Essays on Skilled Labor Force and Structural Transformations

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Chapter 1

Introduction

The phenomenon of structural transformation has been widely analyzed over time. In general, in the process of growth, economies move from less productive sectors to most productive sectors, i.e. from agriculture to industry and, then, to services. At the same time that this phenomenon has happened in most economies, the relative share of skilled workers —those with tertiary education —has increased. The allocation of these skilled workers during structural transformation has been a critical fact for economies to end up in different levels of income and to move towards different sectors. The present thesis consists of three empirical and theoretical essays studying this critical fact. In these essays directed technical change theory and multisector analysis are the fundamentals.

Acemoglu (1998, 2002) argues that when skilled and unskilled workers are weak substitutes then, if the market size effect dominates the price effect, technical change is directed towards the more abundant factor, which increases the productivity of skilled workers. This theory explains the increase in skill premium and, then, it is vital for the allocation of skilled workers to most productive sectors.

The multisector analysis carried out in many studies on structural transformation has unveiled important differences and patterns among economic sectors; see Timmer and de Vries (2009), Duarte and Restuccia (2010), García-Santana et al. (2016), Święcki (2017), Buera et al. (2018), and Herrendorf and Schoellman (2018). Following this insight, six economic sectors are considered in this thesis: Agriculture, High-Tech Industry, Low-Tech Industry, Unskilled Services, Skilled Market Services, and Skilled Non-Market Services. Following Herrendorf and Schoellman (2018) the less productive sectors—or low TFP sectors—are Agriculture, Low-Tech Industry, and Unskilled Services. While the most productive sectors—or high TFP sectors—are High-Tech Industry, Skilled Market Services, and Skilled Non-Market Services. It is important to note that it is the government that decides wages in this last sector and, therefore, allocation of skilled workers in this sector would be driven by economic forces different from those in the market.

The second chapter of the thesis, *Structural Change and the Income of Nations*, is a joint work with Fernando Sánchez-Losada. It looks at the necessary condition that has to exist during structural transformation for skilled workers to be allocated in high TFP sectors. Skilled workers might end up in either high or low TFP sectors, according to two opposite theories of structural change—skill-biased structural transformation and stagnant structural transformation—. It is shown that the existence of directed technical change is the necessary condition to achieve skill-biased structural transformation and, therefore, skilled workers are allocated to high TFP sectors. Macrodata and microdata evidence are used to identify the existence of directed technical change. In the macrodata approach an increasing relative TFP of skilled versus unskilled sectors reveals the existence of directed technical change. While in the microdata approach the interaction term between tertiary education and high TFP sectors in a GLS estimation of wages reveals it.

The results of the macrodata approach suggest that directed technical change has existed in the U.S., France and South Korea given an increasing relative TFP of skilled versus unskilled sectors. Then, skilled workers have been allocated to these sectors during structural transformation leading the economy towards high income levels. This finding is supported at micro level in which the coefficient of the interaction term between tertiary education and high TFP sectors is the highest and significant in the U.S., South Korea and France. Wages increase more if a worker has tertiary education and works in the High-Tech Industry (12.7% more in the U.S., 53.7% more in South Korea and 16.2% more in France) or in the Skilled Market Services (12.8% more in the U.S., 27.5% more in South Korea and 8.3% more in France) rather than in the Unskilled Services. Then, a skilled worker employed at a company in one of these sectors has the highest wage and does not have any incentive to move towards another sector. As a result, the existence of directed technical change in high TFP sectors is confirmed in the U.S., South Korea and France.

The third chapter, *Understanding Women: the Preference for the Skilled Non-Market Services Sector*, studies those characteristics that make skilled women move towards the Skilled Non-Market Services. Namely, in this joint work with Fernando Sánchez-Losada not only a multisector analysis is carried out but also a gender composition within them. It is a known fact that skilled female participation in labor markets has increased over time, but skilled men share is still higher than skilled women share in all economic sectors, except in the Skilled Non-Market Services sector. Why do skilled women end up working mostly in this sector during structural transformation? Our main hypothesis is that specific characteristics of this sector match empowered women's preferences and, then, this phenomenon is explained. Using data from the U.S. Labor Input File and the U.S. ASEC supplement to the CPS we identify three relevant characteristics of this sector: a small gender wage gap, low number of hours to work with a relatively high compensation, and better demographic indicators. A theoretical model that focuses on the preferences of an empowered woman is built. The first relevant characteristic of this sector matches the fact that as gender wage gap increases the fraction of her wage mass devoted to satisfy family consumption decreases in the theoretical model. The largest weight of "own" leisure and family consumption on utility matches the second relevant characteristic. The third characteristic matches the fact that in order for the fraction of her wage mass devoted to satisfy family consumption to increase, she has to work more hours and, then, she faces a high cost: a lower number of children. Then, the trade-off between marriage, having children and participating in the labor market is more favorable for those women in the Skilled Non-Market Services sector since it offers them lower hours to work and a relatively high compensation per hour worked. In order to support these findings a microdata approach is developed. Using data from U.S. ASEC supplement to the CPS the probability to end up working in the Skilled Non-Market Services sector is estimated. Other relevant characteristics that strength skilled women's preferences towards this sector are identified, i.e. a long run stability and job flexibility. Then, skilled women find a balanced trade-off between family and working life in this sector.

The fourth chapter, *The Role of Intangible Capital in Structural Transformation* provides a theoretical framework for understanding why the High-Tech Industry sector uses less services from other sectors as inputs than the Low-Tech Industry sector. Specifically, I focus my analysis on the elasticity of substitution between skilled workers and those characteristic services of industry: software and databases capital services, R&D capital services, and other intellectual property products (OIPP) capital services —known as intangible capital—. In this chapter, through a theoretical framework I study how the elasticity of substitution between intangibles and skilled workers determines whether a sector is skill-biased. I argue that intangibles and skilled workers are complements in high TFP sectors —High-Tech Industry—while they are substitutes in low TFP sectors —Low-Tech Industry—. Then, as investment in intangible capital increases, allocation of skilled workers rises in high TFP sectors. I also provide a microdata approach that shows that this phenomenon might be different in India. Specifically, I perform a linear and a quantile regression to analyze the impact of R&D units on firm' total cost of production. Results suggest that those firms in the highest quantile (90%) actually face lower total cost of production if they do not have a R&D unit and are firms in the High-Tech Industry. Moreover, I find that as the number of workers increases those firms in the highest quantile (90%) also face higher total cost of production if they are firms in the High-Tech Industry. Then, I argue that large firms in India might decide not to invest in R&D units and, as a consequence, they might neither hire skilled workers if they are in the High-Tech Industry sector. This finding might explain why the domestic services value added share of gross exports in the High-Tech Industry sector is higher than in the Low-Tech Industry sector in India, different from other countries.

Finally, the fifth and last chapter summarizes the overall conclusions and provides some proposals for future research.

Chapter 2

Structural Change and the Income of Nations

2.1 Introduction

An increase in tertiary educated labor force —skilled workers —is common across countries. According to the OECD, on average, 20.25% of the population had completed tertiary education in 1998 and rose to 36.91% in 2017. In the U.S., 19.11% of the population aged 25 and over had completed tertiary education in 1981 while in 2017 this number increased to 46.36%[1]. This increase in skilled labor supply has induced a change in the composition of the labor force in the U.S. In 2000, 31.36% of employees aged 25 and over were high school graduates and 31.11% had a bachelor's degree or higher, while in 2017 the proportion of high school graduates dropped to 24.95% and college graduates increased to 42.26%. Moreover, the wage gap between employees who hold a bachelor's degree or higher and high school graduates increased from 41.35% in 1980 to 79.63% in 2017[2].

Technological change theories such as directed technical change explain this increase in skill premium. Acemoglu (1998, 2002) argues that when skilled and unskilled workers are weak substitutes then, if the market size effect dominates the price effect[3], technical change is directed towards the more abundant factor, which increases the productivity of skilled workers. Profit maximizing firms decide to invest in skill-complementary technology due to an increase in relative skilled labor supply. Thus, an increase in human capital induces a skill-biased structural change if there is directed technical change and, then, structural transformation follows a path in which skilled workers are allocated to high TFP sectors. Buera et al. (2018) describe skill-biased structural change as the reallocation of sector value added shares towards high-skill intensive industries, causing an increase in skill premium.

There is another path for structural transformation. In this path, skilled workers are likely to end up in low TFP sectors. Baumol (1967) claimed that if the proportion of output remains between a stagnant sector (with constant labor productivity) and a progressive sector (with increasing labor productivity), production costs and prices would tend to rise

[1] See OECD (2018).

[2] Source: U.S. Bureau of Labor Statistics.

[3] The price effect consists of a reduction in relative skilled wage caused directly by this increase in relative skilled labor supply. The market size effect consists of an increase in relative skilled wage caused by the increase of relative skilled productivity when profit maximizing firms decide to invest in skill-complementary technology due to an increase in relative skilled labor supply.

in the stagnant sector and, therefore, the labor force would move from high TFP growth to low TFP growth sectors.

These opposite paths —stagnant sector structural change and skill-biased structural change —suggest that an increase in skilled workers does not determine by itself whether the economy will achieve high income levels during structural transformation (hereafter, an economy with high income levels is one that is converging with the U.S.; economies are considered to have low income levels otherwise). This chapter provides evidence that an increase in human capital should co-exist with directed technical change for an economy to end up in high income levels. The macrodata and microdata evidence provided helps us to ascertain whether an economy has experienced directed technical change during its structural transformation. The macrodata evidence considers six economic sectors[4] and the existence of directed technical change is identified through an analysis of the relative TFP of skilled versus unskilled sectors and the relative factors used in the production process. The increase in relative skilled TFP suggests the existence of directed technical change because profit maximizing firms develop skill-complementary technologies due to the increase of skilled labor force, which leads to a rise in relative skilled productivity increase. The microdata evidence identifies the existence of directed technical change through the analysis of a GLS estimation of wages as a function of variables, such as workers' education level and economic sector. The highest value and significance of the coefficient of the interaction term between workers' education level and a high TFP economic sector point to the existence of directed technical change.

