices.

Our identification strategy exploits within country-sector and time variation to identify the income and price elasticities. We use World KLEMS data, which is a panel disaggregated at the sector level with comparable information for the U.S., Austria, Belgium, France, Germany, Great Britain, Italy, Spain, and the Netherlands, from 1970 to 2009. Our measurement for the empirical counterparts of the model are as follows: Sectoral labor shares are measured by the ratio of labor hours hired in a sector to the total labor hours demanded in the economy. The sectoral labor productivity is measured with the real value added per worker. Finally, the aggregate consumption C is measured directly with income per capita measures since there are no savings in our model economy. Income per capita measures in real units adjusted by PPP to perform cross-country comparisons are not available in World KLEMS, so we used the OECD as a source instead.

Table 3.1 presents the estimates for the price elasticity of substitution and the sectorial Engel curves relative to manufacturing. Our estimate of the price elasticity of substitution is 0.69, which is in line with the findings in the literature. The null hypothesis of a price elasticity of substitution equal to one is rejected at the one per cent level, in favor for a σ below one. Our estimate of the price elasticity of substitution reflects the presence

Sector	Parameter	Estimate
	$1 - \sigma$	0.31*** (0.06)
Agriculture	$\epsilon_{agr} - \epsilon_{man}$	-0.46*** (0.14)
wholesale and retail and Trade	$\epsilon_{trd} - \epsilon_{man}$	0.50*** (0.08)
Restaurant and Hotels	$\epsilon_{rst} - \epsilon_{man}$	0.65*** (0.14)
Transportation	$\epsilon_{trs} - \epsilon_{man}$	0.55*** (0.09)
Communication	$\epsilon_{com} - \epsilon_{man}$	0.63*** (0.11)
Finance	$\epsilon_{fin} - \epsilon_{man}$	0.71*** (0.12)
Real Estate	$\epsilon_{res} - \epsilon_{man}$	1.17*** (0.17)
Business Services	$\epsilon_{bss} - \epsilon_{man}$	1.76*** (0.11)
Government	$\epsilon_{gov} - \epsilon_{man}$	0.27*** (0.10)
Education	$\epsilon_{edu} - \epsilon_{man}$	0.57*** (0.10)
Health	$\epsilon_{hlt} - \epsilon_{man}$	0.93*** (0.14)
Personal	$\epsilon_{per} - \epsilon_{man}$	0.72*** (0.16)
Number of observations		360
Fixed effects		Yes

Table 3.1: Engel Curves and Price Elasticity estimates. Estimation based on World KLEMS data for Austria, Belgium, France, Germany, Italy, the Netherlands, Spain, Great Britain, and the United States. Clustered standard errors at the country level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of a Baumol-cost disease, in line with the analytical descriptions of Baumol (1967) and Ngai and Pissarides (2007). This means in our framework that the economy is converging to services, as in the traditional literature of structural transformation, and also that within services is converging toward the least productive sectors. Of course, this is only the supply side explanation of the structural transformation.

To account for the demand side of the structural transformation, Table 3.1 illustrates the Engel curves for each sector relative to manufacturing. The null hypothesis is that the Engel curve for a given sector i is the same as

the manufacturing Engel curve. This hypothesis is rejected at the one per cent level of significance for each sector in the economy. Consistent with the development literature, the estimate for the Engel curve in agriculture illustrates that as long as the household grows richer, the resources devoted for the consumption of agriculture grow less than proportional compared to manufacturing, whereas for all the services in the economy the consumption grows more than proportional relative to manufacturing. In addition, the estimates of the Engel curves vary significantly across services. For instance, whereas the difference in the income elasticity for government services relative to manufacturing is of 0.27, for real estate and business services this difference is above one.

Targeting the Initial Employment Shares in the U.S.

We calibrate the model by targeting the initial labor shares in 1970 for each sector in the U.S. economy. For this, we normalize the initial productivity levels A_i to one in each sector. As a consequence of this normalization, the aggregate productivity is normalized to one as well, and therefore $\frac{Y}{L} = A = 1$. Since in our model economy the entirety of income per capita is devoted to consumption, it follows that $C = 1$ for 1970 as a consequence of the normalization of the initial sectorial productivity levels. From equation (3.11), the normalization implies that the labor shares for the initial period of the calibration are given by

$$\frac{l_i}{L} = \frac{\Omega_i}{\sum_j^I \Omega_j}.$$

Since $\sum_j^I \Omega_j = 1$, the initial labor shares for each sector i are given by each Ω_i . The initial labor shares values for the U.S. in 1970 are sufficient to account for the parameterization of each Ω_i so the model and the data match for the first period, by construction. Then, we compute the sectorial labor productivity time paths $\{A_{it}\}_{t=1970}^{2009}$ with the observed growth rates of real value added per worker, and the aggregate consumption time path $\{C_t\}_{t=1970}^{2009}$ with aggregate labor productivity growth rates, measured by the real income per capita growth. Next, we feed these time paths in our model to derive predictions for the evolution of the employment labor shares across sectors as described by equation (3.11). Table 3.2 summarizes the parametrization.

	Value	Target/Comment
Parameters		
σ	0.69	Price elasticity est. (Table 3.1).
ϵ_{agr}	0.53	Engel Curve est. $i = agr$ relative to manufacturing (Table 3.1).
ϵ_{man}	1	Homothetic preferences for manufacturing.
ϵ_{trd}	1.50	Engel Curve est. $i = trd$ relative to manufacturing (Table 3.1).
ϵ_{rst}	1.65	Engel Curve est. $i = rst$ relative to manufacturing (Table 3.1).
ϵ_{trs}	1.55	Engel Curve est. $i = trs$ relative to manufacturing (Table 3.1).
ϵ_{com}	1.63	Engel Curve est. $i = com$ relative to manufacturing (Table 3.1).
ϵ_{fin}	1.71	Engel Curve est. $i = fin$ relative to manufacturing (Table 3.1).
ϵ_{res}	2.17	Engel Curve est. $i = res$ relative to manufacturing (Table 3.1).
ϵ_{bss}	2.75	Engel Curve est. $i = bss$ relative to manufacturing (Table 3.1).
ϵ_{gov}	1.27	Engel Curve est. $i = gov$ relative to manufacturing (Table 3.1).
ϵ_{edu}	1.57	Engel Curve est. $i = edu$ relative to manufacturing (Table 3.1).
ϵ_{hlt}	1.93	Engel Curve est. $i = hlt$ relative to manufacturing (Table 3.1).
ϵ_{per}	1.73	Engel Curve est. $i = per$ relative to manufacturing (Table 3.1).
Ω_{agr}	0.06	Labor share of sector $i = agr$ in 1970 for the U.S.
Ω_{man}	0.30	Labor share of sector $i = man$ in 1970 for the U.S.
Ω_{trd}	0.14	Labor share of sector $i = trd$ in 1970 for the U.S.
Ω_{rst}	0.04	Labor share of sector $i = rst$ in 1970 for the U.S.
Ω_{trs}	0.03	Labor share of sector $i = trs$ in 1970 for the U.S.
Ω_{com}	0.03	Labor share of sector $i = com$ in 1970 for the U.S.
Ω_{fin}	0.03	Labor share of sector $i = fin$ in 1970 for the U.S.
Ω_{res}	0.01	Labor share of sector $i = res$ in 1970 for the U.S.
Ω_{bss}	0.06	Labor share of sector $i = bss$ in 1970 for the U.S.
Ω_{gov}	0.07	Labor share of sector $i = gov$ in 1970 for the U.S.
Ω_{edu}	0.07	Labor share of sector $i = edu$ in 1970 for the U.S.
Ω_{hlt}	0.11	Labor share of sector $i = hlt$ in 1970 for the U.S.
Ω_{per}	0.04	Labor share of sector $i = per$ in 1970 for the U.S.
Time Paths		
$\{A_{i,t}\}$	$\{\cdot\}$	$A_{i,t+1} = A_{i,t}(1 + \gamma_{A_{i,t}})$, where $\gamma_{A_{i,t}}$ is the growth rate of sectoral real value added per hour. $A_{i,t=1970} = 1$.
$\{C_t\}$	$\{\cdot\}$	$C_{t+1} = C_t(1 + \gamma_{C_t})$, where γ_{C_t} is the growth rate of real GDP per capita.

Table 3.2: Parameter values and target for the calibration to the U.S. structural transformation experience, 1970-2009.

3.4 Quantitative Results

3.4.1 Model's Prediction I: U.S. Structural Transformation

Figure 3.2 compares the predicted labor shares of our model to the U.S. data for agriculture and manufacturing. The model does a remarkably good job predicting the observed labor share paths for these two sectors during the sample period. For agriculture, the model predicts almost perfectly the

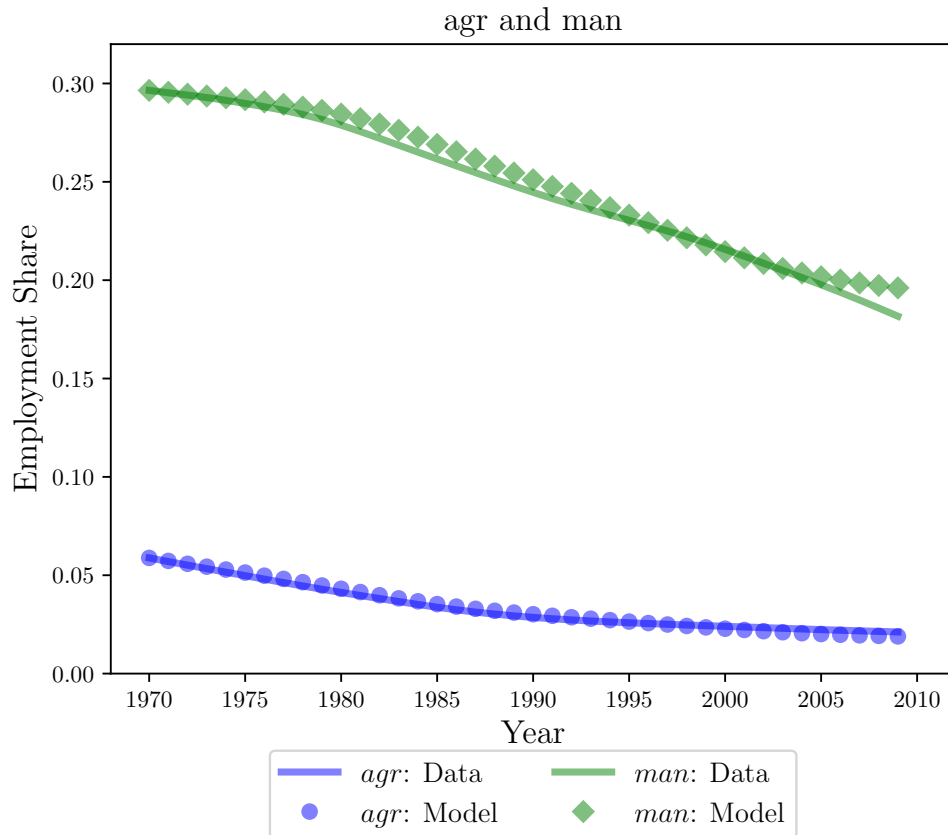


Figure 3.2: Structural Transformation in the U.S., 1970-2009. Agriculture and Manufacturing. Data vs. model.

decline in the labor share. Nonetheless, notice that for 1970 most of the labor in the U.S. economy had already migrated out of agricultural activities. The model also does a good job predicting the observed de-industrialization of the U.S. economy since 1970: Whereas the observed decline of the manufacturing share of employment was from about 30 per cent in 1970 to levels short of 20 per cent in 2009, the predicted decline in the manufacturing employment share is about 21 per cent in 2009.

Figure 3.3 compares the predicted labor shares for the different services in the U.S. economy. The model does follow the labor share paths fairly close for almost every sector, including the steep rise in business services (bss) as shown in the upper right panel of Figure 3.3. The two exceptions are wholesale and retail and trade services (trd), and government (gov). The upper left panel of Figure 3.3 illustrates that for wholesale and retail and trade services, the employment share has remained at a level close to 14

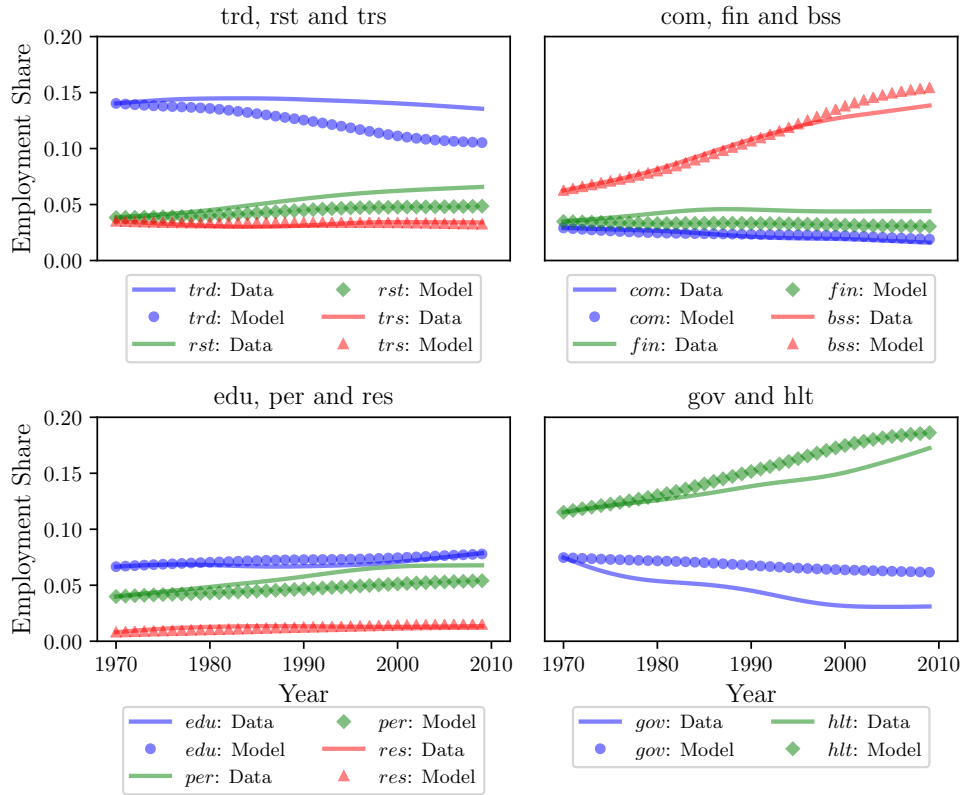


Figure 3.3: Structural Transformation in the U.S., 1970-2009. Services. Data vs. model.

per cent during the sample period, with an observed decline of only half of a percentage point after 1990. The model, however, predicts a decline in the labor share of this sector down to 10 per cent. For government services (see the lower right panel in Figure 3.3) the model under predicts its labor share decline. Whereas the government labor share falls from above 7 per cent in 1970 to about 3 per cent in 2010, our model predicts that this share will decrease only by less than 2 per cent for the same period. This is not surprising. Due to market clearing conditions, the under-prediction for wholesale and retail and trade must be accompanied by an over-prediction in other sector (or in a combination of sectors).