The rest of the chapter is organized as follows. Section 2.2 describes the literature. Section 2.3 shows how the existence of directed technical change can be identified through an analysis of relative skilled TFP. Section 2.4 presents a GLS panel data estimation for various countries and identifies the existence of directed technical change when the coefficient of the interaction term between the level of education and a high TFP economic sector is the highest and significant. Finally, Section 2.5 concludes.

2.2 Literature

This chapter builds on a rich and diverse literature on structural change, a phenomenon observed in the process of growth. The literature generally states that less productive workers are replaced by machines and allocated to other sectors. Thus, less productive workers are allocated first from agriculture to industry and, then, from industry to services. Because of this technological process and reallocation of the labor force, agriculture and industry tend to be the economy's most productive sectors and services tend to be the least productive sector. However, productivity in the services sector varies from one country to another. In high income countries, such as the U.S., labor productivity in services is higher than in low income countries. Moreover, low income countries show low productivity rates not only in the services sector, but in all sectors; see Timmer and de Vries (2009), Duarte and Restuccia (2010), García-Santana et al. (2016) and Święcki (2017). From a demand perspective, structural transformation occurs because of changes in aggregate demand structure. The consumption of goods relative to services differs between rich and poor households; see Boppart (2014). Most of the literature on structural transformation uses consumer non-homothetic prefer-

[4] Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services, Skilled Market Services, and Skilled Non-Market Services.

ences to explain the shift in consumption from agricultural goods to industrial goods and, successively, to services; see Comin et al. (2015). In view of the international evidence shown in all these papers, it seems that structural transformation, by itself, is not a guarantee for a country to achieve a high income per capita.

Jorgenson and Timmer (2011), Barany and Siegel (2017) and Cruz (2019) show that human capital is another important driver of structural transformation. Caselli and Coleman (2001) reveal how workers' skills differ across economic sectors. Skilled labor is increasing in all sectors across countries, affecting relative prices and investment in physical capital and making some economic sectors more productive than others. Therefore, skilled workers might drive structural change to different paths. In particular, there are two paths of structural transformation in which skilled workers can be placed. The first determines that the economy moves towards low TFP sectors and, then, skilled workers might go there. The second path is a skilled-biased structural change.

Beginning with the first path, Baumol (1967) claimed that economy moves towards the stagnant sector. Therefore, the labor force would move from high TFP growth to low TFP growth sectors. This has been theoretically explained from the supply side or the demand side. From the supply side, Ngai and Pissarides (2007) show that structural change depends on the differences in TFP growth rates across sectors and the elasticity of substitution between the goods produced in these sectors. In particular, when TFP growth rates differ among sectors and the elasticity of substitution among the final goods produced in each sector is lower than one —that is, they are complements—, then labor moves from high TFP growth to low TFP growth sectors. From the demand side, Kongsamut et al. (2001) propose a general balanced growth model that is consistent with the Kaldor facts and the massive reallocation of labor from one sector to the others. They use Stone-Geary preferences[5] to explain that when the income of households increases, the proportion of income spent on agricultural goods drops and the proportion spent on the other goods increases —that is, the Engel's Law—. Under a knife-edge condition, the economy grows at a constant rate while there is this shift towards the services sector.

The second path is a skill-biased structural change. This has been theoretically explained from a supply side or a demand side. From the demand side, Buera and Kaboski (2009, 2012) and Buera et al. (2018) describe the skill-biased structural change experienced in advanced economies[6] through a two-sector model —a high skilled labor sector (services) and a low skilled labor sector (goods)—that explains the rise of the skill premium caused by technical change. They assume non-homothetic preferences such that the expenditure share of services increases in income. They show that differences in relative wages are given by changes in the relative supply of high skilled labor, skill-biased technological change and other technological changes. They also suggest that industries could be organized by skill intensity. From the supply side, Rogerson (2008) finds that relative increases in taxes and technological catch-up can account for most of the differences between the European and American time allocations. In the services sector, he considers two types of production: home production —non-taxed substitutive services for those produced in the market—and taxed market production. Since skilled workers are mostly in market services and their productivity is higher than that of unskilled workers, market services productivity grows faster than home productivity.

[5]Stone-Geary preferences are often used to model problems involving subsistence levels of consumption. That is, a certain minimal level of some good has to be consumed regardless of its price and the consumer income before the individual decides to spend a positive amount on other goods.

[6]Australia, Austria, Denmark, France, Germany, Italy, Japan, Netherlands, South Korea, Spain, United Kingdom, and the United States.

Therefore, with an increase in skilled labor, these workers are reallocated into the market services sector and home production falls. He finds that hours worked in Europe decline by almost 45% compared to the U.S. over the analyzed period (1956-2003), which was almost entirely accounted for by the fact that Europe develops a much smaller market services sector than the U.S. Moreover, the U.S. has experienced a shift from home to market production. In addition, Timmer and de Vries (2009) find that productivity improvement in market services is greater than productivity growth in manufacturing. Herrendorf et al. (2014) show that sectoral productivity growth differences are the main factor behind structural transformation among broad sectors in the U.S. In a multi-sector model in which sector differences depend on human capital intensity, Herrendorf and Schoellman (2018) show that average wages in agriculture are lower than those in the other sectors and, at the same time, this sector has less educated workers. Thus, skilled workers end up in high TFP sectors. According to the skill-biased structural change, it seems that if a country increases its human capital, then it will reach this skill-biased structural change.

Acemoglu (1998, 2002) argues that there has been a directed technical change, at least for the U.S. He shows that the increase in relative skilled labor supply has two effects: a price effect and a market size effect. The elasticity of substitution between factors determines which of these two effects dominates. In particular, when both factors are complements, the price effect dominates and when both factors are weak substitutes[7], the market size effect dominates and, then, the relative skilled wage increases at the same time that there is a skill-biased technical change. Then, according to Acemoglu (1998, 2002), an increase in relative skilled workers will induce a skill-biased structural change in the presence of directed technical change.

The aforementioned literature does not address questions related to the final stage of structural transformation across high and low income countries. It suggests that all economies might follow the same path. This chapter highlights the importance of directed technical change in the final stage that an economy can reach during structural transformation when there is an increasing skilled labor supply. The rise of skilled workers might induce directed technical change or not. If these two phenomena do co-exist during structural change, an economy will end up in high TFP sectors. Similar to Kuralbayeva and Stefanski (2013), we develop macrodata and microdata approaches to identify the existence of directed technical change. However, similar to Buera et al. (2018) and Duernecker et al. (2017), we consider more than just the traditional sectors—agriculture, industry and services—. We find that the existence of directed technical change during structural transformation is needed for skilled workers to end up in high TFP sectors. Thus, not all the economies will necessarily follow the same pattern of structural change: some will end up in low TFP sectors —Low-Tech Industry and Unskilled Services—and some in high TFP sectors —High-Tech Industry and Skilled Market Services—. We show that directed technical change has occurred in high income countries such as the U.S., South Korea and France since the relative TFP of skilled sectors compared to unskilled ones has increased over time and relative wages are higher for tertiary educated workers who work in high TFP sectors. This finding can help us to understand why the gap in GDP per capita between South Korea and the U.S. is shrinking over time. Canada has not experienced a directed technical change and, then, its skilled workers have ended up in low TFP sectors during structural change. There is a lack of clear evidence of directed technical change for Italy and Spain.

[7]In particular, the elasticity of substitution has to be higher than 1 and lower than 2. There is general consensus that this is the case between skilled and unskilled workers.

2.3 Macrodata Evidence

2.3.1 Sectoral Facts

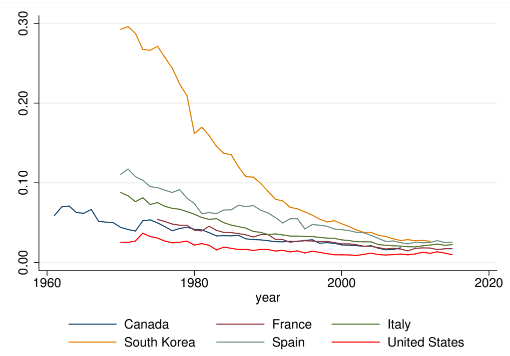
It is important to analyze how structural transformation has taken place in several economies. The usual structural transformation has been characterized by shifting the value added (and the labor force) out of the agriculture sector and allocating it first to the industry sector and, after, to the services sector. We analyze this structural transformation by dividing the economy into six sectors: Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services, Skilled Market Services, and Skilled Non-Market Services. We follow Herrendorf and Schoellman (2018), who consider that skilled services are those that employ workers with at least thirteen years of education on average, and Dix-Carneiro (2014), who uses the OECD criterion that classifies industries according to their technology intensity in the report "Towards a Knowledge Based Economy"[8]. We use EU KLEMS and WORLD KLEMS databases, which have sector information about value added, labor and capital for some countries. Figure 2.1 shows the share of value added of our six sectors for Canada, France, Italy, South Korea, Spain, and the U.S.[9]. We can see that the share of the value added of the Agriculture sector has decreased in all countries over time, as structural change theories predict. South Korea is the only country that exhibits an increasing tendency in the High-Tech Industry sector, a high TFP sector. This sector produced 5.71% of the total value added in 1970, which rose to 21.76% in 2012. The Unskilled Services sector rose considerably in Spain only; it produced 21.64% of the total value added in 1970 and 31.43% in 2017. Spain is the only country where this sector has the highest level of value added. The Skilled Market Services sector (the other high TFP sector in addition to the High-Tech Industry) also shows an increasing behavior in all these countries. In the U.S., this sector produced 20.36% of the total value added in 1970 and rose to 31.69% in 2015. France, Italy and the U.S. show similar patterns in production but have shifted from Unskilled Services to Skilled Market Services in different periods of time[10]. Canada shows relatively constant behavior of its sectors over time. Figure 2.2 compares the share of the value added produced by high TFP sectors relative to the U.S. The share of value added of the High-Tech Industry sector in South Korea is much higher than in the U.S. over time and shows a constant increase.

[8] In addition to Herrendorf and Schoellman (2018), we classify the skilled services sector into Skilled Market Services (finance and insurance activities, real state activities, professional, scientific, technical, administrative and support service activities, and utilities) and Skilled Non-Market Services (education, health and public administration, and defense). The Skilled Market Services sector is defined as the sector that uses high skilled labor at the same time that prices and wages are determined by the market. This latter assumption is important given that the income determined by these prices is expected to be higher than in other market sectors. We make the distinction between Market and Non-Market Skilled Services because it is the government that decides the wages and, therefore, the value added in the Skilled Non-Market Services. In fact, and in general, these wages are the same for the same job in the geographical area they are provided. These skilled services have a greater resemblance to market services when they are provided at regional or municipal level. Then, wages do not necessarily capture the differences in productivity between skilled and unskilled workers. Furthermore, we also divide the industry sector into High-Tech and Low-Tech Industry, as in Dix-Carneiro (2014), classifying according to the technology intensity. High-Tech Industry includes alcohol production, nuclear fuels, oil refining, coke, chemical products, machinery and equipment, office, accounting and computing machinery, electrical machinery and apparatus, radio, television and communications equipment, medical, precision and optical instruments, motor vehicles, trailers and semi-trailers, and other transportation equipment. Low-Tech Industry includes food and beverage, tobacco products, textiles, apparel, leather products and footwear, wood products, paper, cellulose, paper products, editing and printing, rubber and plastic products, non-metallic mineral products, basic metals, fabricated metal products (except machinery and equipment), furniture, and recycling.

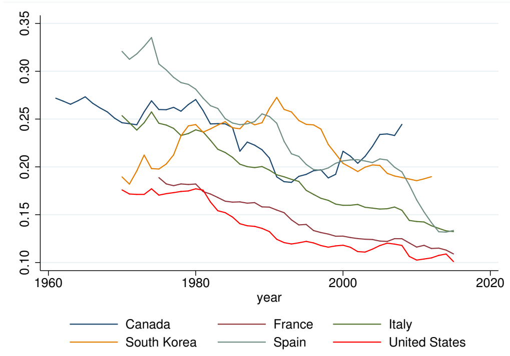
[9] Given that in Section 2.4 we make a complementary analysis with microdata information, we will refer only to those countries for which we have available data at both levels —micro and macro—.

[10] See Figure 2A2 in Appendix.

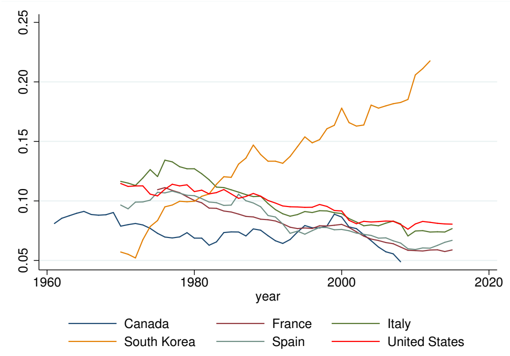
The other analyzed countries show declining and lower shares of the value added of this sector compared to the U.S. Regarding the Skilled Market Services, South Korea shows a constant increase in the share of value added of this sector, but it is still lower than the U.S. The evolution of this sector in France is similar to the U.S. The other European countries —Spain and Italy—also show increasing shares of the value added of this sector compared to the U.S. but a slower rate than South Korea.



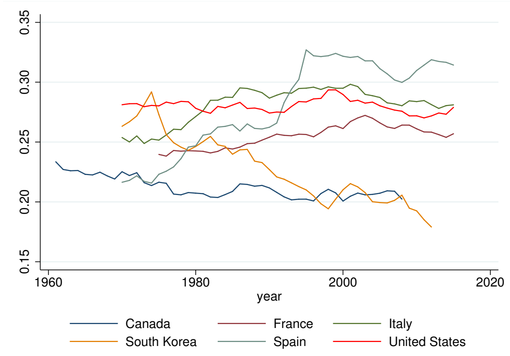
(a) Agriculture



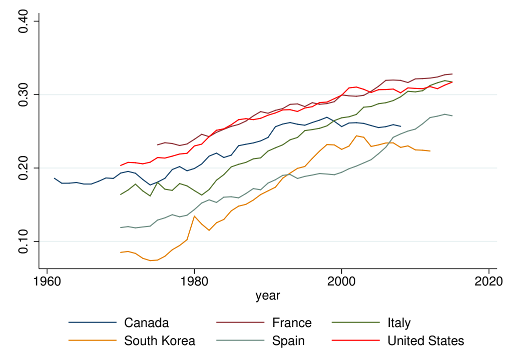
(b) Low-Tech Industry



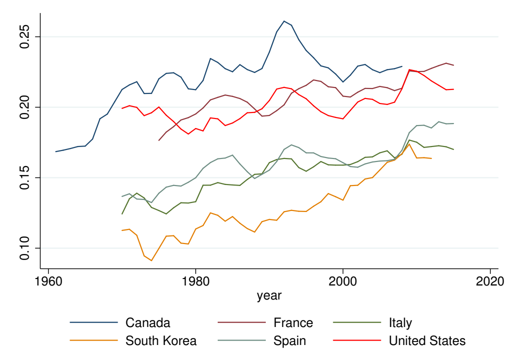
(c) High-Tech Industry



(d) Unskilled Services



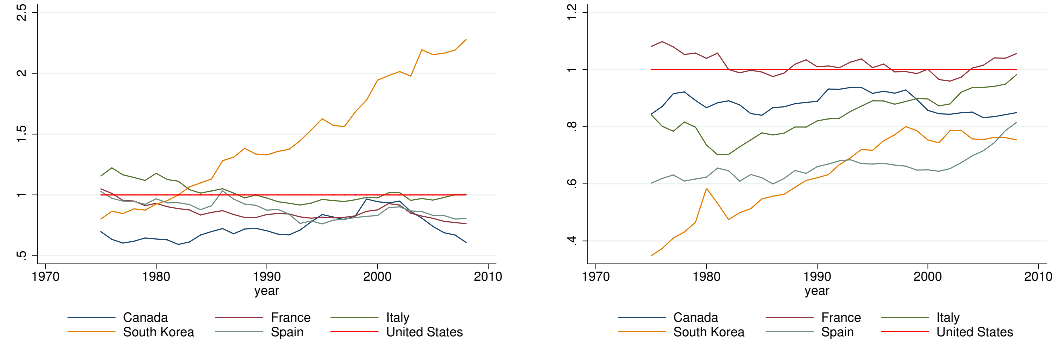
(e) Skilled Market Services



(f) Skilled Non-Market Services

Figure 2.1: Share of Value Added

Source: EU KLEMS and WORLD KLEMS Databases.



(a) High-Tech Industry **(b)** Skilled Market Services

Figure 2.2: Share of Value Added Compared to the U.S.

Source: EU KLEMS and WORLD KLEMS Databases.

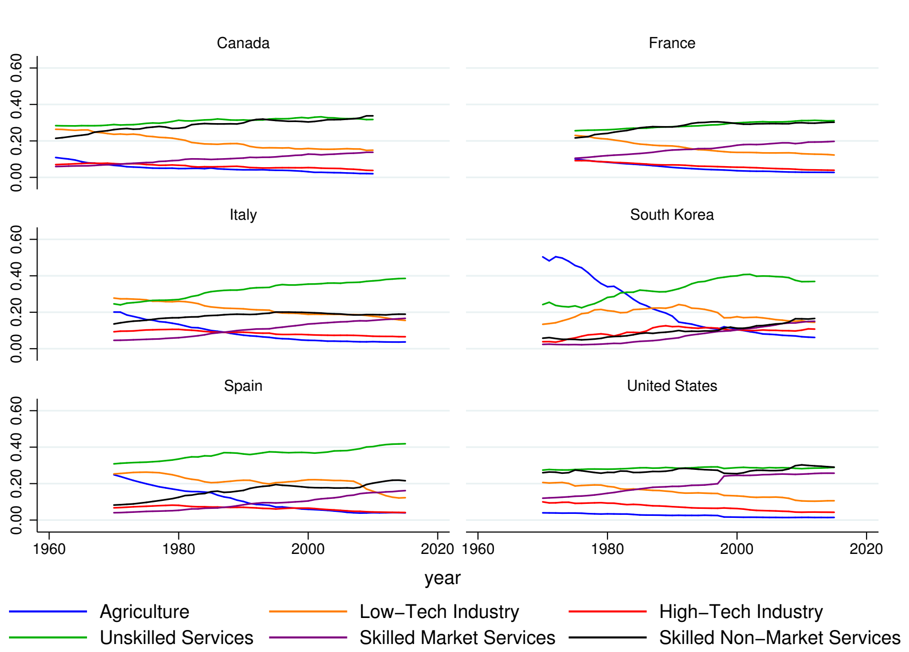


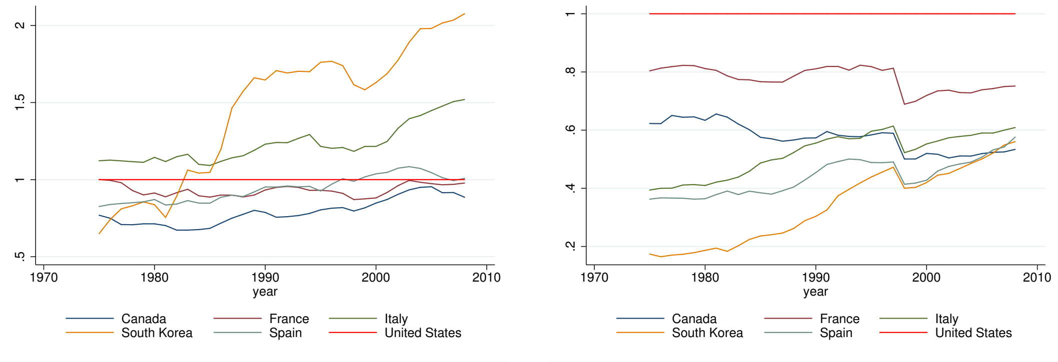
Figure 2.3: Share of Labor

Source: EU KLEMS and WORLD KLEMS Databases.