To shed more light on the model's predictions for the structural transformation within services, Figure 3.4 plots the sectoral labor productivity time paths for each service in the U.S. for the period 1970-2009. Communications (*com*), wholesale and retail and trade (*trd*), financial services (*fin*) and to a lesser degree transportation (*trs*), business services (*bss*) and even

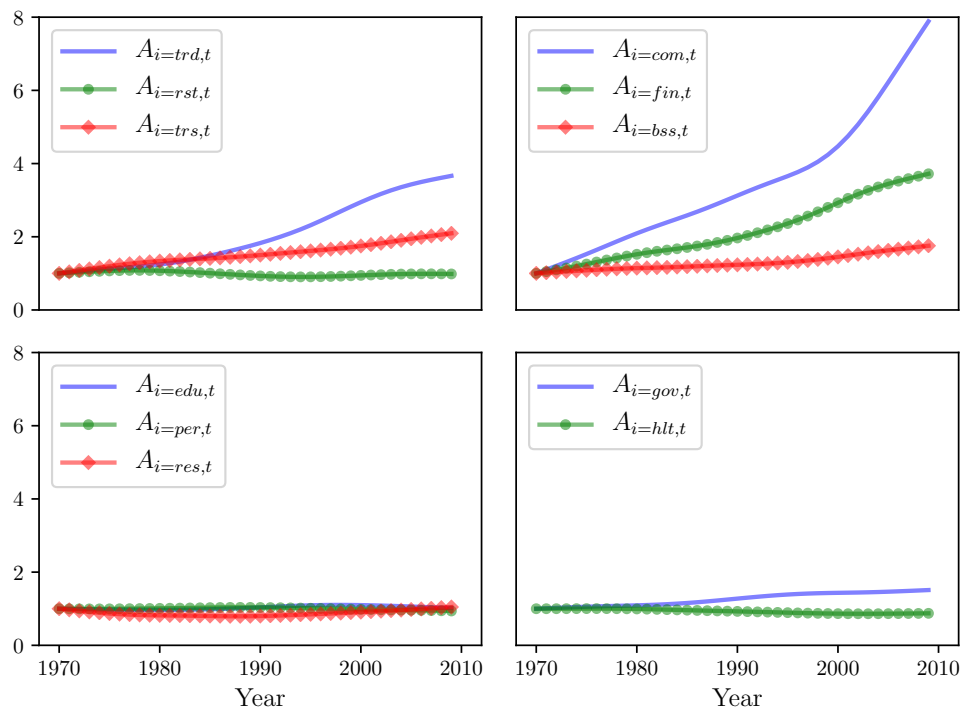


Figure 3.4: Sectoral labor productivity in the U.S., 1970-2009. Labor productivity is measured as the real value added per hour worked. Initial productivity levels are normalized to 1.

government (gov) are the sectors with superior performance in labor productivity. The productivity in communications has increased by a factor of 8 from 1970 to 2009, while the productivity has multiplied its 1970 base more than 3.5 times in wholesale and retail and trade, and financial services. Transportation, business services and government also have multiplied their productivity base by a factor of 2.1 and 1.7 and 1.5 respectively. The rest of the service sectors had experienced virtually no growth in its labor productivity, even in sectors such as health services, whose participation in the labor force exceeded 18 per cent in 2009.

Can the evidence presented in Figure 3.4 explain why the model is not following closely the labor shares in wholesale and retail and trade (trd) and government (gov)? We believe that, in spite of the simplicity of our model economy, the answer is yes. There are two drivers of the structural transformation in our model economy: Engel curves and heterogenous labor productivity growth rates trough the price elasticity of substitution. We already showed that the income elasticity for each sector belonging to services

is statistically superior to the manufacturing Engel curve. Are the income elasticities in services statistically different from each other? The answer depends on the sector. The three sectors displayed in the upper left panel of Figure 3.3 have Engel curves that are not statistically different from each other, but they are statistically lower than the Engel curves for real estate or business services. Therefore, the differences in our model predictions between wholesale and retail and trade, restaurants and hotels, and transportation are to be found in the labor productivity differences. The upper left panel of Figure 3.4 shows that wholesale and retail and trade has the strongest productivity growth among these three services, and therefore, according to our model, this sector should reduce its participation in the labor force. This prediction is in contrast with the observed labor shares, suggesting that in the U.S. it is not necessarily true that the labor productivity growth is shrinking the employment participation in wholesale and retail and trade.

On the other hand, government services do have an Engel curve significantly lower than the rest of the services with the exception of whole/sale and retail, and it is experiencing positive productivity growth. These two forces imply in our model a decrease in the government employment share, but both mechanisms are not sufficient to address the deployment of the labor force out of government services that are evident in the U.S. data. Nevertheless, with important caveats for whole/sale and retail services and for government, we consider that our model successfully accounts for the structural transformation in the U.S.

3.4.2 Model's Prediction II: Structural Transformation in Europe

Following Duarte and Restuccia (2010), we use our model to measure the initial productivity *levels* in Europe *vis-à-vis* the U.S. This is an important accounting step to overcome the lack of sectoral PPP-adjusted value added data. Recall our preference structure is different from Duarte and Restuccia (2010). This implies that we also need to account explicitly for the initial income differences when backing up the initial sectorial productivity levels. We proceed as follows: First, we use the calibrated parameters summarized in Table 3.2 to recover the productivity levels for each sector and for each

European country consistent with the normalization of productivity levels in the U.S. *and* with the income level of each European country relative to the U.S. Since the U.S. income level is normalized to 1 in 1970, the relative income per capita is simply the ratio of GDP per capita of each European country to the U.S. in 1970. We use the OECD GDP per capita measures since they are measured USD constant prices of 2010 adjusted by PPPs, thus PPP-adjusting the initial sectoral productivity levels that our model is recovering. Then, we compute the labor productivity and income time paths with the observed growth rates of sectoral real value added per hour and real income per capita respectively, just as we did for the U.S. in the previous section. Last, with the recovered PPP-adjusted time paths, we compute the model's predictions and compare the structural transformation predicted by our model to the European data. This procedure delivers time paths that are comparable across countries, without the risk of mismeasurement due to exchange rates or PPP adjustments.

Measurement of Sectoral Labor Productivity in Europe

Figures 3.5 and 3.6 plot the productivity levels for each sector in each country relative to the United States for the first and last sample periods. Figure 3.5 shows three different patterns for agriculture, manufacturing and services. First, the agricultural productivity levels (relative to the U.S.) were either stagnant or relative higher in 1970 compared to 2009 with the exceptions of France and Germany, where minor improvements were experienced. The productivity levels are surprisingly high for Great Britain, but still they show an important fall in relative productivity between 1970 and 2009. However, these differences do not play a minor role in the aggregate labor productivity because the structural transformation has reduced the agricultural labor shares dramatically for each of these countries during our sample period.

Second, European countries have been catching up with the U.S. from 1970 to 2009 in manufacturing productivity without exception, although no country reached the U.S. labor productivity during our sample period. Notice that whereas Austria, Belgium, France and the Netherlands experienced about a two-fold increase in manufacturing productivity, the productivity growth in manufacturing was more modest in Germany, Great Britain, Italy and Spain.

Last, with the notable exception of Belgium, no European country experienced a significant catch up in services relative to the U.S.; most countries have remained either stagnant or have experienced a decline. Since the employment share in services has increased, these results confirm the main finding of Duarte and Restuccia (2010): The reason for the European under-performance lies in the service sector.

Figure 3.6 plots the relative labor productivity between 1970 and 2009 for each sector within services and for each European country. Within services, European countries are in generally more productive than the U.S. in telecommunications, education, and health services⁸, but they are signif-

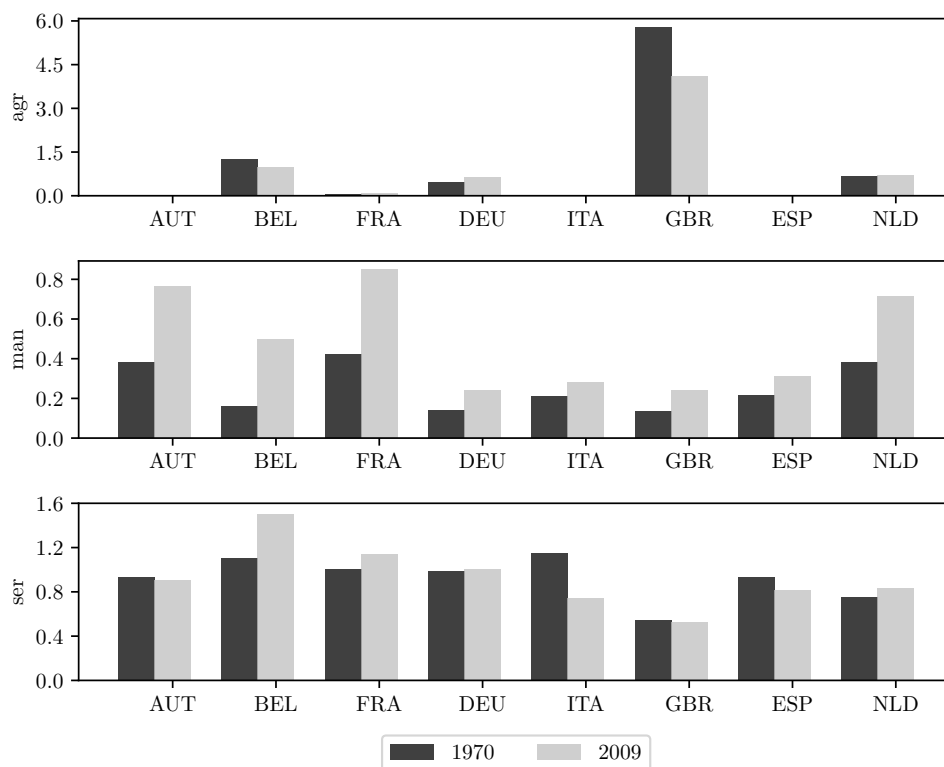


Figure 3.5: Recovered sectoral labor productivity levels in 1970 and 2009 for major European countries relative to the sectorial U.S. labor productivity level. Agriculture and manufacturing.

⁸It is interesting to note that health services are much less productive in the U.S. than in Europe. In addition, productivity gap widened significantly during the sample period. The labor productivity in this sector is a source of major concern for the U.S. as it employed approximately 17 per cent of the labor force in 2009. Nevertheless, the finding that Europe is more productive than the U.S. in health services, as well as in education, should be taken with some caution. Whereas in the U.S. both education and health are services mainly provided by the private sector, in most European countries education and

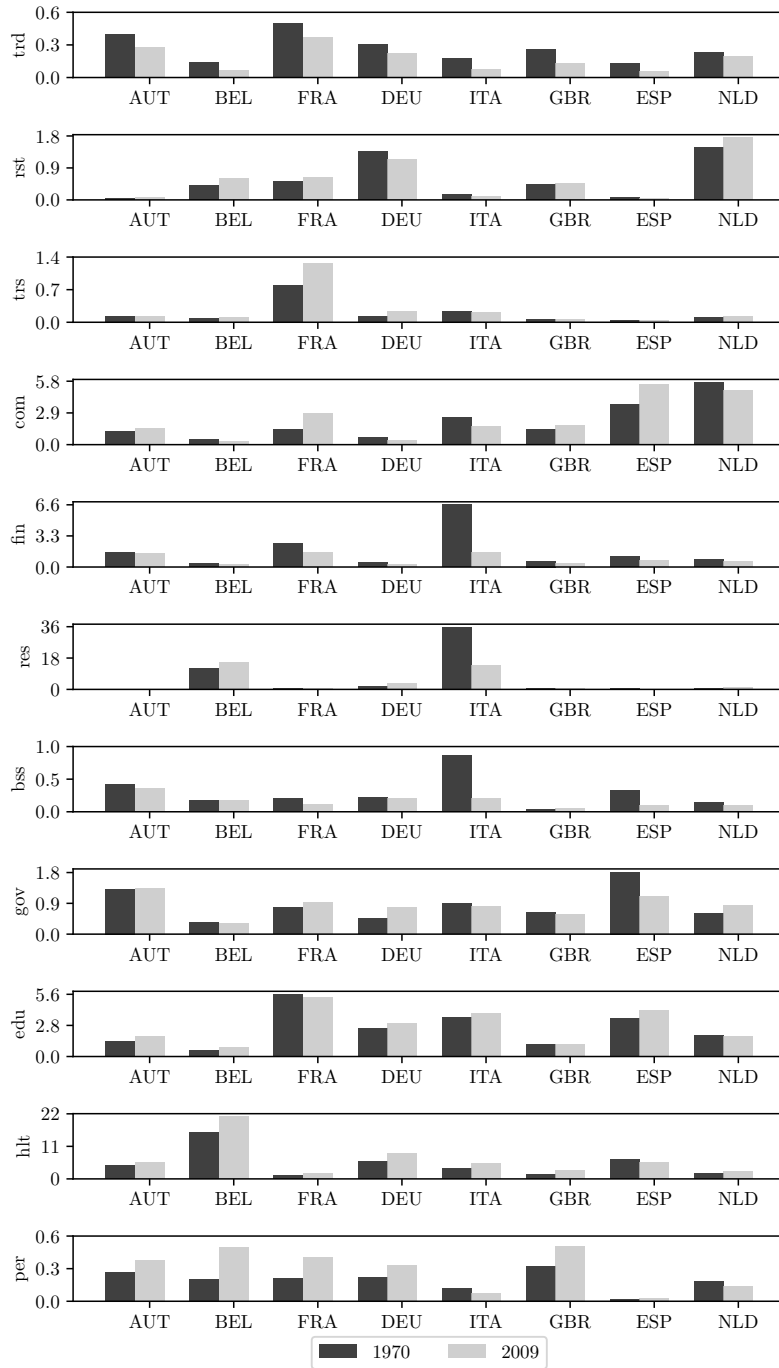


Figure 3.6: Recovered sectoral labor productivity levels in 1970 and 2009 for major European countries relative to the sectorial U.S. labor productivity level. Services.

icantly less productive in wholesale and retail trade. Moreover, the productivity levels for this sector have widen out between 1970 and 2009 in every single European country.

The sector of business services in Europe is also less productive compared to the U.S. without exception, although the productivity gaps have not widened in every country. For instance, Germany and Belgium did not experienced a fall in the relative productivity, but Italy on the other hand experienced a dramatic increase in the productivity gap between 1970 and 2009 in business services relative to the U.S. As we will show, the employment shares of these two sectors have been relatively large in the years of our study. Hence, the levels of labor productivity in wholesale and retail trade and in business services do matter significantly for the differences in aggregate productivity between Europe and the U.S. For the rest of the service sectors the evidence is mixed across countries. An important case to highlight is financial services. Austria, France, Italy and Spain were countries with more productive financial services compared to the U.S. in 1970, and in spite of the sharp drop in productivity, they were still more productive in 2009, except for the case of Spain. Nevertheless, without exception, all countries in Europe experienced an important reduction in their productivity relative to the U.S. in financial services.

Structural Transformation Within Services in Europe

In order to address whether our model is successful in explaining the structural transformation in Europe, Figure 3.7 plots a scatter between the observed labor share for each sector in 2009 and the prediction of our model for the same period. It also plots a solid line that represents the 45 degree line starting at the origin of the y and x -axis. The closer the pair between the observed labor share (y -axis) and our model's prediction (x -axis) to the 45 degree line, the more accurate our model is in capturing the process of structural transformation.⁹ Figure 3.7 illustrates that the model success-

health systems are managed by the government, and the labor hired in these two sub-sectors qualifies as public employment. This fact raises potential concerns on the extent of comparability of sectoral productivity in education and health between Europe and the U.S., even though we use our model to correct potential measurement biases in the available data.

⁹Unlike the employment share in manufacturing, there are no well-defined hump-shaped patterns in the structural transformation in services. For this reason we consider

3.4.3 Model's Prediction III: Aggregate Labor Productivity in Europe *vis-à-vis* the U.S.

Can our model generate the motivating facts presented in Figure 3.1? If we consider the aggregate labor productivity to be the weighted average of the sectoral labor productivities, where the weights are nothing but the labor shares of employment in each sector, *i.e.* the structural transformation, then our model's predictions can be compared directly to the evidence on aggregate labor productivity in Europe *vis-à-vis* the U.S. presented in Figure 3.1.¹⁰ One can address the capacity of the model in generating the labor productivity ratios by using our predicted labor shares for each sector to weight the sectorial productivity levels in order to generate aggregate labor productivity time paths for each country.

Figure 3.8 compares the model's prediction to the data for the aggregate labor productivity in each European country relative to the U.S. and for the European aggregate productivity relative to the U.S. as well.¹¹ After matching by construction the initial observations, the model does follow very close the observed gaps in aggregate labor productivity between Europe and the U.S., regardless on whether the country's convergence stopped, as in France or Germany, or whether the country is falling behind the U.S., as in Belgium or the Netherlands.

In summary, we judged quantitatively the model's performance in three dimensions: i) The U.S. structural transformation, ii) the European structural transformation, and iii) the aggregate labor productivity in Europe relative to the U.S. Our exercises show that our theoretical framework is successful in accounting quantitatively the participation of employment in agriculture, manufacturing and several services in the U.S. and Europe, and it also accounts for the aggregate differences in income per capital between these two regions, and for each country individually. These results are reassuring that our theoretical framework is quantitatively valid, and supports the credibility of the numerical experiments we expose hereafter.

¹⁰Recall that we discipline the initial labor productivities in Europe with the relative, PPP-adjusted, income per capita measures, matching the model and the data by construction for the first period.

¹¹The aggregate productivity in Europe is computed as the average of the eight European countries' aggregate productivity, weighted by their national GDP.

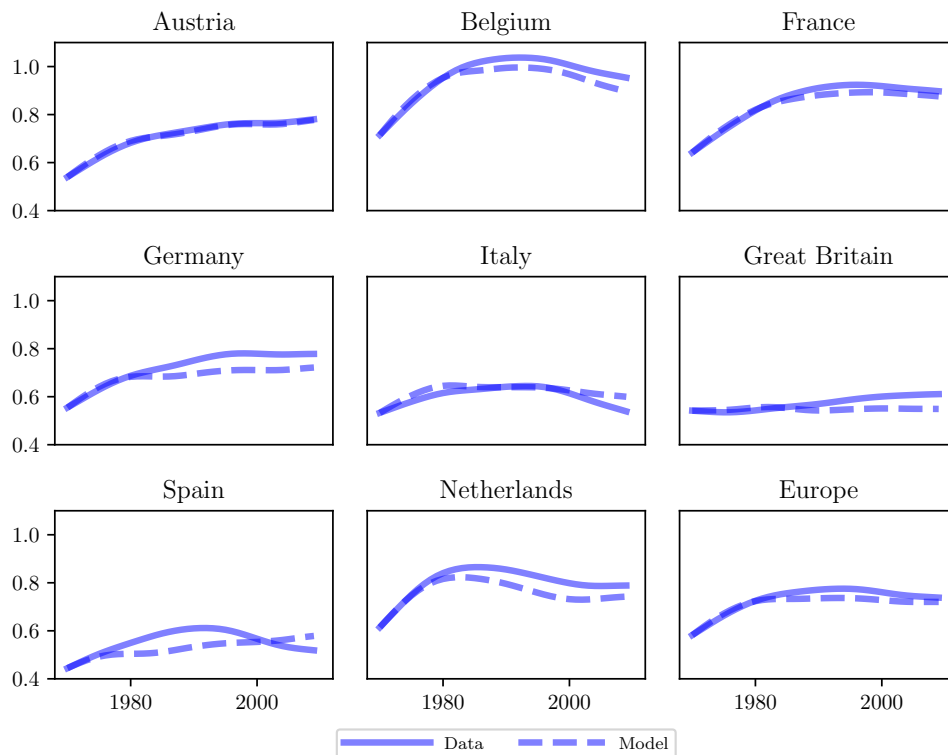


Figure 3.8: Aggregate labor productivity for the European countries relative to the U.S. Europe’s aggregate productivity is the average of the eight European countries’ aggregate productivity, weighted by their national GDP. Model vs. Data. The model’s aggregate labor productivity is the weighted average of sectorial labor productivity, where the weights are the model’s predicted labor shares for each sector.

3.5 Numerical Experiments

After illustrating the quantitative success of the theory in explaining the structural transformation and the aggregate labor productivity for Europe and the U.S., we proceed to use our parametrized model economy to perform a set of numerical experiments addressed to understand the role of sectoral analysis in aggregate productivity. Our aim is to identify which sectors are largely responsible for the slowdown in European labor productivity during the last two decades relative to the United States.

3.5.1 Europe keeping the Pace with the U.S. from 1970 to 2009

Our first counterfactual experiment asks what would have happened with the aggregate labor productivity in Europe if they have experienced the observed sectorial productivity growth in the U.S. from 1970 to 2009. We ask this question for each sector individually, for services as an entire sector, and for all the sectors simultaneously. We perform the numerical experiment for each country and for Europe as a whole. More specifically, we use our model to predict the structural transformation in Europe with the observed U.S. labor productivity growth rate in each sector and compute the counterfactual aggregate productivity. Then, we compare this aggregate productivity with our benchmark prediction from Figure 3.8 to address the differences between our counterfactual scenario and the benchmark prediction for the aggregate productivity.¹² This experiment seeks to answer which sectors are responsible for the relative aggregate productivity slow down.

Table 3.3 illustrates our findings when we feed the labor productivity growth rates from 1970 to 2009. The top panel of Table 3.3 show the results of this exercise when a European country counterfactually experiences the observed labor productivity growth rate in the U.S., in order to assess changes in aggregate labor productivity as a consequence of changes in the productivity of a single sector. Each row of the top panel represents one of the 13 sectors in our model economy, and each column represents a European country with the exception of the last column, which represents Europe as a weighted average of the countries in our European sample.

The results for agriculture are not conclusive. Whereas some countries would have performed better such as Belgium and the Netherlands, for the rest of the European countries our model predicts that the aggregate labor productivity level would be actually lower. Nevertheless, with the exception of the Netherlands, these results have minimal implications for aggregate

¹²As Figure 3.8 shows, our model is successful in predicting the dynamics for the aggregate labor productivity. However, one can repeat this exercise by comparing the counterfactual prediction directly to the observed aggregate productivity level. We decided to compare the counterfactual scenarios to our benchmark predictions because our model successfully accounts for the aggregate labor productivity and because by comparing models' predictions we can address with certainty that the differences arise solely due to the numerical experiment. However, if one decides to compare directly to the actual data the conclusions would not change dramatically.

	AUT	BEL	FRA	DEU	ITA	GBR	ESP	NLD	Europe
$\gamma_i = \gamma_i^{USA}$									
agr	-0.1	1.3	-1.6	-1.2	-0.2	-0.2	-1.5	6.3	0.4
man	-11.0	-14.3	-12.2	-7.6	-4.2	-9.2	-4.9	-7.7	-8.9
trd	4.3	6.5	3.9	3.4	7.7	1.8	6.3	7.1	5.1
rst	-0.0	-0.1	-1.6	-1.2	0.1	-0.4	-0.3	-0.3	-0.5
trs	-1.5	-1.0	-0.5	0.6	0.9	-0.6	0.6	-0.2	-0.2
com	-1.2	1.5	-7.0	2.0	4.8	2.6	-7.0	-2.5	-0.9
fin	0.6	1.0	3.7	2.4	17.7	1.0	2.2	1.9	3.8
res	-0.3	-0.7	-0.3	-0.7	4.8	-0.5	0.4	0.3	0.4
bss	1.3	-0.2	4.0	0.6	11.7	2.6	6.6	-2.7	3.0
gov	-0.2	0.4	-1.0	-2.8	0.5	-1.8	3.5	0.4	-0.1
edu	-1.7	-1.4	0.5	-1.4	-0.9	0.4	-1.7	-0.1	-0.8
hlt	-3.7	-10.9	-5.9	-10.1	-7.3	-4.7	3.8	-8.4	-5.9
per	-1.0	-2.3	-1.8	-1.1	1.2	0.9	-1.5	-1.3	-0.9
$\gamma_i = \gamma_{i,i \in \text{ser}}^{USA}$	-3.5	-7.7	-6.4	-8.6	44.7	1.2	13.3	-6.1	3.4
$\gamma_i = \gamma_{i,\forall i}^{USA}$	-14.3	-20.4	-19.5	-16.8	38.6	-8.4	5.9	-7.5	-5.3

Table 3.3: Numerical experiment: Europe keeping the U.S. Pace for the period 1970 - 2009. Percentage change of the 2009 aggregate labor productivity level. Benchmark prediction vs. counterfactual.

productivity. As a whole, Europe would have had an increase in aggregate labor productivity of 0.4% had they experienced the U.S. productivity in agriculture. These minor results are not surprising. All these economies are at advanced stages of development, with low levels for the size of agriculture in the economy even for 1970, and in steady decline since then.

On the other hand, the message for manufacturing is not ambiguous. Had the European countries experienced the U.S. labor productivity growth in manufacturing during our sample period, their aggregate labor productivity in 2009 would be lower regardless of the country. Naturally, Europe as a whole would have had a lower aggregate productivity. The upper bound of this decline is Italy, with a predicted drop of 4.2%, whereas the lower bound is Belgium, with a staggering drop of 14.7%. Manufacturing is not responsible for the European underperformance *vis-à-vis* the U.S. On the contrary, it helped Europe in its path toward convergence during our sample period.

With regards to services, our counterfactual experiment suggests that the slowdown in the aggregate labor productivity comes mainly from three sec-

tors: wholesale and retail trade (trd), financial services (fin) and business services (bss). It also suggests that Europeans are significantly more productive in health services (hlt). Let's discuss the results of each of these four sectors in detail.¹³

First, during the sample period, the aggregate labor productivity in every single European country would have increased significantly had the wholesale and retail trade sector experienced the U.S. labor productivity growth in Europe. The lower bound for this prediction is for Great Britain, with an increase in aggregate labor productivity of 1.8%, whereas the upper bound is Italy with an increase of 7.7%. The prediction for Europe indicates that this sector alone would have been responsible for an aggregate labor productivity 5.1% higher than our benchmark prediction in 2009.

Second, financial services also would have helped to reduce the labor productivity gap had the European countries experienced the same labor productivity growth observed in this sector for the U.S. Europe as a whole would have had a labor productivity level 3.8% higher than our benchmark prediction. Furthermore, every single European country would have experienced higher aggregate labor productivity if their financial services were as productive as in the U.S., although the results for Italy are substantially higher to the rest of Europe.

Third, with the exception of Belgium and the Netherlands, the labor productivity would also be higher for the European countries if they have had the U.S. labor productivity growth in business services. Once again, the order of magnitude of this result is substantially higher for Italy compared to the rest of Europe.

Last, our results also illustrate that Europe would have had lower aggregate productivity have they had the U.S. labor productivity growth observed in health services. With the exception of Spain, every single European country would have underperformed have they had the U.S. labor productivity growth in the health sector. It is well known that the U.S. is the advanced economy with the most expensive health sector, and our simple models shows that part of these higher costs are captured by its relatively lower labor productivity in this sector. Nevertheless, the question of productivity in health services is one of great difficulty. Labor productivity is measured as the real value

¹³For the rest of the sectors the results are ambiguous depending on the country, and the aggregate effect on labor productivity is not large.

added per worker, but without a proper adjustment for quality it is difficult to address whether more health services per hour reflect more productivity in the health sector. Still, our model captures reasonably well the idea that the U.S. provides health services that are much more expensive compared to their European counterparts.

The middle and lower panel of Table 3.3 show what would have happened if Europe would have experienced the productivity growth rates observed in the U.S. in all services and all sectors simultaneously, respectively. Europe would have experienced some convergence during this period if their services have experienced the U.S. labor productivity growth; the aggregate labor productivity would have been 3.4% higher than our benchmark prediction. However, if *all* sectors had grown like the U.S., the gains obtained in services would be out-weighted by a poorer performance in manufacturing, which helped the convergence during our sample period, yielding an overall loss of the aggregate labor productivity of 5.3% compared to our benchmark prediction.

3.5.2 Europe keeping the Pace with the U.S. from 1990 to 2009

It has been established in this paper that the aggregate productivity in Europe was converging to the U.S. before 1990 and after this year, a process of either slowdown or falling behind started, depending of the country that one is considering. Our second counterfactual experiment asks what would had happened if Europe have continued with the U.S. labor productivity growth rates after 1990, which is the period where the process of convergence came to a halt. We followed the same set of exercises from the previous section, with the only difference that the U.S. growth rates that are counterfactually feed start in 1990 rather than in 1970.

Table 3.4 shows the results of the numerical experiments for the period 1990-2009 by comparing the benchmark prediction to the counterfactual aggregate labor productivity. There are some important differences with the numerical experiments for the period 1970-2009 worth highlighting.

First, whereas the results for agriculture are still negligible, the sharp drop in the aggregate labor productivity with the U.S. manufacturing labor pro-

	AUT	BEL	FRA	DEU	ITA	GBR	ESP	NLD	Europe
$\gamma_i = \gamma_i^{USA}$									
agr	-0.3	1.3	-0.8	-1.5	-0.2	0.3	-0.2	-1.0	-0.3
man	-2.8	-1.5	-1.4	-1.3	3.1	0.9	2.5	-1.7	-0.3
trd	4.0	4.3	4.2	2.3	4.2	1.6	3.0	2.4	3.2
rst	0.5	0.2	-0.1	-0.7	0.1	-0.2	0.7	-0.1	0.0
trs	-0.2	-0.1	0.1	0.6	0.3	0.6	0.8	-0.4	0.2
com	-0.9	1.0	-4.2	-0.1	-3.3	-6.5	-3.0	-5.9	-2.9
fin	-1.0	-0.5	1.7	1.7	1.0	0.7	0.3	-0.7	0.4
res	0.2	2.2	-0.0	0.0	2.6	0.3	0.9	0.4	0.8
bss	0.9	2.2	2.6	3.1	4.5	2.8	3.7	-0.8	2.4
gov	0.1	0.1	-0.5	-0.8	-1.1	-0.5	-0.4	-0.6	-0.5
edu	-0.4	0.4	0.9	0.2	0.1	1.5	-2.4	0.4	0.1
hlt	-1.9	-3.4	-1.2	-8.1	-1.6	-0.2	0.4	-5.7	-2.7
per	-0.5	-0.7	-0.8	-0.4	0.4	-0.3	-0.4	-0.7	-0.4
$\gamma_i = \gamma_{i,i \in \text{ser}}^{USA}$	0.7	5.7	2.6	-2.3	7.4	-0.3	3.6	-11.6	0.7
$\gamma_i = \gamma_{i,\forall i}^{USA}$	-2.4	5.4	0.4	-5.2	10.6	0.9	6.0	-14.2	0.2

Table 3.4: Numerical experiment: Europe keeping the U.S. Pace for the period 1990 - 2009. Percentage change of the 2009 aggregate labor productivity level. Benchmark prediction vs. counterfactual.

ductivity for the period 1970-2009 virtually vanishes when we feed the productivity growth rates only since 1990. This confirms our previous finding: Manufacturing was responsible for the catch-up observed during the 1970s and 1980s. After these years, the productivity growth in manufacturing is not as critical as before to understand the aggregate labor productivity mainly because the weight of manufacturing has fallen due to the ongoing process of structural transformation.

Second, wholesale and retail trade (trd) and business services (bss) continue to be of great importance to account for the European slowdown that took place after 1990. The aggregate labor productivity would have been significantly higher in every European country had they experienced the U.S. labor productivity growth in these two sectors, with the only exception of the Netherlands for the case of business services (bss). On the other hand, financial services (fin) are no longer critical to account for the slowdown, in contrast with the counterfactual for the whole sample period.