Having described the value added evolution, we now look at the reallocation of the labor force. Figure 2.3 shows that the labor force has been allocated as structural change theories suggest —from agriculture to industry and, then, from industry to services—. Canada and France have allocated the labor force mostly into the Unskilled Services and the Skilled Non-Market Services: in Canada, 65.51% of the total labor force in 2010 was working in these sectors while in France it was 61.35% in 2015[11]. In Italy, South Korea and Spain the labor force has been allocated mostly in the Unskilled Services sector over time: in Italy, 38.57% of the total labor force in 2015 was working in this sector while in South Korea it was 36.90% in 2012 and in Spain it was 41.88% in 2015. In the U.S., the labor force in the

[11] 31.75% of the total labor force in Canada was working in the Unskilled Services and 33.76% in the Skilled Non-Market Services in 2010 while in France these numbers were 31.10% and 30.25% in 2015, respectively.

Skilled Market Services sector has increased over time and has extended to nearly the same level of labor force in the Unskilled Services and the Skilled Non-Market Services: in the U.S., 25.71% of the total labor force in 2015 was working in the Skilled Market Services, 28.91% in the Unskilled Services and 29.04% in the Skilled Non-Market Services. Figure 2.4 compares the share of labor in high TFP sectors relative to the U.S. We see that the share of labor allocated into the High-Tech Industry in South Korea and Italy is higher than in the U.S. while the share of labor allocated into the Skilled Market Services sector in all of the analyzed countries is low compared to the U.S.[12]



(a) High-Tech Industry

(b) Skilled Market Services

Figure 2.4: Share of Labor Compared to the U.S.
Source: EU KLEMS and WORLD KLEMS Databases.

Our objective is to determine whether an increase of skilled labor supply leads an economy towards high income levels[13]. It is expected that if the increasing skilled labor supply is allocated in high TFP sectors, then the economy would end up in high income levels, since the value added produced by these sectors is always higher. Figure 3A1 shows that the value added of high TFP sectors indeed depends positively on the increase in the skilled labor force in the U.S., France, South Korea, Italy and Spain whereas it depends negatively on this increase in Canada[14]. This evidence shows that the increase of the skilled labor supply alone does not determine whether the economy will end up in high income levels. We argue that an economy ends up in high income levels if directed technical change exists at the same time that there is an increase in the skilled labor supply. As a result, if these two phenomena coexist, the gap in GDP per capita relative to the U.S. would shrink over time, as in South Korea[15] (South Korean GDP per capita increased from 17.37% of U.S. GDP in 1980 to 66.27% in 2017); see Figure 3.6.

[12]In the Appendix we include different figures that help to describe the evolution of labor and capital share in the analyzed countries.

[13]See Figure 2A1 in the Appendix for the share of population with completed tertiary education in the analyzed countries.

[14]The results of the linear fit are given in Tables 3A2 and 2A2 in the Appendix. We use data from EU KLEMS and WORLD KLEMS for the share of value added produced by the skilled and unskilled sectors. We use data from the OECD for the share of population with completed tertiary education. In Figure 3A1 and Tables 3A2 and 2A2 we use data from 1990 to 2008 for Canada, from 1997 to 2015 for France, from 1998 to 2015 for Italy, from 1997 to 2012 for South Korea, from 1997 to 2015 for Spain and from 1981 to 2015 for the U.S. We use these samples in each country since they have information about both the share of value added and the share of population with completed tertiary education.

[15]For France, Spain and Italy, the gap in GDP per capita relative to the U.S. might not shrink for reasons other than the non-existence of directed technical change: a decline of the hours worked compared to the U.S., the high level of unemployment and the relatively small number of skilled workers; see Rogerson (2008).

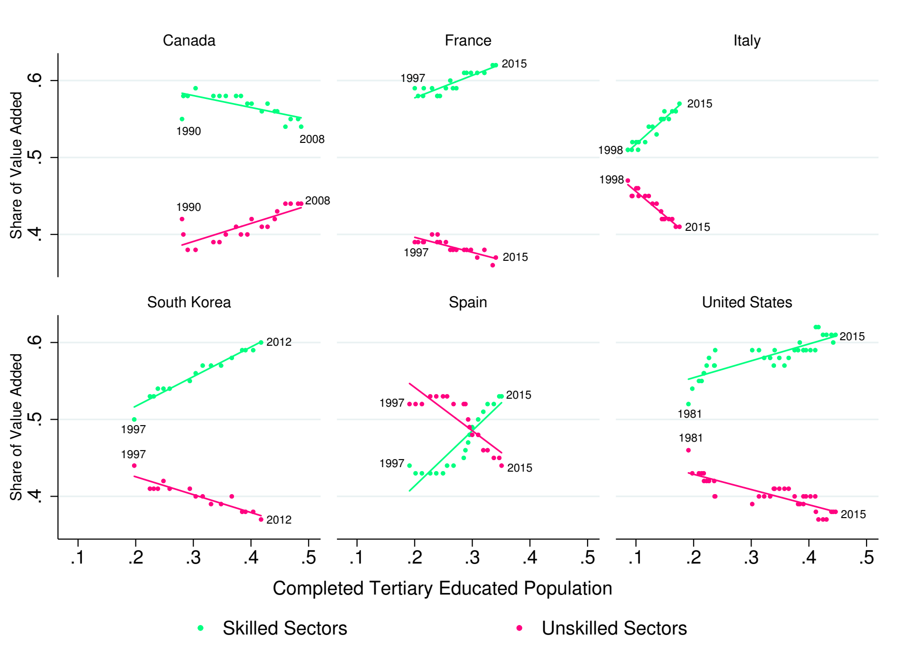


Figure 2.5: Share of Value Added of the Skilled and Unskilled Sectors vs Completed Tertiary Educated Population.

Source: EU KLEMS and WORLD KLEMS Databases and OECD.

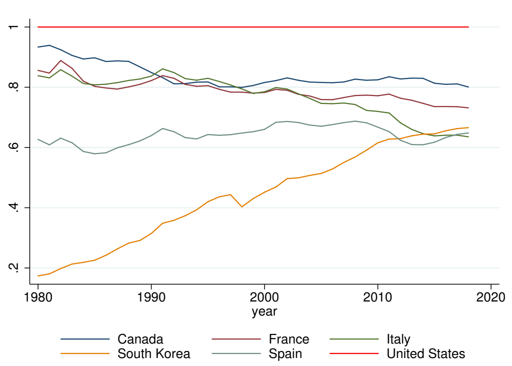


Figure 2.6: GDP per Capita Relative to U.S. GDP per Capita.

Source: World Economic Outlook.

In light of this evidence, it seems that the two patterns of structural change discussed in Section 2.2 can emerge when different countries are analyzed. Some countries may allocate their skilled workers in high TFP sectors in the process of structural transformation and others may not. What is important to assess is whether the increase in skilled workers occurred with a directed technical change. If this is the case, an economy would end up at high income levels after structural transformation since skilled workers would be allocated to high TFP sectors. To identify whether directed technical change exists during the structural transformation, we next make a Solow residual decomposition for skilled sectors relative to unskilled ones. Through the analysis of relative TFP, we can determine whether directed technical change has existed at the same time as the increase in skilled labor supply.

2.3.2 Solow Residual Decomposition

Acemoglu (1998) considers a unique final good that is produced from two inputs: one using skilled labor and the other using unskilled labor. To have directed technical change, the elasticity of substitution between both inputs has to be between 1 and 2. Instead we consider two different final goods in each sector: one produced using skilled labor and the other using unskilled labor, with elasticity of substitution between them in the utility function between 1 and 2. Thus, since the model is isomorphic to that of Acemoglu (1998), we would obtain the same conclusions. But now, we can do a Solow residual decomposition for each sector. This decomposition can be used to identify the relative supply of factors and, more importantly, the relative TFP. It is this relative TFP that will inform us whether directed technical change has existed.