Third, the results for health services are in the same direction compared to the entire sample period, but the order of magnitude of the result is

about half of what it was for the 1970-2009 period, although still represent a large distance between the benchmark and the counterfactual aggregate productivity for each country, again with the exception of Spain. In addition, for the period between 1990 and 2009 a new sector emerges in which the Europeans would be worse off if they have had the U.S. labor productivity growth: Communications. With the exception of Belgium, all countries in Europe would have had lower aggregate productivity have they had the U.S. labor productivity in communications, and this difference is large in France, Italy, Great Britain, Spain and the Netherlands.

Last, the middle and lower panel of Table 3.4 illustrate that for this period, the European countries would be modestly more productive have they had the U.S. labor productivity growth observed in the service sector. In addition, they would have been virtually the same have they had the labor productivity growth in each sector in the economy since 1990.

3.5.3 Europe Sectors Catching Up with the U.S. Productivity Levels in 2009

After identifying the sectors largely responsible for the European slowdown, our last numerical experiments ask how much the aggregate labor productivity would have grown if either wholesale and retail trade (trd), financial services (fin), or business services (bss) would have had the productivity growth needed to catch up with the U.S. labor productivity *level* in each sector by 2009. We assume that this convergence takes place only in one sector at a time to compute the annualized growth rate consistent with the catch up to the U.S. labor productivity in the sector in question while keeping the observed growth rates for the rest of the sectors.

Table 3.5 shows the implied change in aggregate productivity when each of these three sectors mentioned before converges to the U.S. labor productivity level in 2009.¹⁴ Have Europe converged to the U.S. productivity level in 2009 in whole sale and retail trade (trd) or in business services (bss), the aggregate productivity gains would be substantial. For instance, Europe as a whole would have had an aggregate productivity level 25.8% higher

¹⁴Our model is suited to perform this numerical experiment for any sector in the economy, but for the sake of space, we decide to show only the three sectors that we identify as largely responsible for the European slowdown during the period 1970-2009.

	AUT	BEL	FRA	DEU	ITA	GBR	ESP	NLD	Europe
trd	19.0	30.6	15.0	22.1	33.8	22.7	33.8	29.4	25.8
bss	10.3	13.4	17.7	15.1	13.3	24.2	15.3	27.9	17.1
fin	-1.9	4.6	-2.3	5.8	-2.5	2.3	1.8	4.3	1.5

Table 3.5: Numerical experiment: Europe catching up the U.S. sectoral productivity *level* in 2009. Implied (annualized) growth rates under *full* catch-up in whole sale and retail trade (trd), business services (bss) and financial services (fin). Percentage change of the 2009 aggregate labor productivity level (benchmark prediction vs. counterfactual).

had they converged in whole sale and retail trade, and of 17.1% have their productivity converged in business services. These two sectors alone are largely responsible for the European slowdown relative to the U.S. Moreover, no European country would have experienced a reduction of its observed aggregate labor productivity have their labor productivity converged to the U.S. by 2009 in either of these two sectors. Whereas the lower bound of the prediction is of 15% if France have had a catch up in whole sale and retail trade, the lower bound of the increase in aggregate labor productivity is of 10.3% for Austria have they experienced a catch up in business services.

On the other hand, financial services (fin) are not unambiguously a source of slowdown between Europe and the U.S. The last row of Table 3.5 shows that have Europe experienced a full catch up in the labor productivity of financial services relative to the U.S. 2009 level, Austria, France and Italy would have had lower aggregate labor productivity. Moreover, even Germany – the most successful counterfactual scenario with an aggregate productivity 5.8% higher compared to its 2009 benchmark prediction – falls short when compared to the lower bound of the predictions for wholesale and retail trade (trd) or for business services (bss).

Figure 3.9 illustrates the effect of a full catch up wholesale and retail trade (trd) on the aggregate labor productivity over time, from 1970 to 2009. Had the European countries converged to the 2009 labor productivity levels in wholesale and retail trade, they would have continued their path toward convergence after 1990, with a mild deceleration in a few countries. Figure 3.9 shows that every single country in Europe would have had improved its position relative to the U.S. without exception. Moreover, Austria and France would have virtually closed the labor productivity gap with the U.S. and

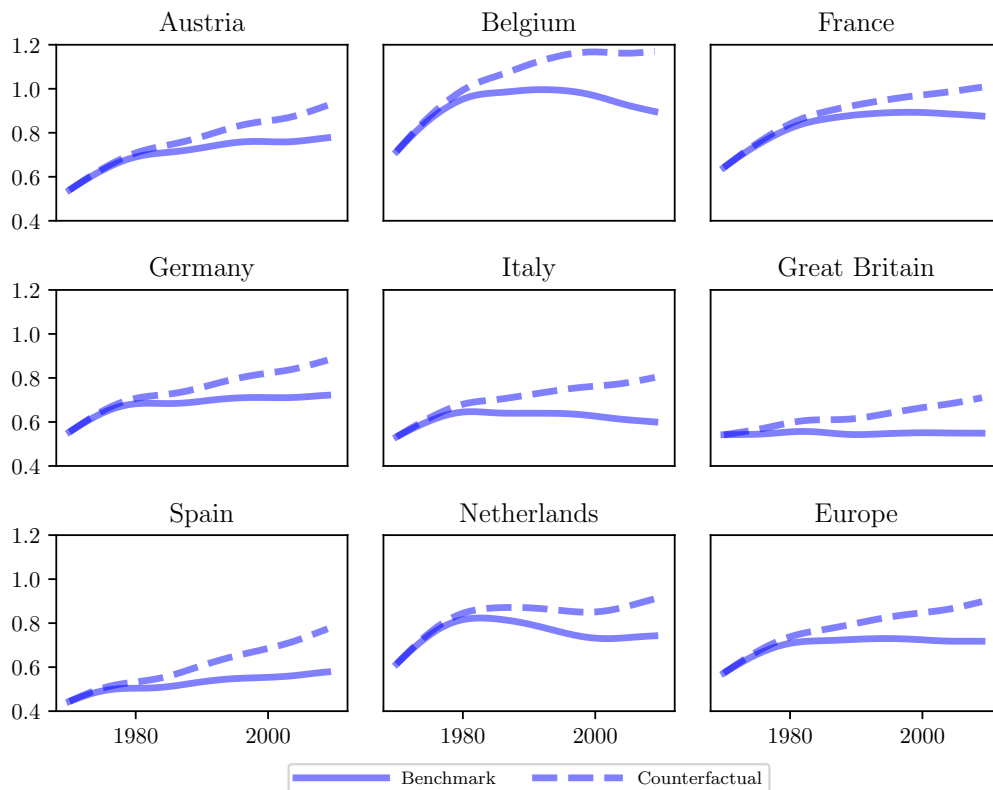


Figure 3.9: Aggregate labor productivity in Europe *vis-à-vis* the U.S. under full catch up in the labor productivity in the wholesale and retail trade (trd) sector. Benchmark prediction vs. counterfactual.

Belgium would have surpassed the American aggregate labor productivity level by 2009. The rest of the countries still would have not closed the gap, but they would not have fallen behind either have they closed the gap in wholesale and retail trade. Europe as a whole would have closed more than half of the gap in labor productivity have they closed the labor productivity gap in this specific sector alone.

As W. W. Lewis (2004, p. 34) puts it, “In the United States, wholesalers [...] began to consolidated their warehouses and improve the productivity of the operations in those warehouses. This change was the largest single contribution to the productivity acceleration in the U.S. economy in the late 1990s not the efforts of Microsoft of Silicon Valley”.

Similarly, Figure 3.10 illustrates the effect of a full catch up in business services (bss) on the aggregate labor productivity time path between 1970 and 2009. The results are qualitatively similar to our previous numerical

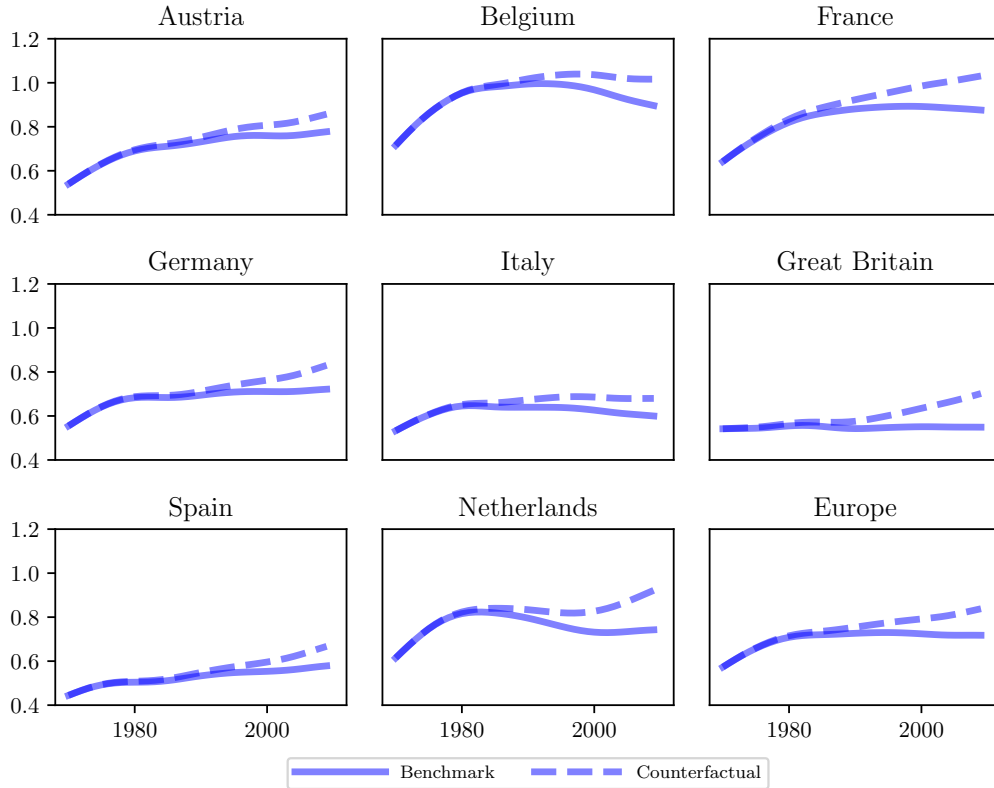


Figure 3.10: Aggregate labor productivity in Europe *vis-à-vis* the U.S. under full catch up for the labor productivity in the business services (bss) sector. Benchmark prediction vs. counterfactual.

experiment illustrated in Figure 3.9, but the magnitude of the effect from catching up in business services is much smaller compared to a full catch up in wholesale and retail trade. Still, if Europe would have experienced a full catch up in the productivity of business services by 2009, the aggregate labor productivity would have been higher in every single country, and with the exception of Italy every country would have continued to close the aggregate productivity gap with respect to the U.S. after 1990 when Europe started to fall behind. Moreover, Belgium and Great Britain would have closed the aggregate productivity gap by catching up to the U.S. only in business services, and Europe as a whole would have closed about two thirds of the aggregate productivity gap with respect to the United States.

Overall, our counterfactual experiments highlight the importance of sectoral analysis on accounting, through the lenses of a theory of structural transformation, which are the sectors responsible for the widening labor pro-

ductivity gap between Europe and the U.S. After opening the service sector into 11 comparable sectors, we find that wholesale and retail trade, business services and to a lesser extent financial are the sectors largely responsible for the aggregate productivity gap. Had these sectors kept the pace with the U.S., the gap would have vanished significantly by 2009.

3.6 Conclusion

In this paper we propose a multi-sector model of structural transformation that disaggregates services in order to quantitatively study the labor productivity differences between Europe and the U.S. in the service sector. We conclude that the structural transformation within the service sector is an important phenomenon, which helps understand why European countries have suffered a lower labor productivity than the U.S., especially since the 90's.

Although the reallocation of labor toward the various types of services has followed similar patterns both in Europe and the U.S., the levels of labor shares are largely different among service sub-sectors and between the two regions. At the same time, the service sub-sectors' labor productivities are remarkably different between the U.S. and Europe. Hence, the interaction of cross-country variations in labor share and labor productivity within the service sector is a major determinant of differences in the aggregate productivity of these economies.

We identify wholesale and retail trade and business services as the types of services that principally caused low service productivity in Europe, and ultimately lead to the divergence of European aggregate productivity from U.S. levels since the 90's. Wholesale and retail trade has always employed a large share of labor, while business services has experienced an astonishing increase in its employment share over the period of our analysis. These patterns are similar both in the U.S. and in Europe. However, labor productivity growth in these sectors has been particularly slower in Europe than in the United States. High and/or increasing labor shares and underperforming labor productivity growth in these two sectors is at the core of the outcome uncovered by our quantitative analysis.

Our findings, together with the rising importance of services in the economy, imply that the efforts of a deeper understanding of the labor productiv-

ity differences between Europe and the U.S. should be focused on wholesale and retail trade and business services. Preliminary empirical findings of our own suggest that insufficient capital deepening – both in information and communication technologies (ICT) and in physical capital – and lower TFP levels are responsible for the differences in these two sectors.

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APPENDIX A

ADDITIONAL MATERIAL FOR CHAPTER

1

A.1 Shooting Algorithm

The first step is to redefine the per capita variables dividing by their balanced growth path values to find a steady state. Defining $A_t^{1-\Theta_t} = A_{xt}$, the aggregate production function is

$$Y_t = A_t^{1-\Theta} K_t^\Theta L_t^{1-\Theta},$$

using the fact that in the long run the economy converges to a one-sector neoclassical growth model with constant capital income shares ($\Theta_t \rightarrow \Theta$). Dividing by L_t and assuming no unemployment, one gets an expression for income per capita as $y_t = \frac{Y_t}{L_t}$, then

$$y_t = A_t^{1-\Theta} k_t^\Theta.$$

Defining $\frac{J_{t+1}}{J_t} = (1 + \gamma_J)$ for any arbitrary variable J one gets

$$1 + \gamma_y = (1 + \gamma_A)^{1-\Theta} (1 + \gamma_k)^\Theta.$$

In the balanced growth path, the only source of growth is the exogenous technical rate γ_A , thus $\gamma_A = \gamma_k = \gamma_y$. Assuming that $A_{ct} = A_{xt}$ ¹ the aggregate price P_t is equal to one in each and every period. Therefore,

$$Y_t = C_t + X_t$$

and

¹If the production of output is independent of its destination as final consumption or investment good, it is reasonable to neglect the differences between the TFP of consumption and investment goods.

$$y_t = c_t + x_t$$

$$\begin{aligned} \text{Aside: } x_t &= \frac{X_t}{L_t} \\ &= \frac{K_{t+1}}{L_t} - \frac{K_t}{L_t}(1 - \delta) \\ &= \frac{K_{t+1}}{L_t} - k_t(1 - \delta). \end{aligned}$$

End of Aside

Using the aside, one gets

$$y_t = c_t + \frac{K_{t+1}}{L_t} - k_t(1 - \delta).$$

To find an expression for the growth rates in the balanced growth path, one can find the ratio $\frac{y_{t+1}}{y_t}$ using the fact that $\frac{k_{t+1}}{k_t} = \left(\frac{K_{t+1}}{L_{t+1}}\right) / \left(\frac{K_t}{L_t}\right)$, which yields the expression

$$1 + \gamma_y = 1 + \gamma_c + \frac{\gamma_K}{\gamma_L} - \frac{\gamma_K}{\gamma_L},$$

therefore $\gamma_y = \gamma_c = \gamma_k = \gamma_A$, *i.e.* all per capita variables are growing according to the TFP growth rate. Dividing the per capita variables by the balance growth path values one gets

$$\hat{k}_t = \frac{k_t}{(1 + \gamma_A)^t}; \quad \hat{c}_t = \frac{c_t}{(1 + \gamma_A)^t}; \quad \hat{y}_t = \frac{y_t}{(1 + \gamma_A)^t}.$$

Since all variables are growing at the same rate in the balanced growth path, one can simply use γ as the TFP growth rate. The household's preferences with the redefined variables are described by

$$\sum_{t=0}^{\infty} \beta^t \log(1 + \gamma)^t \hat{c}_t,$$

and the resources' restriction is

$$\hat{c}_t + (1 + n)(1 + \gamma)\hat{k}_{t+1} = \hat{y}_t + \hat{k}_t(1 - \delta),$$

where $\frac{L_{t+1}}{L_t} = (1 + n)$.

Given the non-increasing returns to scale in the production function and the convex and locally non-satiated preferences of the household, the Second Welfare Theorem implies that the Social Planner's problem supports a competitive equilibrium allocation. Therefore, the Social Planner's problem

is described as follows:

Social Planner's Problem

$$\begin{aligned} \max_{\{\hat{c}_t, \hat{k}_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \log(1 + \gamma)^t \hat{c}_t \text{ s.t. } & \textit{i)} \quad \hat{k}_t^{\Theta} + (1 - \delta)\hat{k}_t \geq \hat{c}_t + (1 + n)(1 + \gamma)\hat{k}_{t+1} \\ & \textit{ii)} \quad \hat{k}_0 > 0. \end{aligned} \tag{A.1}$$

The first-order conditions yield the following Euler equation

$$\frac{c_{t+1}^{\hat{c}}}{\hat{c}_t} = \frac{\beta(\Theta \hat{k}_{t+1}^{\Theta-1} + (1 - \delta))}{(1 + n)(1 + \gamma)}, \tag{A.2}$$

and the steady state capital is

$$\hat{k}^{ss} = \left[\frac{\Theta}{\frac{1}{\beta}(1 + n)(1 + \gamma) - (1 - \delta)} \right]^{\frac{1}{1-\Theta}}. \tag{A.3}$$

For the shooting algorithm, I need to express the Euler equation (A.2) as a second order differential equation with respect to the capital. The consumption can be expressed as the first order differential equation

$$\hat{c}_t = \hat{k}_t^{\Theta} + \hat{k}_t(1 - \delta) - (1 + n)(1 + \gamma)\hat{k}_{t+1}. \tag{A.4}$$

Plugging (A.4) into (A.2) one gets

$$\frac{\hat{k}_{t+1}^{\Theta} + \hat{k}_{t+1}(1 - \delta) - (1 + n)(1 + \gamma)\hat{k}_{t+2}}{\hat{k}_t^{\Theta} + \hat{k}_t(1 - \delta) - (1 + n)(1 + \gamma)\hat{k}_{t+1}} = \frac{\beta(\Theta \hat{k}_{t+1}^{\Theta-1} + (1 - \delta))}{(1 + n)(1 + \gamma)}. \tag{A.5}$$

With values for the parameters, \hat{k}_t and \hat{k}_{t+1} , one can use equation (A.5) to solve for \hat{k}_{t+2} . The shooting algorithm uses equation (A.5) to solve for the entire time-path for $\{\hat{k}_t\}$ and consequently, for the paths of $\{C_t, W_t, R_t\}$ as a function of $\{A_t, K_t\}$. The computation of the shooting algorithm involves the following steps:

1. With values for the parameters, compute the steady state capital \hat{k}^{ss} (equation (A.3)) and define \hat{k}_0 as one per cent of the steady state cap-

ital.

2. Take a guess for \hat{k}_1 .
3. Compute \hat{k}_2 using equation (A.5).
4. Compute the entire time-path $\{\hat{k}_t\}$ recursively using equation (A.5).
5. Check in each period of the time-path $\{\hat{k}_t\}$ for the following two conditions:
 - (a) In each period, \hat{k}_t should be ascending.
 - (b) While ascending, the level for \hat{k}_t should still be below \hat{k}^{ss} before the last period of the time-path.
6. If both conditions from step 5 are met, then the time-path for \hat{k}_t is optimal. If not, the capital is either not converging to its steady state value or converging too fast. If this is the case, then go back to step 2 with a different guess until the two conditions from step 5 are met.

A.2 Estimation of Income and Substitution Elasticities

To derive a system of relative labor demands I use the closed model economy framework mainly for three reasons. First, the system is more tractable without trade since not all the sectors in the economy are open to make a comparison one to one between sectors with regards to the trade adjustment term. Second, preference parameters should be independent on the nationality of the consumption good so in principle opening the economy does not bring much value to discover the “deep structural parameters” pertinent to the intra-temporal choice. In addition, after including trade controls as a robustness check for income and price elasticities I found that it is safe to disregard the open economy assumption for this particular exercise.²

From the definition of the expenditure shares and equation (1.16) from the intra-temporal optimal allocations one obtains

$$\frac{p_{it}c_{it}}{P_t C_t} = \Omega_i \left(\frac{p_{it}}{P_t} \right)^{1-\sigma} C_t^{\epsilon_i-1}. \quad (\text{A.6})$$

²Comin et al. (2015) also found similar estimates for income and price elasticities with and without trade controls.

Additionally, using equation (1.23) the demand for sectors $j \in \{a, s\}$ relative to manufacturing is

$$\frac{l_j}{l_m} = \frac{(1 - \theta_j) \frac{p_j c_{jt}}{P_t C_t}}{(1 - \theta_m) \frac{p_m c_{mt}}{P_t C_t}}. \quad (\text{A.7})$$

Combining equations (A.6) and (A.7) and taking logs on both sides yields

$$\log \left(\frac{l_{it}}{l_{mt}} \right) = \log \left(\frac{1 - \theta_j}{1 - \theta_m} \right) + (1 - \sigma) \log \left(\frac{p_j}{p_m} \right) + (\epsilon_j - \epsilon_m) \log C_t + \log \left(\frac{\Omega_j}{\Omega_m} \right), \quad (\text{A.8})$$

for $j \in \{a, s\}$. From equation (A.8) I obtain the following estimating equations for the labor demand in agriculture and services relative to manufacturing

$$\log \left(\frac{l_{at}}{l_{mt}} \right) = \alpha_0 + \alpha_1 \log \left(\frac{1 - \theta_{at}}{1 - \theta_{mt}} \right) + (1 - \sigma) \log \left(\frac{p_{at}}{p_{mt}} \right) + (\epsilon_a - \epsilon_m) \log C_t + \nu_{am,t}, \quad (\text{A.9})$$

and

$$\log \left(\frac{l_{st}}{l_{mt}} \right) = \alpha_3 + \alpha_4 \log \left(\frac{1 - \theta_{st}}{1 - \theta_{mt}} \right) + (1 - \sigma) \log \left(\frac{p_{st}}{p_{mt}} \right) + (\epsilon_s - \epsilon_m) \log C_t + \nu_{sm,t}. \quad (\text{A.10})$$

Equations (A.9) and (A.10) must be estimated jointly with the cross equation restriction for the elasticity of substitution. The elasticities of interest are $(1 - \sigma)$, $(\epsilon_a - \epsilon_m)$ and $(\epsilon_s - \epsilon_m)$. α_1 and α_3 represent country fixed effects to control for the time invariant parameters Ω_i .³ An important difference with respect to Comin et al. (2015) is that sector fixed effects in this framework does not control for the capital intensity changing over time, so α_2 and α_4 should be estimated explicitly to control for the capital intensity in order to estimate income and price elasticities.

The variables of interest are C_t , $\frac{p_{at}}{p_{mt}}$, and $\frac{p_{st}}{p_{mt}}$. For the panel estimations, C_t is measured as the expenditure-side real GDP at chained PPPs (in millions of 2011US\$) available at the Penn World Tables (version 9.0).⁴ For prices at

³Unlike Duarte and Restuccia (2010), I am not using the model to compare productivity levels across countries, so the weights on the preferences do change across countries in order to account for the initial observations consistent with the normalization of sectoral TFP.

⁴To construct the time series of real income in the model I used the growth rates of

	(1)	(2)
$1 - \sigma$	0.322*** (0.12)	0.204** (0.09)
$\epsilon_a - \epsilon_m$	-0.639*** (0.07)	-0.598*** (0.05)
$\epsilon_s - \epsilon_m$	0.270** (0.11)	0.387*** (0.04)
Trade Controls	No	Yes
Country Fixed Effects	Yes	Yes
Observations	283	126
R^2	0.960	0.955

Table A.1: Estimates for income and substitution elasticities. C_t is measured as the expenditure-side real GDP at chained PPPs (in millions of 2011US\$) available at the Penn World Tables (version 9.0). Prices at the sector level are measured as the ratio of nominal value added to real value added per sector from World KLEMS. Trade controls are the trade balance in logs available at the Penn World Tables (version 9.0). Controls for measures of capital intensity included. The countries included are Belgium, Canada, Spain, Great Britain, Japan, South Korea and the United States. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the sector level I used the ratio of nominal value added to real value added per sector from World KLEMS to obtain sectoral prices.

Table A.1 presents the estimation of equations (A.9) and (A.10) with and without trade controls (measured as the log of the balance of trade). Only the coefficients for income and substitution elasticities are reported. Column 1 presents the baseline estimation without trade controls. The estimated elasticity of substitution is of 0.68, which is in line with other estimates in the literature, and it still it is statistically lower than one. Recall that this elasticity is computed controlling for the role of capital income shares on the system of relative labor demands.

the trended income per capita available at the Maddison-Project since I'm not interested in the business cycle. However, for purposes of estimating equations (A.9) and (A.10) the variation of income levels is critical. For this reason I consider expenditure-side real GDP at chained PPPs instead of the Maddison's income per-capita levels. Nevertheless, after some inspection, the growth rates of income for these two different sources are very similar although the expenditure-side real GDP present slightly more volatile series, making them more desired for the purposes of the estimation.

With regards to the income elasticity, if one normalizes ϵ_m to 1, or in other words, if one imposes homothetic preferences on the consumption of manufactures, the interpretation of the Engel curves is straightforward. The income elasticity for agricultural goods ϵ_a is 0.36, which reinforces the notion of Engel curves for agriculture in the traditional literature of development: As long as income grows, households devote a smaller proportion of the income growth toward the consumption of food. Additionally, the income elasticity of services is 1.27, which means that households consume disproportionately more services as long as they become wealthier.

The key message of Table A.1 are not the punctual estimates of income elasticities but rather their relative ranking across sectors. Relative to manufactures, the income elasticity for agricultural goods is inferior while the opposite is true for services. Column 2 of Table A.1 controls the estimation of income and price elasticity for trade and shows that the message is not altered and the punctual estimates are not altered dramatically. For the calibration of the model I will use the estimates illustrated in Column 1 of Table A.1.

A.3 Computation of Sectoral TFPs.

The computation of Sectoral TFPs with time-varying capital intensities is straightforward. From the production technology (equation (1.17)) TFP *levels* are defined as

$$A_{it} = \frac{y_{it}}{i_{it}} \left(\frac{\theta_{it}}{1 - \theta_{it}} \frac{W_t}{R_t} \right)^{-\theta_{it}}.$$

Taking the total derivative with respect to time one gets

$$\frac{\dot{A}_{it}}{A_{it}} = \frac{\left(\frac{\dot{Y}_{it}}{L_{it}} \right)}{\left(\frac{Y_{it}}{L_{it}} \right)} - \dot{\theta}_{it} \left[\log \left(\frac{W_t}{R_t} \right) + \log \theta_{it} + \log(1 - \theta_{it}) - 1 \right] - \theta_{it} \left[\frac{(1 - \dot{\theta}_{it})}{(1 - \theta_{it})} + \frac{\left(\frac{\dot{W}_t}{R_t} \right)}{\left(\frac{W_t}{R_t} \right)} \right], \quad (\text{A.11})$$

where $\dot{x} \sim \Delta x = x_t - x_{t-1}$. Adjusting the labor productivity is just a matter of using the observed growth rates in capital income shares and the computed time series for relative input prices to obtain TFP measures consistent with

time-varying capital intensities.

A.4 Model's Main Prediction with Exogenous Aggregate Time Series

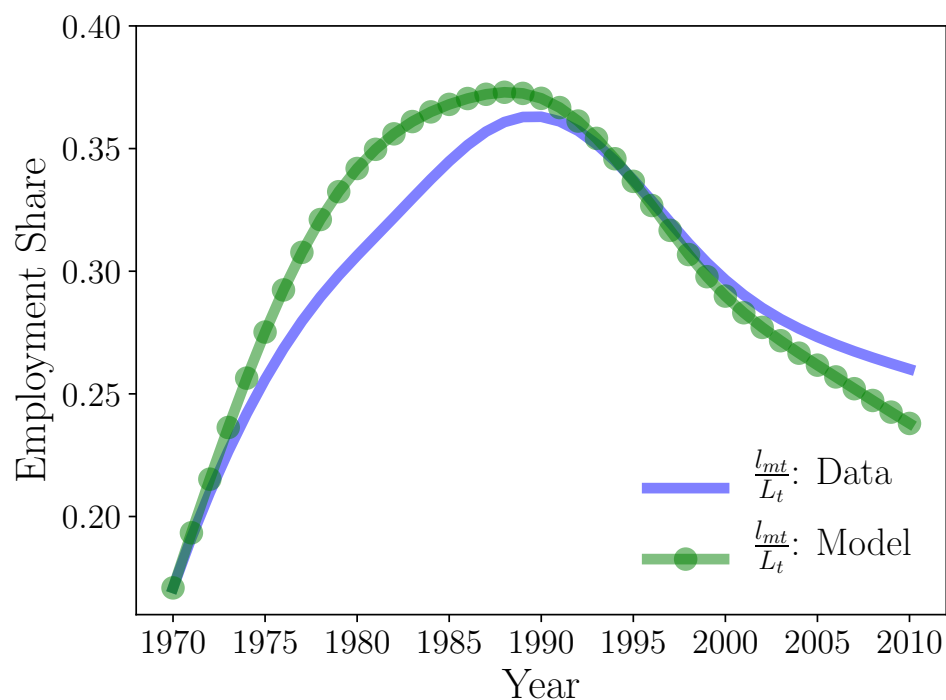
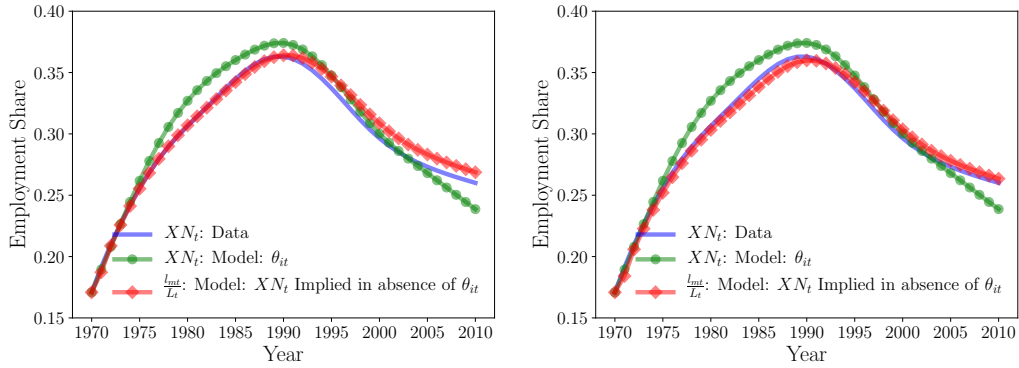


Figure A.1: Labor shares in Korea over time, 1970-2010. Data vs. model. The aggregate time series $\{C_t, \frac{W_t}{R_t}\}$ are computed with exogenous growth rates to illustrate that the hump-shape does not depend on any assumption used in the aggregation of the model to a one-sector neoclassical growth model.