Technology in each sector i is

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}, \tag{2.1}$$

where Y_i is the production of sector i, K_i is the amount of capital used in sector i, L_i is the labor force allocated to sector i, and A_i is the corresponding TFP for sector i. Taking logarithms on both sides of the equation and isolating the TFP term leads to

$$ln(A_i) = ln(Y_i) - \alpha ln(K_i) - (1-\alpha)ln(L_i). \tag{2.2}$$

Thus, the TFP for each sector can be identified. We assume the conventional value of $\alpha = 1/3$ for the share of capital in income. Once the sector specific TFP has been found, we can compute the relative share of TFP between sector i and j as

$$ln\left(\frac{A_i}{A_j}\right) = ln\left(\frac{Y_i}{Y_j}\right) - \alpha ln\left(\frac{K_i}{K_j}\right) - (1-\alpha)ln\left(\frac{L_i}{L_j}\right), i \neq j. \tag{2.3}$$

Given this equation, we can identify whether an increase in the relative skilled labor supply has indeed implied a directed technical change.

We calculate logarithms of the relative value added of the skilled sectors relative to the unskilled ones, the relative supply of labor, the relative accumulation of capital and the relative TFP. By analyzing the relative TFP we can conclude whether directed technical change has existed in the process of structural transformation and, then, whether the economy will end up in high income levels. If the relative TFP between skilled and unskilled sectors increases over time while there is also an increase in relative skilled labor, directed technical change has existed during structural transformation.

We use information provided in EU KLEMS and WORLD KLEMS databases. Basic and Capital Input Files are used to compute the shares of production —value added[16] —, labor and capital for the six sectors in the U.S., South Korea, Spain, Italy, France, and Canada. We use all the available information for each country[17]. We also use OECD information about the tertiary educated population aged 25 and over.

Given that structural transformation moves towards the services sector, we first analyze the relative TFP of this sector. Figure 3.7 shows that in general the relative TFP of the

[16] See Buera et al. (2018).

[17] U.S. and Spain: from 1970 to 2015. South Korea: from 1970 to 2012. Italy: from 1970 to 2015 for the value added and the share of labor and from 1995 to 2014 for the share of capital. France: from 1975 to 2015 for the value added and the share of labor and from 1978 to 2015 for the share of capital. Canada: from 1961 to 2010 for the shares of labor and capital and from 1961 to 2008 for the value added.

Skilled (Skilled Market and Skilled Non-Market; solid line) and the Skilled Market (dashed line) Services relative to the Unskilled Services seems to increase over time for the analyzed countries (left axis) at the same time that the number of tertiary educated workers increased (right axis). Relative accumulation of capital has diminished and relative TFP has increased while the skilled labor supply has also increased for countries such as South Korea, France and the U.S. Spain's relative TFP seems to have increased only in the last five years and, therefore, the increase in relative value added might be explained only by the increase in the relative share of labor and not by the increase in relative TFP. Because of the few observations available for Italy and the behavior of the relative accumulation of capital for Canada that seems to be flat, we could have an ambiguous interpretation of the evolution of relative TFP for these countries[18].

[18] If we analyze only the Skilled Market Services sector—dashed lines—we see that its relative TFP is above the relative TFP of the Skilled Services sector in all the countries. This fact indicates that the relative productivity of the Skilled Non-Market Services sector is lower than that of the Skilled Market Services sector. This means that the wages decided by the government are lower than those of the market.

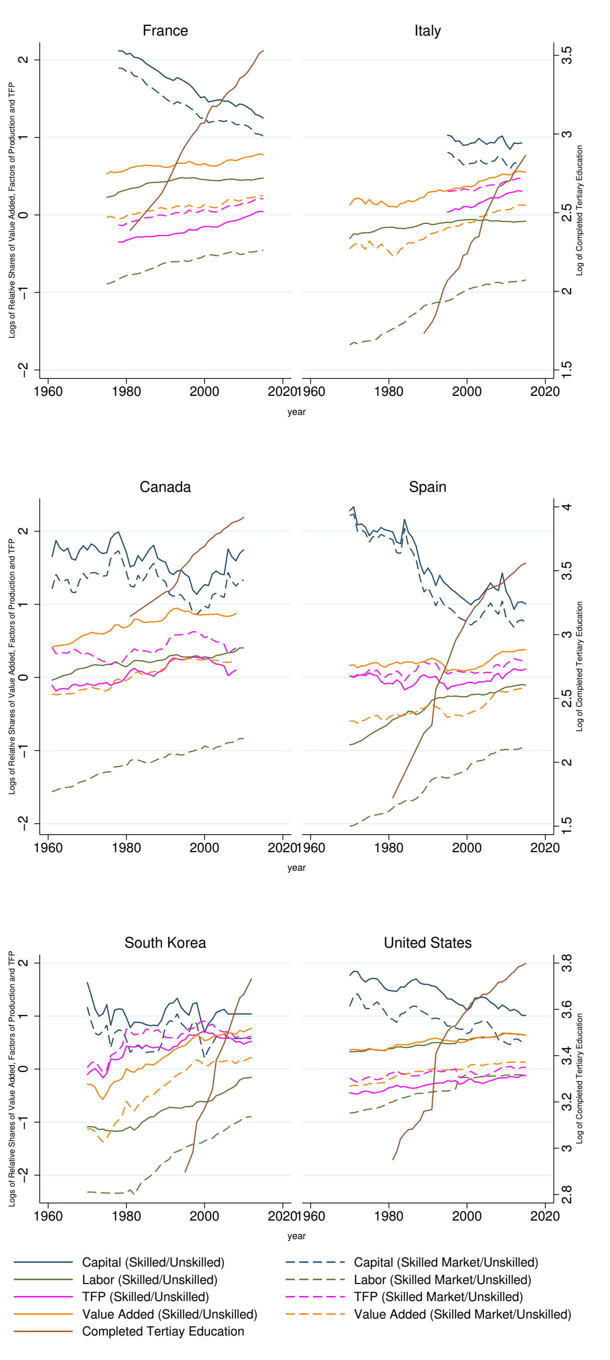


Figure 2.7: Relative Value Added, Relative Supply of Labor, Relative Accumulation of Capital, Relative TFP of the Skilled (and Skilled Market) Services Sector vs the Unskilled Services Sector - Completed Tertiary Education.

Source: EU KLEMS and WORLD KLEMS Databases.

Figure 2.8 shows the linear regression of the log of the relative TFP of the Skilled Services vs the Unskilled Services and the log of the share of completed tertiary educated population. The share of completed tertiary educated population has a positive impact on the relative TFP of the Skilled Services vs the Unskilled Services in France and the U.S. However, it shows a negative impact on South Korea. We believe that this unexpected finding for

South Korea is due to the few observations we have on the share of completed tertiary educated population. For this variable we only have 17 out of the 43 observations that determine the evolution of relative TFP in South Korea. The share of completed tertiary educated population also has a negative impact on relative TFP in Canada, which suggests that directed technical change has not occurred. The share of completed tertiary educated population has a positive impact on relative TFP in Italy and Spain as well. However, previous findings in the behavior of the relative TFP prevent us from drawing relevant conclusions for these countries. Given the insights of Figures 3.7 and 2.8, we might conclude that a directed technical change has occurred in the Skilled Services and in the Skilled Market Services sectors for South Korea, France and the U.S. It seems that directed technical change in these sectors has not yet taken place in Canada, and for Spain and Italy we cannot draw convincing conclusions.

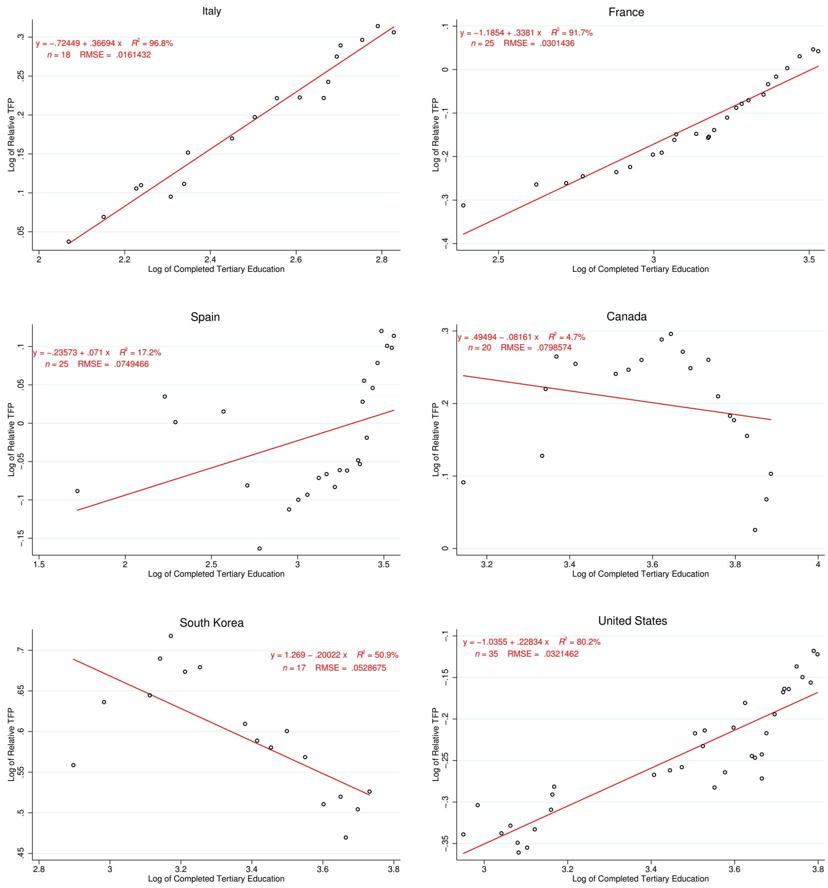


Figure 2.8: Regression of the Log of the Relative TFP —Skilled Services vs Unskilled Services —and the Log of Completed Tertiary Education.