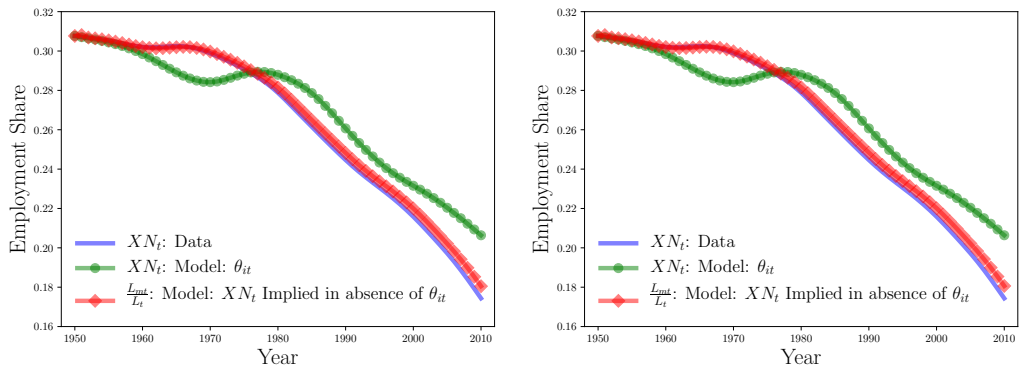
A.5 Predicted Manufacturing Labor Share with Implied Balance of Trade



(a) Average Capital Income Shares

(b) Initial Capital Income Shares

Figure A.2: Predicted manufacturing labor share with implied balance of trade for Korea, 1970-2010.



(a) Average Capital Income Shares

(b) Initial Capital Income Shares

Figure A.3: Predicted manufacturing labor share with implied balance of trade for the United States, 1948-2010.

A.6 Pattern of Development in South Korea

<i>Exports</i>	<i>Primary ISI</i>	<i>Primary EOI</i>	<i>Secondary ISI/EOI</i>
Rice, beans.	Food, beverages tobacco, textiles, clothing, footwear cement, light manu- factures (wood, leather, rubber, and paper products).	Textiles and apparel, electronics, plywood wigs, intermediate goods (chemicals, petroleum, paper, and steel products).	Automobiles, ship- building, steel and metal products, petro- chemicals, textiles and apparel, electronics, videocassette recorders, machinery.

Note: ISI = import-substituting industrialization; EOI = export-oriented industrialization.

Table A.2: South Korean pattern of development. Source: Gereffi (1990, p. 20).

A.7 Predicted Capital Income Shares for Other Countries

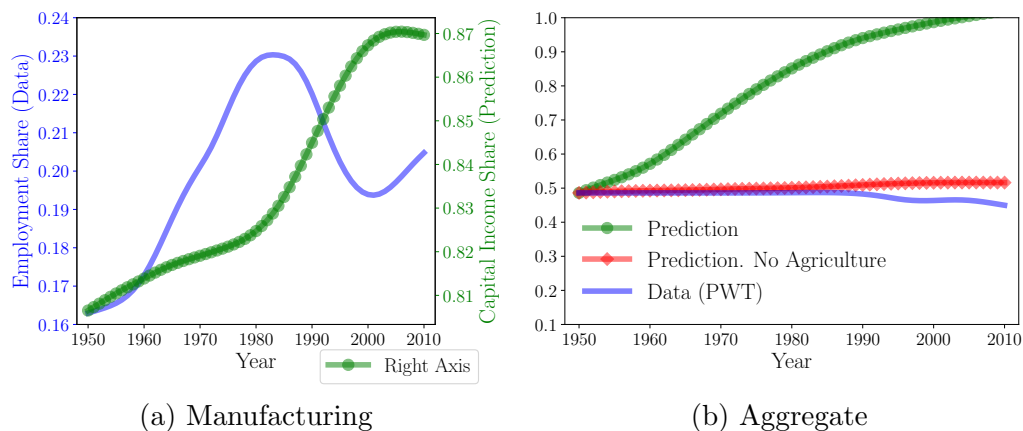
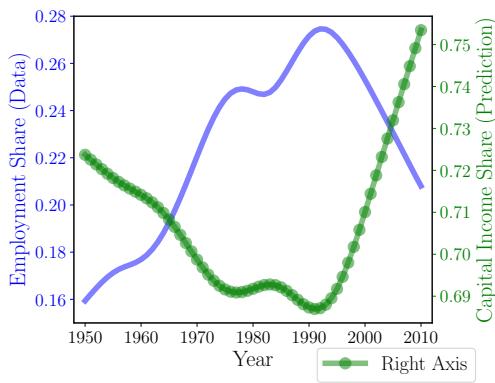
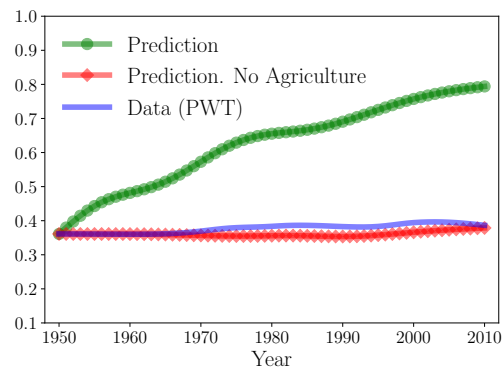


Figure A.4: Brazil. Implied capital income shares

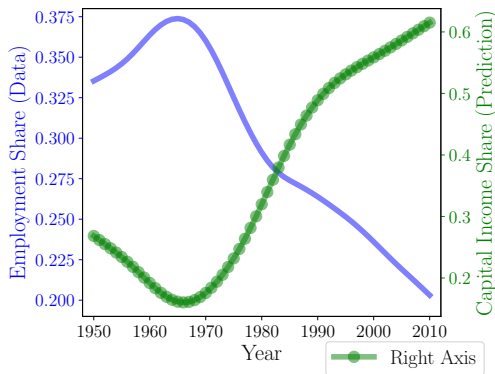


(a) Manufacturing

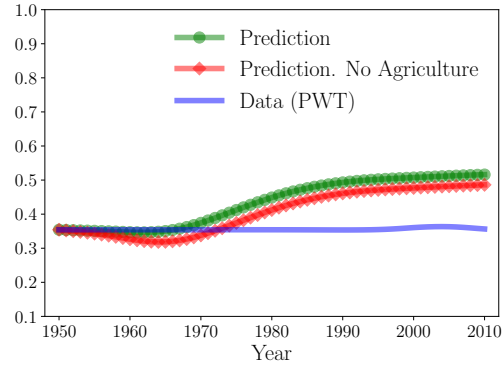


(b) Aggregate

Figure A.5: Costa Rica. Implied capital income shares

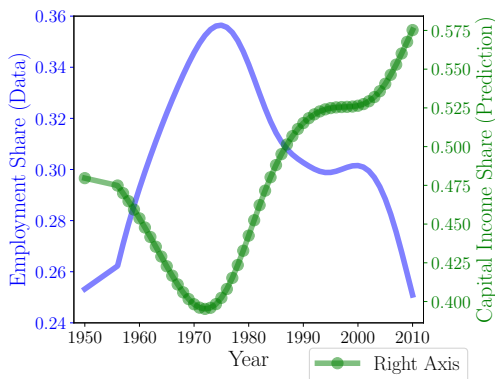


(a) Manufacturing

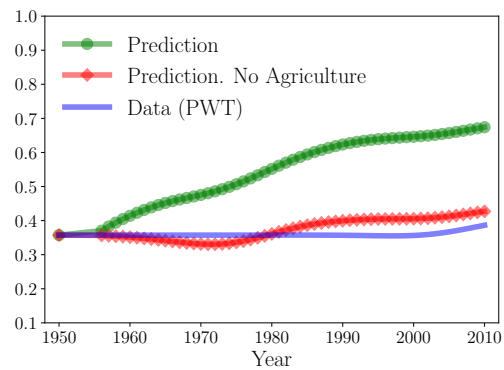


(b) Aggregate

Figure A.6: Denmark. Implied capital income shares

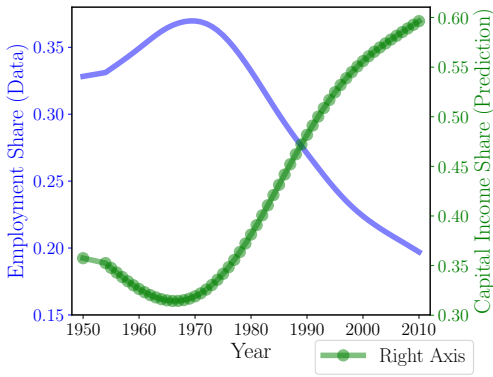


(a) Manufacturing

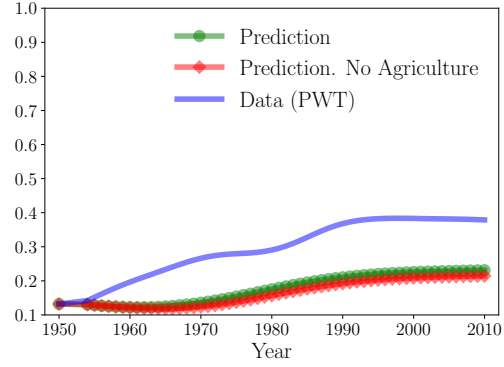


(b) Aggregate

Figure A.7: Spain. Implied capital income shares

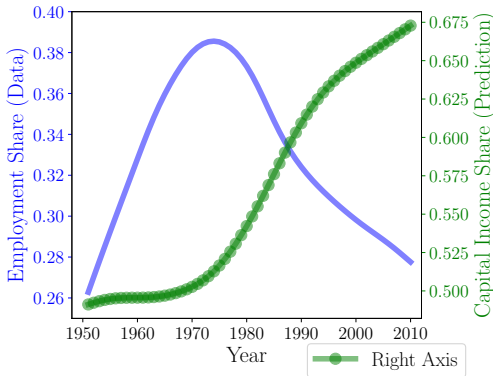


(a) Manufacturing

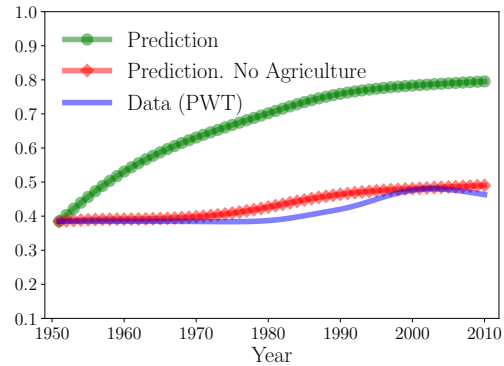


(b) Aggregate

Figure A.8: France. Implied capital income shares

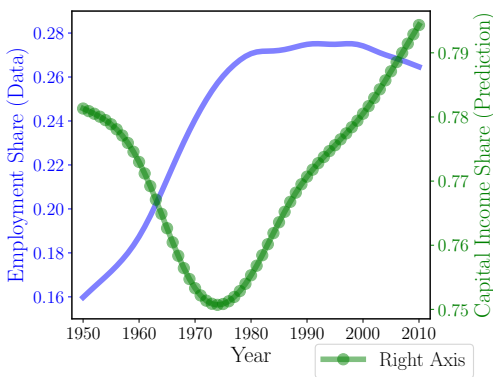


(a) Manufacturing

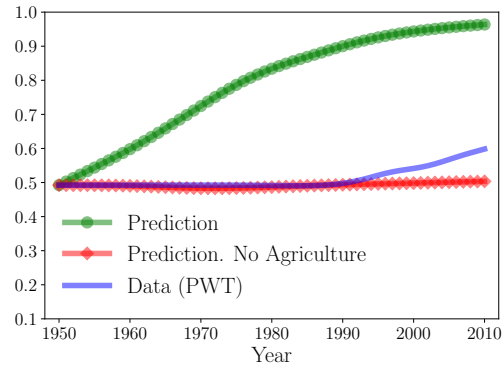


(b) Aggregate

Figure A.9: Italy. Implied capital income shares

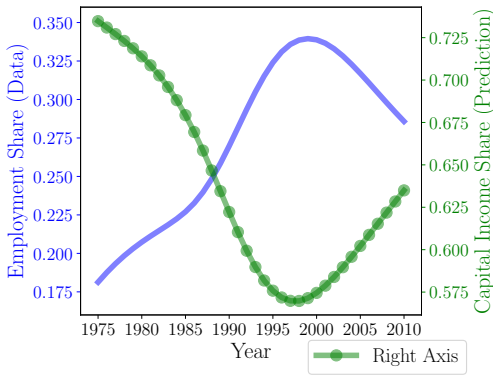


(a) Manufacturing

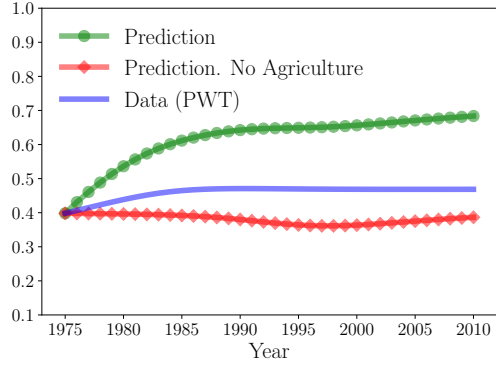


(b) Aggregate

Figure A.10: Mexico. Implied capital income shares

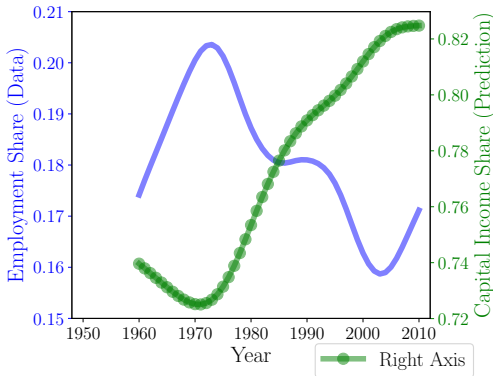


(a) Manufacturing

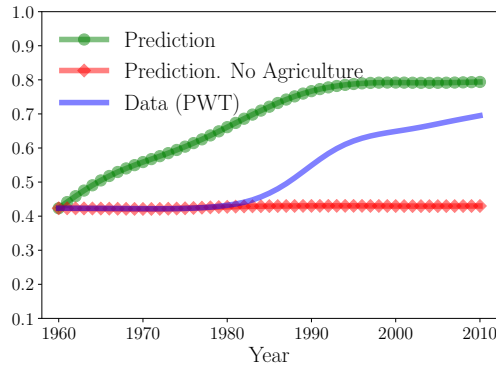


(b) Aggregate

Figure A.11: Malaysia. Implied capital income shares

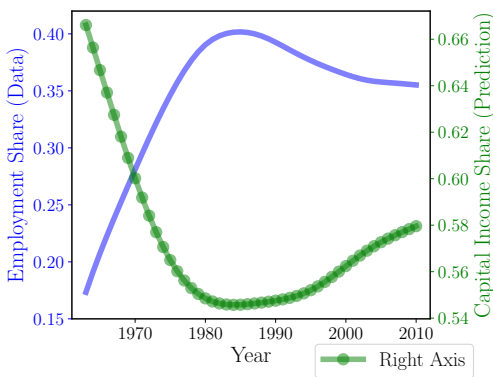


(a) Manufacturing

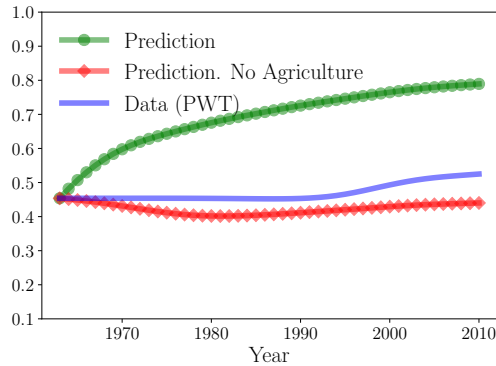


(b) Aggregate

Figure A.12: Peru. Implied capital income shares

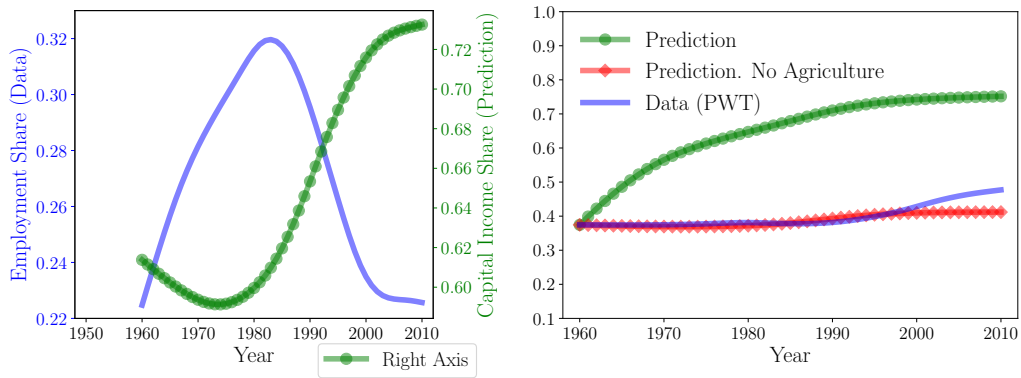


(a) Manufacturing



(b) Aggregate

Figure A.13: Taiwan. Implied capital income shares



(a) Manufacturing

(b) Aggregate

Figure A.14: South Africa. Implied capital income shares

APPENDIX B

ADDITIONAL MATERIAL FOR CHAPTER

2

B.1 EAM Classification of Production and Non-Production Personnel

Non-Production Personnel (Managers):