Source: EU KLEMS and WORLD KLEMS Databases.

We now group all the high TFP sectors (Skilled Services and High-Tech Industry) and repeat the same analysis. We see in Figure 3.8 that the relative TFP shows almost the same behavior as before for almost all the economies. Spain's relative TFP has a higher slope than before, which indicates that there may have been a directed technical change in the High-Tech Industry. In addition, the relative TFP of Canada shows a flatter path, which suggests that at least for Canada, a directed technical change in high TFP sectors has not yet occurred. For Italy, we cannot draw relevant conclusions due to the short period of time for the capital series, which prevents us from analyzing how that economy has evolved.

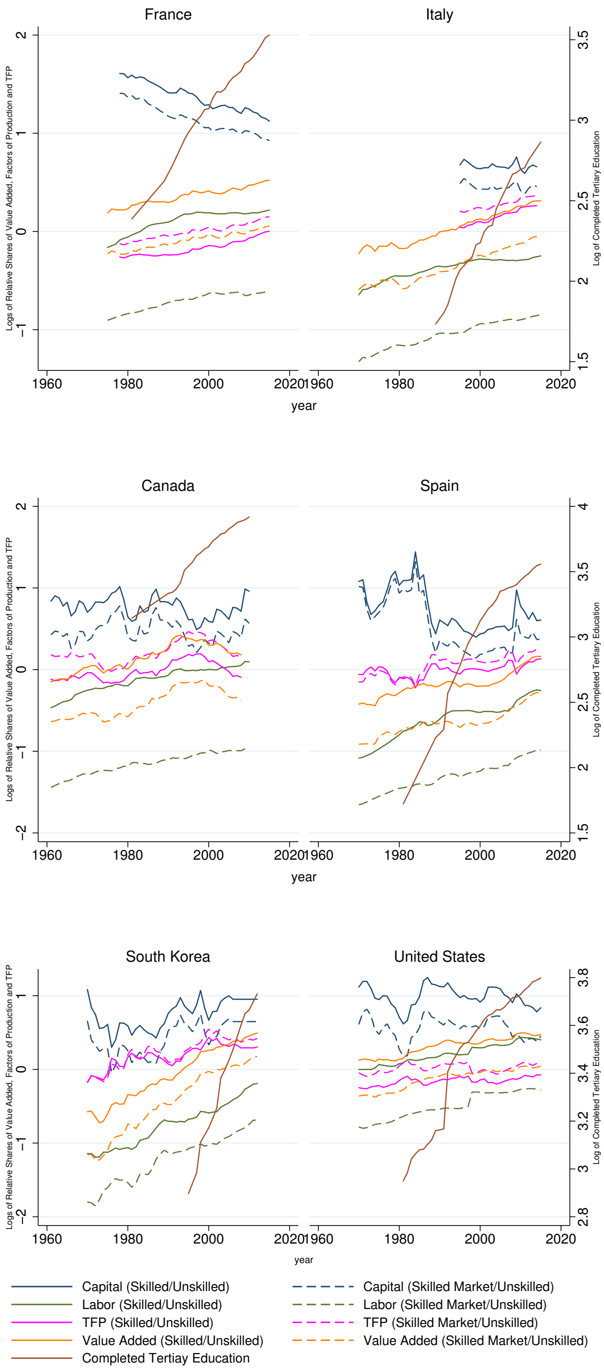


Figure 2.9: Relative Value Added, Relative Supply of Labor, Relative Accumulation of Capital, Relative TFP of the Skilled (and Skilled Market) Sectors vs the Unskilled Sectors - Completed Tertiary Education.

Source: EU KLEMS and WORLD KLEMS Databases.

Figure 2.10 supports the insights from Figure 3.8. The share of completed tertiary educated population has a positive effect on the relative TFP of the Skilled Sectors vs the Unskilled Sectors in France and the U.S. South Korea again shows a negative slope. However, it is now flatter than that of Figure 2.8. As previously stated, we consider that this unexpected finding for South Korea is due to the few observations we have for the share of completed tertiary educated population. Furthermore, we see a more negative impact of the share of completed tertiary educated population on the relative TFP of these sectors in Canada, which is consistent with the insights described in previous paragraphs. Lastly, the share of completed tertiary educated population has a positive impact on the relative TFP in Italy and Spain, but we face the same restrictions as before for these countries.

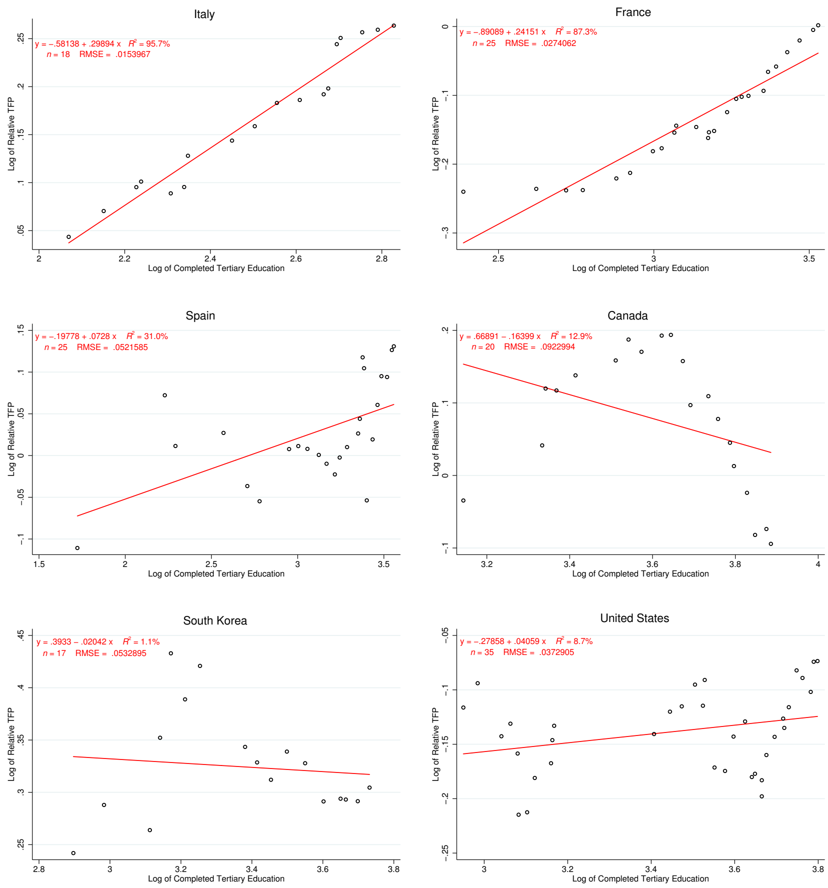


Figure 2.10: Regression of the Log of the Relative TFP —Skilled Sectors vs Unskilled Sectors—and the Log of Completed Tertiary Education.

Source: EU KLEMS and WORLD KLEMS Databases.

From the analysis in this section, we conclude first that it is key to consider more economic subsectors than the usual three sectors, to gain a deeper understanding of how structural change has evolved across countries. Second, an increasingly skilled labor supply is only a necessary condition to shift structural transformation towards high income sectors, but directed technical change is also required as it leads to skilled workers ending up in high TFP sectors. Moreover, an economy will follow one of the two possible paths of structural transformation depending on the existence of directed technical change. If an economy experiences directed technical change during structural transformation, we would see that the relative TFP of the skilled sectors versus the unskilled sectors rises. We would also see a positive impact of the share of completed tertiary educated population on the relative TFP of sectors. This is the case of France, South Korea and the U.S. As Canada shows a flat relative TFP, and a negative impact of the share of completed tertiary educated population on the relative TFP of sectors, we argue that directed technical change has not yet occurred in this economy. In Spain, we argue that directed technical change might have existed in the High-Tech Industry as the relative TFP increases when we consider not only the services sector but the industry sector. We do not draw any certain conclusions about Italy since we have few observations on capital accumulation and, then, on the relative TFP. Finally, we argue that the existence of directed technical change might drive a reduction in the GDP per capita gap relative to the U.S., as in South Korea[19].

To confirm our findings in this section, we next perform a GLS panel data estimation of wages as a function of education level and economic sectors. The results (in particular, the positive value and the significance of the coefficient of the interaction term between these variables) will inform us whether the increase in skilled labor supply has caused innovation by profit maximizing firms in the skilled sectors making the skill premium increase. This would lead to skilled workers ending up in high TFP sectors.

2.4 Microdata Evidence

2.4.1 Framework

The existence of directed technical change implies that an increase in the supply of skilled labor relative to unskilled labor makes the profits of innovating skill-complementary technologies increase, which triggers an increase in skilled workers' wages. If we assume that labor supply is inelastic at a given period of time, each worker will choose the sector that provides the highest wage, since utility is increasing in the wage. Consequently, given that the production of each sector is an indirect function of wage, we make a panel data estimation[20] where the wage is the endogenous variable and specific characteristics of workers are used as exogenous variables. The model specification is

$$ln(w_{ij}) = \beta_j s_j + \beta_x X_{ij} + \beta_E E_{ij} + \beta_I(s_j E_{ij}) + \beta_t t + \epsilon_{ij}, \tag{2.4}$$

where w_{ij} is the wage of worker i in a company of sector j, s_j is a sector dummy, X_{ij} are controls for characteristics of the worker —age, age square, gender, and geographic area—, E_{ij} is a dummy of the level of education of worker i in sector j, s_jE_{ij} is the interaction term between the level of education of worker i and the economic sector j of her company, β_t is the time fixed effect, and ϵ_{ij} is an i.i.d. error with zero mean.