Includes the people who run the economic, financial and administrative aspects of the establishment and who are responsible for developing and driving overall company policy, as managers, assistant managers and directors paid. This includes: administrative officers, typists, supervisors, security personnel, orderlies, service personnel who do not work in the production area, vendors, dealers and/or distributors. Excludes personnel warehouses, administrative offices , management , storage and other auxiliary units that do not depend directly on the property or that are located in a different physical location of the production plant (EAM, 2011, [pp.25](#)).

Production Personnel (Workers):

Corresponds to the employees dedicated to the manufacture, processing, assembly, installation, maintenance, inspection, storage, packing, loading and unloading workers, such as workshop or internal messengers, firemen, cleaners equipment, supervisors and foremen working manually, drivers transporting supplies, materials or products only within the establishment, maintenance workers and repair (mechanical, electrical , etc.) of machinery and industrial equipment. Administrative managers, typists, supervisors principally engaged in the surveillance of working personnel,

security personnel, orderlies, service personnel who work in the production area (EAM, 2011, pp.26).

B.2 Simulation Algorithm

In principle, the coefficients of production and relative costs are sufficient to simulate input demands. However, the system of equations portrayed in (2.8) consider time and fixed effects that are desirable to include in the simulation to be able to predict more accurately the input *levels*. The inclusion of time fixed effects is particularly relevant capture the impact of the market oriented reforms on relative prices with the interaction term coefficient. Therefore, the simulation algorithm that I used is as follows:

1. Obtain $\bar{x}_j = \frac{1}{N} \sum_{i=1}^N x_{ij}$, namely the average of the predictions for the demand of each input j based on the estimation of (2.8) with instrumental variables, where $x_{ij} = \log X_{ij}$ and N is the total number of observations in the sample. Notice that here i represents individual observations rather than plants while j still represents the inputs indexed in J .
2. Obtain $\bar{c}_j = \frac{1}{n} \sum_{i=1}^n c_{ij}$, the average relative cost for each input used in the prediction stored in step 1, where $c_{ij} = \log C_{ij}$.
3. Compute $\hat{\beta}_2^j \times \bar{c}_j$, the coefficient of relative costs times the average relative cost from step 2 and subtract this product from the average input demand obtained in step 1, *i.e.* $\bar{x}_j - \hat{\beta}_2^j \times \bar{c}_j$.
4. Generate a sequence $\{\tilde{c}_j\}$ of relative costs for each input that reflects a reduction in capital costs. This sequence will have observations above and below the average relative costs stored in step 2. Therefore, by construction the simulation will necessary cross at some point through the average input demand.
5. Multiply each element of the sequence of relative costs with the coefficient $\hat{\beta}_2^j$, and add this product to the quantity stored in step 3, *i.e.*

$\{\tilde{x}_j\} = \bar{x}_j - \hat{\beta}_2^j \times \bar{c}_j + \hat{\beta}_2^j \times \{\tilde{c}_j\}$. This will generate a simulated sequence of input demands based on the IV coefficients and the simulated sequence of relative costs.

The same algorithm is extended to include the interaction term between the relative costs and the binary variable PR to generate simulated input demands that capture the effect of market oriented reforms on relative prices.

B.3 Robustness Checks: Figures and Tables

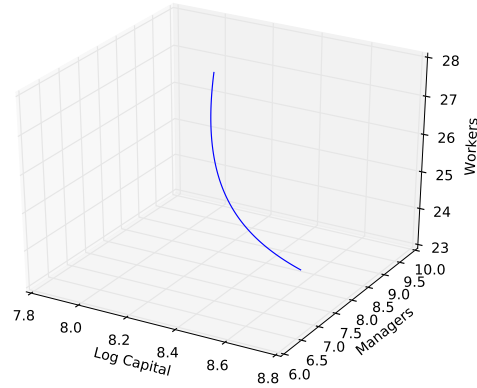
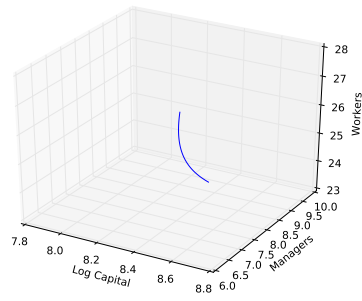
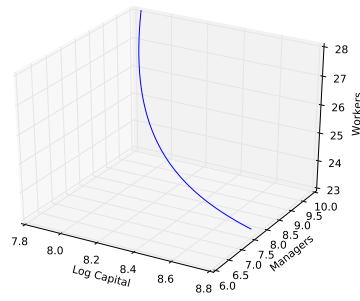


Figure B.1: Survivor plants. Demand predictions for capital, managers, and workers. Predictions are based on the IV elasticities from Table B.1. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Survivor plants are defined as establishments that reported production in t and in $t + 1$.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.2: Survivor plants. Demand predictions for capital, managers, and workers. Pre and post-reform elasticities: The predictions are based on the IV elasticities from Table B.1. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Survivor plants are defined as establishments that reported production in t and in $t + 1$.

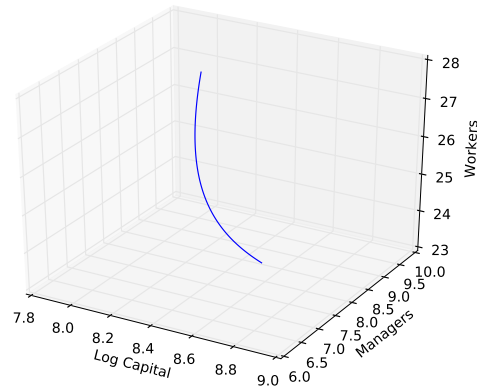
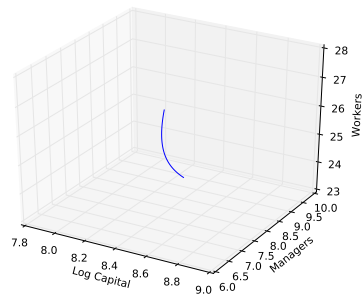
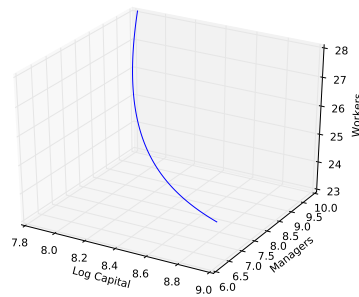


Figure B.3: Exit plants. Demand predictions for capital, managers, and workers: Predictions are based on the IV elasticities from Table B.2. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Exit plants are defined as establishments that reported production in t but not in $t + 1$.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.4: Exit plants. Demand predictions for capital, managers, and workers. Pre and post-reform periods: Predictions are based on the IV elasticities from Table B.2. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Exit plants are defined as establishments that reported production in t but not in $t + 1$.

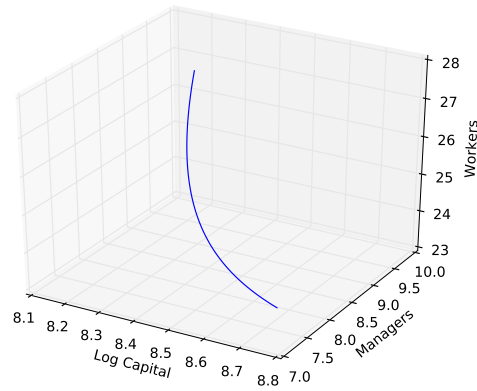
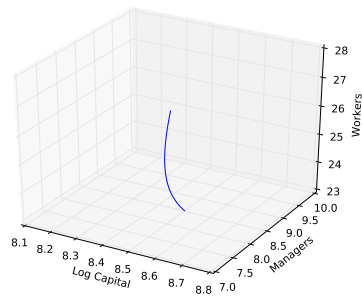
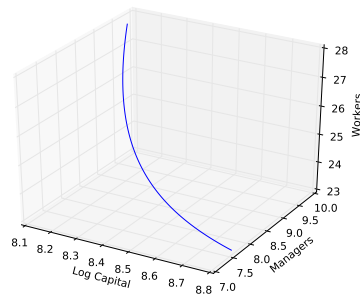


Figure B.5: Incumbent plants. Demand predictions for capital, managers, and workers: Predictions are based on the IV elasticities from Table B.3. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Incumbent plants are defined as establishments that reported production in t and in $t - 1$.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.6: Incumbent plants. Demand predictions for capital, managers, and workers: Pre and post-reform periods: Predictions are based on the IV elasticities from Table B.3. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Incumbent plants are defined as establishments that reported production in t and in $t - 1$.

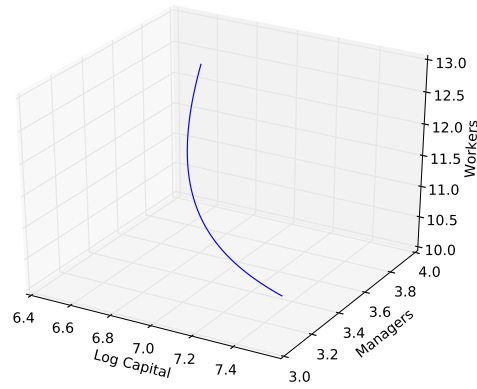
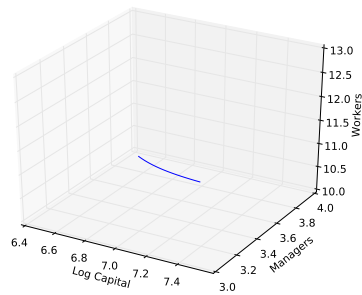
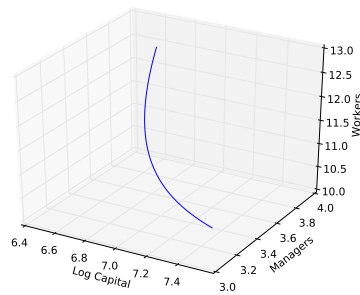


Figure B.7: Entry plants. Demand predictions for capital, managers, and workers: Predictions are based on the IV elasticities from Table B.4. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Entry plants are defined as establishments that reported production in t but not in $t - 1$.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.8: Entry plants. Demand predictions for capital, managers, and workers: Pre and post-reform periods: Predictions are based on the IV elasticities from Table B.4. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Entry plants are defined as establishments that reported production in t but not in $t - 1$.

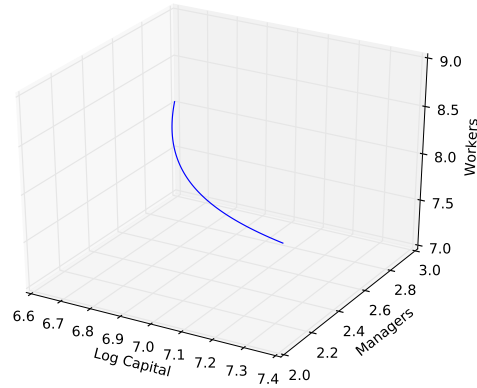
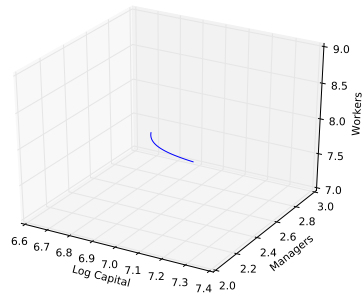
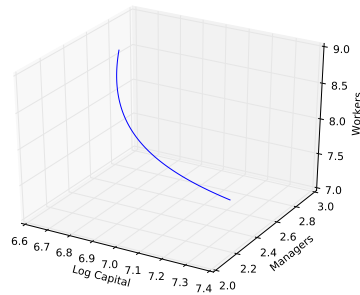


Figure B.9: Small plants. Demand predictions for capital, managers, and workers: The predictions are based on the IV elasticities from Table B.5. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Small plants are defined as establishments with a number of employees below the percentile 33 in the sample (17 employees).



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.10: Small plants. Demand predictions for capital, managers, and workers. Pre and post-reform elasticities: Predictions are based on the IV elasticities from Table B.5. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Small plants are defined as establishments with a number of employees below the percentile 33 in the sample (17 employees).

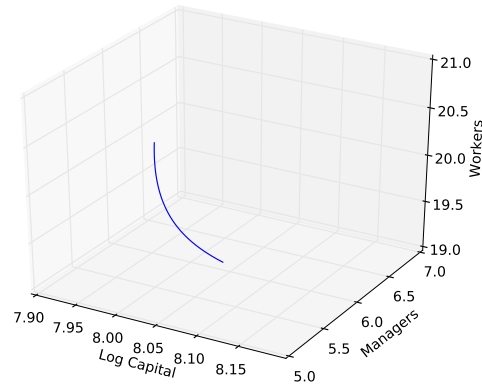
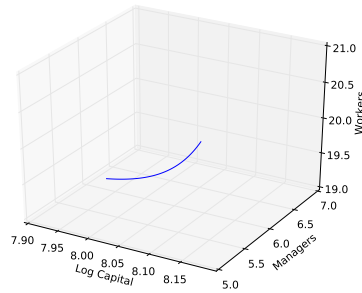
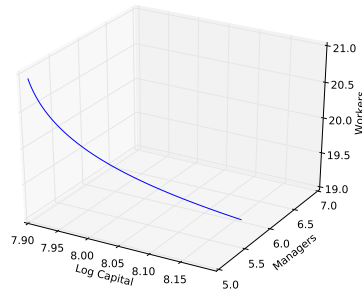


Figure B.11: Medium plants. Demand predictions for capital, managers, and workers: The predictions are based on the IV elasticities from Table B.6. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Medium plants are defined as establishments with a number of employees between the percentile 33 (17 employees) and percentile 66 (44 employees) in the sample.



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.12: Medium plants. Demand predictions for capital, managers, and workers. Pre and post-reform elasticities: Predictions are based on the IV elasticities from Table B.6. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Medium plants are defined as establishments with a number of employees between the percentile 33 (17 employees) and percentile 66 (44 employees) in the sample.

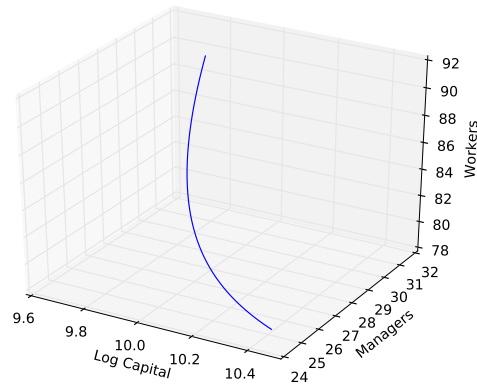
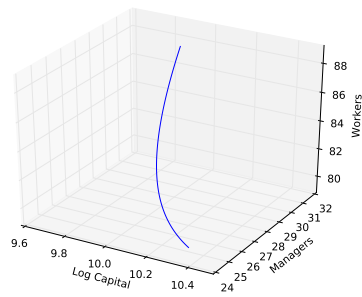
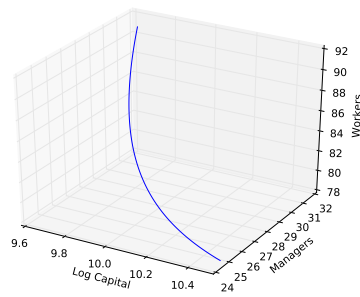


Figure B.13: Large plants. Demand predictions for capital, managers, and workers: The predictions are based on the IV elasticities from Table B.7. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Large plants are defined as establishments with a number of employees above the percentile 66 in the sample (44 employees).



(a) Pre-Reform Period



(b) Post-Reform Period

Figure B.14: Large plants. Demand predictions for capital, managers, and workers. Pre and post-Reform elasticities: Predictions are based on the IV elasticities from Table B.7. The Capital Cost Index simulation starts at three times its 1982 level, falling down continuously to 50 per cent of its 1982 level. Large plants are defined as establishments with a number of employees above the percentile 66 in the sample (44 employees).

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.653*** (0.068)	0.651*** (0.068)	0.682*** (0.061)	0.682*** (0.061)	0.683*** (0.055)	0.683*** (0.055)
Relative Capital Cost Index	-0.343*** (0.066)	-0.161** (0.052)				
Relative Capital Cost Index x PR		-0.372** (0.115)				
Relative Industrial Wage Index			-0.330*** (0.088)	-0.173* (0.068)		
Relative Industrial Wage Index x PR				-0.275** (0.104)		
Relative Minimum Wage Index					-0.178** (0.066)	-0.0820 (0.053)
Relative Minimum Wage Index X PR						-0.178* (0.078)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.694*** (0.072)	0.695*** (0.072)	0.721*** (0.074)	0.721*** (0.074)	0.726*** (0.075)	0.726*** (0.075)
Relative Capital Cost Index	0.808*** (0.134)	0.623*** (0.089)				
Relative Capital Cost Index x PR		0.384** (0.134)				
Relative Industrial Wage Index			0.883*** (0.148)	0.700*** (0.098)		
Relative Industrial Wage Index x PR				0.322* (0.131)		
Relative Minimum Wage Index					0.874*** (0.147)	0.689*** (0.102)
Relative Minimum Wage Index X PR						0.344* (0.135)
Constant	7.833*** (0.415)	7.622*** (0.407)	7.784*** (0.417)	7.582*** (0.414)	7.725*** (0.423)	7.520*** (0.422)
Observations	74,775	74,775	73,109	73,109	75,902	75,902
Number of id	8,439	8,439	8,304	8,304	8,539	8,539
Adjusted R^2	0.253	0.255	0.268	0.269	0.267	0.268
F	86.29	81.20	85.05	99.43	89.99	88.34

Table B.1: Input demands for survivor plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Survivor plants are defined as establishments that reported production in t and in $t + 1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.803*** (0.220)	0.803*** (0.221)	0.629*** (0.069)	0.629*** (0.069)	0.585*** (0.075)	0.585*** (0.076)
Relative Capital Cost Index	-0.390 (0.311)	0.00917 (0.506)				
Relative Capital Cost Index x PR		-0.453 (0.525)				
Relative Industrial Wage Index			-0.410** (0.145)	-0.399 (0.228)		
Relative Industrial Wage Index x PR				-0.0120 (0.134)		
Relative Minimum Wage Index					-0.299* (0.120)	-0.394* (0.155)
Relative Minimum Wage Index X PR						0.105 (0.127)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.656*** (0.087)	0.655*** (0.087)	0.764*** (0.086)	0.764*** (0.085)	0.750*** (0.100)	0.750*** (0.099)
Relative Capital Cost Index	1.216*** (0.124)	1.003*** (0.185)				
Relative Capital Cost Index x PR		0.241 (0.181)				
Relative Industrial Wage Index			1.195*** (0.094)	0.951*** (0.170)		
Relative Industrial Wage Index x PR				0.264 (0.166)		
Relative Minimum Wage Index					1.366*** (0.135)	1.142*** (0.167)
Relative Minimum Wage Index X PR						0.248 (0.129)
Constant	7.960*** (0.411)	7.732*** (0.410)	7.494*** (0.469)	7.229*** (0.486)	7.780*** (0.504)	7.540*** (0.522)
Observations	1,746	1,746	1,836	1,836	2,127	2,127
Number of id	823	823	850	850	983	983
Adjusted R^2	0.243	0.244	0.247	0.248	0.246	0.247
F	76.74	70.41	65.21	66.13	59.31	58.55

Table B.2: Input demands for exit plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Exit plants are defined as establishments that reported production in t but not in $t + 1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Manages	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.541*** (0.047)	0.540*** (0.047)	0.640*** (0.051)	0.640*** (0.052)	0.645*** (0.047)	0.645*** (0.047)
Relative Capital Cost Index	-0.264*** (0.054)	-0.0999* (0.044)				
Relative Capital Cost Index x PR		-0.286*** (0.085)				
Relative Industrial Wage Index			-0.313*** (0.079)	-0.169* (0.076)		
Relative Industrial Wage Index x PR				-0.217** (0.080)		
Relative Minimum Wage Index					-0.211*** (0.057)	-0.132* (0.054)
Relative Minimum Wage Index X PR						-0.126 (0.065)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.774*** (0.074)	0.774*** (0.074)	0.777*** (0.078)	0.777*** (0.078)	0.782*** (0.077)	0.782*** (0.077)
Relative Capital Cost Index	0.908*** (0.128)	0.717*** (0.101)				
Relative Capital Cost Index x PR		0.333** (0.112)				
Relative Industrial Wage Index			0.988*** (0.146)	0.807*** (0.111)		
Relative Industrial Wage Index x PR				0.272* (0.113)		
Relative Minimum Wage Index					0.982*** (0.145)	0.802*** (0.118)
Relative Minimum Wage Index X PR						0.286* (0.108)
Constant	7.621*** (0.418)	7.404*** (0.406)	7.666*** (0.415)	7.474*** (0.409)	7.620*** (0.422)	7.427*** (0.416)
Observations	75,708	75,708	72,494	72,494	75,135	75,135
Number of id	8,510	8,510	8,224	8,224	8,442	8,442
Adjusted R^2	0.244	0.246	0.249	0.250	0.248	0.249
F	75.73	64.74	57.76	51.69	75.30	66.99

Table B.3: Input demands for incumbent plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Incumbent plants are defined as establishments that reported production in t and in $t - 1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Manages	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.834*** (0.131)	0.847*** (0.137)	0.548*** (0.100)	0.548*** (0.097)	0.552*** (0.106)	0.555*** (0.105)
Relative Capital Cost Index	-0.520 (0.301)	-0.209 (0.629)				
Relative Capital Cost Index x PR		-0.299 (0.440)				
Relative Industrial Wage Index			-0.312* (0.146)	0.0172 (0.292)		
Relative Industrial Wage Index x PR				-0.338 (0.202)		
Relative Minimum Wage Index					-0.239* (0.105)	-0.0429 (0.203)
Relative Minimum Wage Index X PR						-0.209 (0.229)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.632*** (0.106)	0.616*** (0.108)	0.651*** (0.083)	0.651*** (0.081)	0.723*** (0.104)	0.717*** (0.102)
Relative Capital Cost Index	0.183 (0.234)	-0.459 (0.407)				
Relative Capital Cost Index x PR		0.613 (0.319)				
Relative Industrial Wage Index			0.726 (0.441)	0.123 (0.408)		
Relative Industrial Wage Index x PR				0.617 (0.324)		
Relative Minimum Wage Index					0.527 (0.384)	0.0548 (0.358)
Relative Minimum Wage Index X PR						0.501 (0.257)
Constant	7.095*** (0.624)	6.440*** (0.666)	7.510*** (0.758)	6.860*** (0.705)	6.899*** (0.813)	6.411*** (0.765)
Observations	678	678	1,568	1,568	1,860	1,860
Number of id	333	333	736	736	869	869
Adjusted R^2	0.185	0.194	0.187	0.193	0.187	0.191
F	8.696	14.89	23.79	23.77	14.94	15.36

Table B.4: Input demands for entry plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Entry plants are defined as establishments that reported production in t but not in $t - 1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.425*** (0.116)	0.422*** (0.115)	0.437*** (0.085)	0.436*** (0.085)	0.337*** (0.060)	0.336*** (0.059)
Relative Capital Cost Index	-0.335 (0.174)	-0.163 (0.171)				
Relative Capital Cost Index x PR		-0.281** (0.097)				
Relative Industrial Wage Index			-0.289* (0.119)	-0.132 (0.080)		
Relative Industrial Wage Index x PR				-0.231** (0.079)		
Relative Minimum Wage Index					-0.104 (0.085)	0.00489 (0.072)
Relative Minimum Wage Index X PR						-0.170*** (0.049)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.543*** (0.098)	0.545*** (0.098)	0.563*** (0.092)	0.564*** (0.092)	0.562*** (0.094)	0.563*** (0.094)
Relative Capital Cost Index	0.857*** (0.201)	0.589*** (0.153)				
Relative Capital Cost Index x PR		0.446** (0.122)				
Relative Industrial Wage Index			1.005*** (0.217)	0.710*** (0.166)		
Relative Industrial Wage Index x PR				0.436** (0.125)		
Relative Minimum Wage Index					0.951*** (0.223)	0.667*** (0.176)
Relative Minimum Wage Index X PR						0.446*** (0.121)
Constant	7.840*** (0.581)	7.533*** (0.550)	7.899*** (0.562)	7.570*** (0.538)	7.827*** (0.575)	7.509*** (0.548)
Observations	28,184	28,184	25,566	25,566	28,144	28,144
Number of id	5,116	5,116	4,787	4,787	5,076	5,076
Adjusted R^2	0.105	0.109	0.113	0.116	0.108	0.112
F	52.15	64.65	79.09	84.35	72.48	51.90

Table B.5: Input demands for small plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Small plants are defined as establishments with a number of employees below the percentile 33 in the sample (17 employees).

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.453*** (0.070)	0.452*** (0.070)	0.351*** (0.052)	0.351*** (0.052)	0.310*** (0.039)	0.310*** (0.039)
Relative Capital	-0.0711 (0.080)	0.0795 (0.088)				
Relative Capital Cost Index x PR		-0.312** (0.095)				
Relative Industrial Wage Index			-0.125 (0.066)	-0.0345 (0.067)		
Relative Industrial Wage Index x PR				-0.154* (0.061)		
Relative Minimum Wage Index					-0.0557 (0.042)	-0.0535 (0.041)
Relative Minimum Wage Index X PR						-0.00401 (0.037)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.679*** (0.085)	0.679*** (0.085)	0.699*** (0.082)	0.699*** (0.082)	0.704*** (0.082)	0.704*** (0.082)
Relative Capital	0.669*** (0.088)	0.543*** (0.081)				
Relative Capital Cost Index x PR		0.263* (0.099)				
Relative Industrial Wage Index			0.741*** (0.096)	0.618*** (0.084)		
Relative Industrial Wage Index x PR				0.208* (0.088)		
Relative Minimum Wage Index					0.727*** (0.100)	0.615*** (0.088)
Relative Minimum Wage Index X PR						0.201* (0.082)
Constant	7.463*** (0.480)	7.322*** (0.480)	7.428*** (0.474)	7.295*** (0.469)	7.387*** (0.481)	7.265*** (0.472)
Observations	26,319	26,319	26,468	26,468	27,177	27,177
Number of id	4,421	4,421	4,458	4,458	4,533	4,533
Adjusted R^2	0.205	0.206	0.213	0.213	0.215	0.216
F	45.13	34.72	56.54	48.99	68.18	56.04

Table B.6: Input demands for medium plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Medium plants are defined as establishments with a number of employees between the percentile 33 (17 employees) and percentile 66 (44 employees) in the sample.

	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Managers	Managers	Workers	Workers
<i>Panel A. Second Stage</i>						
Output	0.646*** (0.083)	0.647*** (0.082)	0.662*** (0.089)	0.662*** (0.088)	0.580*** (0.087)	0.580*** (0.086)
Relative Capital	-0.371*** (0.097)	-0.252* (0.112)				
Cost Index						
Relative Capital Cost Index x PR		-0.212* (0.099)				
Relative Industrial Wage Index			-0.337*** (0.075)	-0.330*** (0.097)		
Relative Industrial Wage Index x PR				-0.0108 (0.103)		
Relative Minimum Wage Index					-0.198*** (0.056)	-0.150* (0.064)
Relative Minimum Wage Index X PR						-0.0799 (0.087)
<i>Panel B. First Stage. Dependent Variable: Output</i>						
Demand Shocks	0.613*** (0.102)	0.613*** (0.102)	0.639*** (0.107)	0.638*** (0.107)	0.641*** (0.105)	0.640*** (0.105)
Relative Capital	0.727*** (0.126)	0.619*** (0.091)				
Cost Index						
Relative Capital Cost Index x PR		0.191 (0.139)				
Relative Industrial Wage Index			0.799*** (0.146)	0.702*** (0.105)		
Relative Industrial Wage Index x PR				0.152 (0.139)		
Relative Minimum Wage Index					0.798*** (0.143)	0.709*** (0.106)
Relative Minimum Wage Index X PR						0.145 (0.134)
Constant	9.121*** (0.516)	9.005*** (0.509)	9.038*** (0.532)	8.934*** (0.529)	9.032*** (0.518)	8.938*** (0.515)
Observations	29,907	29,907	30,127	30,127	30,371	30,371
Number of id	3,309	3,309	3,344	3,344	3,353	3,353
Adjusted R^2	0.288	0.289	0.294	0.294	0.293	0.294
F	81.91	89.20	80.15	81.01	71.93	75.77

Table B.7: Input demands for large plants: capital, managers, and workers. IV Estimations: Standard errors clustered at the three-digit sector level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables are in logs. The Relative Minimum Wage Index is calculated as the ratio of The Minimum Wage Index to the sum of the Capital Cost Index, the Industrial Wage Index and the Materials Price Index. The Energy Price Index was not included due to its abnormal volatility in the sample. $PR = 1$ for post-reform years (1991-1998). Demand Shocks with different sector elasticities come from Eslava et al. (2004). Columns (1) through (6) include plant and time fixed effects. Large plants are defined as establishments with a number of employees above the percentile 66 in the sample (44 employees).