We expect that the Mincer returns for skilled workers —those with completed tertiary education —will be higher than those for unskilled workers—those with non-completed tertiary education—. However, our emphasis is on the Mincer returns for skilled workers in high TFP sectors[21]. Therefore, we include the interaction term s_jE_{ij}. We expect the highest

[19] See Appendix for figures that plot each element in equation (3.9) and compare them across countries.

[20] In the data sets used, we can identify an individual—or a household—in different periods of time. However, these data sets are unbalanced.

[21] We make the same classification for sectors as in Section 2.3; i.e., we create a variable with the classification of the main economic activity of the company into Agriculture, Low-Tech Industry, High-Tech Industry,

value and significance of the coefficient of the interaction term between skilled workers and high TFP sectors if directed technical change exists.

2.4.2 Microdata

Table 2.1 describes the sources used for our microdata analysis. As mentioned earlier, we only present results for countries that have information available at micro and macro levels and, then, comparisons can be done[22]. In each data set, we drop those observations that did not have the required information to run the regression[23]. The main variables for the estimation such as wages, level of education and economic activity usually have some missing or unknown observations, so we drop these observations and perform the analysis with the remaining data set. We also use the CPI index (yearly, monthly or quarterly, depending on the frequency of the database) published by the OECD to calculate real wages and avoid ambiguous interpretations of salary increases owing to inflation. Given that there are a varying number of geographic areas across countries, we group them into four groups based on the last available GDP for each area, since we believe that firms in major cities are more likely to pay higher salaries and, then, we must control for that. We use the 25%, 50%, and 75% percentile of the GDP to create these groups. The geographical areas included in the 25% percentile will be the reference category in our estimations. Tables 2A3 to 3A1 in the Appendix show the results of GLS panel data estimations for the six countries mentioned before using the Unskilled Services sector as the category of reference. Model (1) does not include geographic controls nor time fixed effects. Model (2) includes geographic controls but no time fixed effects. Model (3) includes both. As this latter model gives the best estimates among the three models, we describe only its results below[24].

Table 2.1: Sources of Information for the Panel Data Estimation.

Country	Source
U.S.	**IPUMS International:** U.S. Labor Survey. Yearly available data: 1960, 1970, 1980, 1990, 2000, 2005, 2010.
South Korea	**Korea Labor Institute:** Korean Labor & Income Panel Study. Yearly available data: from 1998 to 2016.
France	**National Institute of Statistics and Economic Studies:** Labor Force Survey. Quarterly available data: from 2003 to 2012.
Canada	**Statistics Canada:** Labor Force Survey. Monthly available data: from 1997 to 2015.
Italy	**National Institute of Statistics:** Labor Force Survey. Quarterly available data: from 2009 to 2018.
Spain	**National Institute of Statistics:** Wage Structure Survey. Yearly available data: 2010, 2014.

Unskilled Services, Skilled Market Services, and Skilled Non-Market Services.

[22]IPUMS International has a wide data set at micro level for countries such as India, Indonesia, South Africa, Brazil, and others, which would have helped us to make a wider analysis. But the required information at macro level is not available for the value added, labor and accumulation of capital across sectors for these countries. Additionally, microdata information was requested for other countries for which we have information at macro level but, unfortunately, we could not access it.

[23]We do not use imputation techniques for individuals with missing or unknowns since these missing or unknowns are not only in the numerical variables but in the categorical variables. Moreover, the dropped observations had similar characteristics to observations that were kept for the estimation.

[24]The Wage Structure Survey of Spain does not include any geographic area information. Therefore, Table 3A1 only shows model (1) —with no geographic controls and no time fixed effects—and model (2) —with no geographic controls but with time fixed effects—. The results of model (2) are described in Tables 2.1 and 2.2.
We also use the Agriculture sector as the category of reference and we obtain the same conclusions for the existence of directed technical change in the U.S., South Korea, France, Canada and Italy; see Tables 3A3, 3A4, 2A11, 2A12, and 2A13 in the Appendix. The Wage Structure Survey of Spain does not include information about the Agriculture sector either.

2.4.3 Results: Mincer Returns by Sectors

Table 2.2 shows the results of the GLS estimation of Mincer returns by sector for the analyzed countries. We see that Mincer returns for tertiary education are positively high. The wages of workers who have completed tertiary education are 54.2% on average higher than those of workers who have non-completed tertiary education in the U.S., 12.9% in South Korea, 37.2% in France, 27.1% in Canada, 23.6% in Italy, and 47.0% in Spain.

Wages in the Low-Tech Industry and the Skilled Non-Market Services are higher than in the Unskilled Services: the Low-Tech Industry pays wages that are 18.1% higher than the Unskilled Services in the U.S., 3.7% in South Korea, 7.2% in France, 39.4% in Canada, 11.1% in Italy, and 17.3% in Spain; while the Skilled Non-Market pays wages that are 14.0% higher than the Unskilled Services in the U.S., 25.7% in South Korea, 1.5% in France, 21.6% in Canada, 20.5% in Italy, and 32.5% in Spain. More importantly, wages in the high TFP sectors are higher than in the Unskilled Services in almost all countries: the High-Tech Industry pays wages that are 34.9% higher than the Unskilled Services in the U.S., 0.3% in France, 46.4% in Canada, 18.2% in Italy, and 34.3% in Spain; while the Skilled Market Services pays wages that are 22.6% higher than the Unskilled Services in the U.S., 23.4% in South Korea, 7.2% in France, 26.3% in Canada, and 8.1% in Italy. Wages in the High-Tech Industry are lower than in the Unskilled Services in South Korea while they are lower in the Skilled Market Services in Spain, however, the corresponding coefficients are not significant.

Results in Table 2.2 suggest not only that the Mincer returns for skilled workers are higher than those for unskilled workers but they also suggest that high TFP sectors offer higher wages in most countries. We emphasize the allocation of skilled workers in high TFP sectors and, then, we include an interaction term between the education of the individual and the economic sector she works in. The coefficient of this interaction term informs us about the existence of directed technical change.

Table 2.2: Mincer Returns by Sectors.

Variables	U.S.	South Korea	France	Canada	Italy	Spain
Education (Tertiary)	0.542***	0.129**	0.372***	0.271***	0.236***	0.470***
	(0.001)	(0.022)	(0.004)	(0.001)	(0.002)	(0.003)
Low-Tech Industry	0.181***	0.037***	0.072***	0.394***	0.111***	0.173***
	(0.001)	(0.014)	(0.003)	(0.001)	(0.001)	(0.003)
High-Tech Industry	0.349***	-0.003	0.003***	0.464***	0.182***	0.343***
	(0.001)	(0.027)	(0.004)	(0.001)	(0.001)	(0.005)
Skilled Market Services	0.226***	0.234***	0.072***	0.263***	0.081***	-0.004
	(0.001)	(0.019)	(0.003)	(0.001)	(0.001)	(0.003)
Skilled Non-Market Services	0.140***	0.257***	0.015***	0.216***	0.205***	0.235***
	(0.001)	(0.026)	(0.003)	(0.001)	(0.001)	(0.004)
Graphic Controls	YES	YES	YES	YES	YES	NO
Time Fixed Effects	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

2.4.4 Results: The Interaction Term

Table 2.3 shows the results of the GLS estimation of Mincer returns that includes this interaction term. As expected, the coefficients of the interaction term between the level of education and the high TFP sectors (High-Tech Industry and Skilled Market Services) are the highest and significant in the U.S., South Korea and France. Wages increase more if a worker has tertiary education and works in the High-Tech Industry (12.7% more in the U.S., 53.7% more in South Korea and 16.2% more in France) or in the Skilled Market Services (12.8% more in the U.S., 27.5% more in South Korea and 8.3% more in France) rather than in the Unskilled Services. This means that a skilled worker employed at a company in one of these sectors has the highest wage and does not have any incentive to move towards another sector. Therefore, we can conclude that the increase in skilled labor supply has made profit maximizing firms invest in innovation in these high TFP sectors making productivity (and then wages) increase, implying at the same time an increase in the incentives for skilled workers to work in these sectors. As a result, we can confirm that a directed technical change has occurred in the U.S., South Korea and France in high TFP sectors. Thus, skilled workers have been allocated to these sectors during the structural transformation leading the economy towards high income levels.

In Canada, workers with tertiary education earn 10.9% more if they work in the Skilled Non-Market Services rather than in the Unskilled Services and 3.7% higher if they work in the Skilled Market Services. Therefore, workers have higher incentives to move towards the Skilled Non-Market Services. Considering these results and the insights for Canada in Section 2.3, we can conclude that a directed technical change has not taken place in this economy and, therefore, skilled workers will be allocated mainly to the Skilled Non-Market Services.

In Italy, workers with tertiary education earn 11.1% more if they work in the Skilled Market Services rather than in the Unskilled Services and 8.1% more if they work in the High-Tech Industry. Considering these results, at microdata level, we argue that directed technical change might have occurred in Italy. However, in Section 2.3 it was not possible to analyze how that economy has evolved at macro level. Then, we cannot draw any certain conclusions about the existence of directed technical change in Italy.

In Spain, workers with tertiary education earn 10.3% less if they work in the Low-Tech Industry rather than in the Unskilled Services, 9.0% less if they work in the High-Tech Industry, 11.1% less if they work in the Skilled Non-Market Services, but 19.9% more if they work in the Skilled Market Services. Given these results, we argue that directed technical change might have occurred only in the Skilled Market Services in this country. However, in Section 2.3 we claimed that directed technical change might have existed in the High-Tech Industry but not in the Skilled Market Services. Therefore, the macrodata and microdata evidence are opposite and we cannot draw any certain conclusions about the existence of directed technical change in Spain. Table 2.4 sums up the findings from macrodata and microdata evidence about the existence of directed technical change in the analyzed countries.

Table 2.3: The Interaction Term.

Variables	U.S.	South Korea	France	Canada	Italy	Spain
Low-Tech Industry Education (Tertiary)	0.039***	0.080**	0.026***	-0.110***	0.067***	-0.103***
	(0.002)	(0.035)	(0.007)	(0.001)	(0.004)	(0.006)
High-Tech Industry Education (Tertiary)	0.127***	0.537***	0.162***	-0.096***	0.081***	-0.090***
	(0.002)	(0.055)	(0.007)	(0.002)	(0.003)	(0.008)
Skilled Market Services Education (Tertiary)	0.128***	0.275***	0.083***	0.037***	0.111***	0.199***
	(0.001)	(0.036)	(0.006)	(0.001)	(0.003)	(0.006)
Skilled Non-Market Services Education (Tertiary)	-0.053***	0.230***	0.038***	0.109***	0.011***	-0.111***
	(0.001)	(0.039)	(0.005)	(0.001)	(0.002)	(0.005)
Graphic Controls	YES	YES	YES	YES	YES	NO
Time Fixed Effects	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.4: Existence of Directed Technical Change.

	U.S.	South Korea	France	Canada	Italy	Spain
Macrodata Approach	YES	YES	YES	NO	— Few observations	YES In High-Tech Industry
Microdata Approach	YES	YES	YES	NO	YES	YES Few observations
Conclusion	**YES**	**YES**	**YES**	**NO**	— Lack of clear evidence	— Lack of clear evidence

2.5 Conclusions

An increase in skilled labor supply is common across countries, but the existence of directed technical change is crucial to allocate skilled workers to high TFP sectors and lead economies towards high income levels. We have faced two paths of structural change suggested in previous literature —skill-biased structural transformation and stagnant structural transformation —and we argue that if there is no directed technical change, skilled workers end up in low TFP sectors, as the path of stagnant structural transformation suggests. We have proposed an identification of directed technical change through the analysis of relative TFP between skilled and unskilled sectors and an estimation of wages. We present macrodata and microdata evidence for the U.S., South Korea, France, Canada, Italy, and Spain. With the macrodata evidence, we identify that an increasing relative TFP of skilled versus unskilled sectors suggests that there is directed technical change in the U.S., France and South Korea. This finding is supported at micro level through a GLS estimation of wages, in which the coefficients of the interaction term between tertiary education and high TFP sectors are the highest and significant. This behavior is also found in the U.S., France and South Korea. Canada has not experienced directed technical change yet, and we cannot draw any definite conclusions about the existence of directed technical change in Italy and Spain. Directed technical change can lead to a reduction of the gap in GDP per capita among countries —relative to the U.S.—, as observed in the case of South Korea.

2.6 Appendix

Figures

Figure 2A1 plots the share of population with completed tertiary education over time.

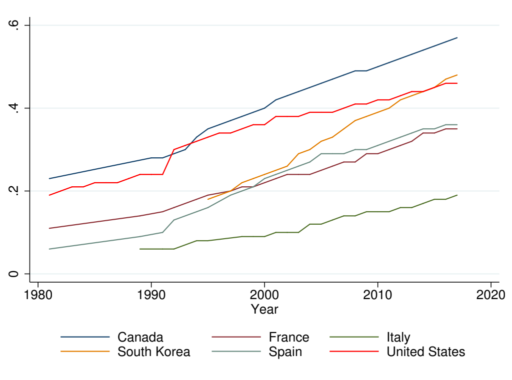


Figure 2A1: Completed Tertiary Education.
Source: OECD.

Figure 2A2 plots the share of valued added over time for Canada, France, Italy, South Korea, Spain and the U.S.

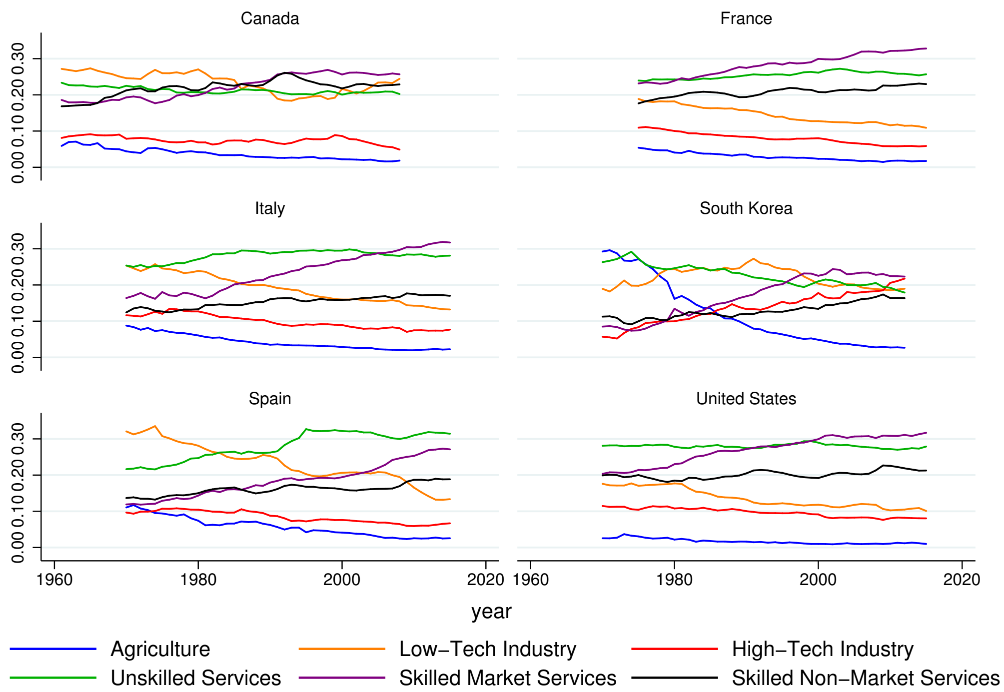


Figure 2A2: Share of Value Added, by Countries
Source: EU KLEMS and WORLD KLEMS Databases.

Figure 2A3 plots the share of the value added produced by Agriculture, Low-Tech Industry, Unskilled Services and Skilled Non-Market Services relative to the U.S.

(a) Agriculture

(b) Low-Tech Industry

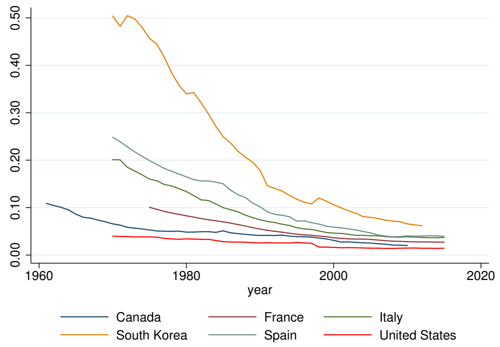
(c) Unskilled Services

(d) Skilled Non-Market Services

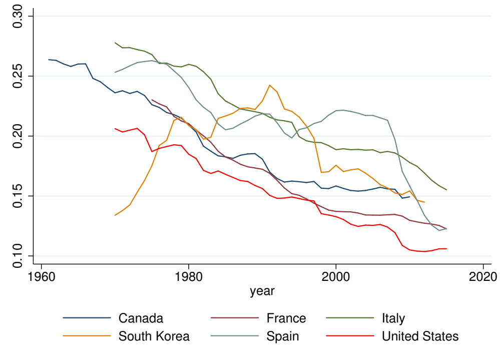
Figure 2A3: Share of Value Added Compared to the U.S., by Sectors

Source: EU KLEMS and WORLD KLEMS Databases.

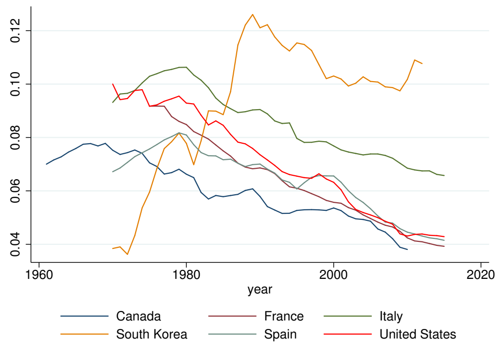
Figure 2A4 plots the share of labor by sector. Figure 2A5 plots the share of labor in Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services and Skilled Non-Market Services relative to the U.S.



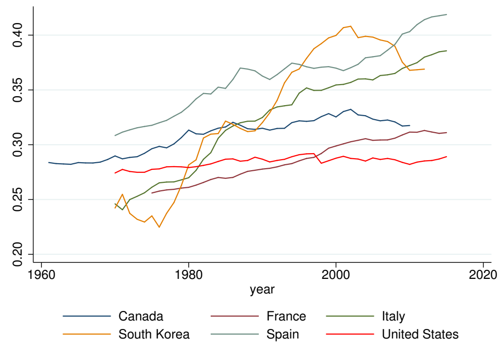
(a) Agriculture



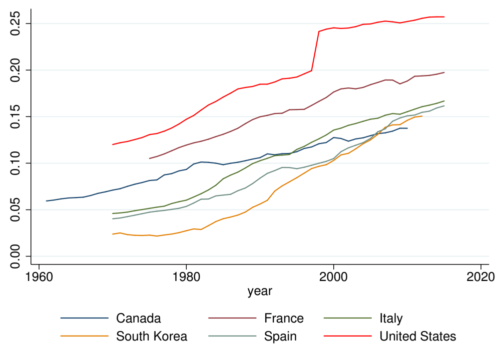
(b) Low-Tech Industry



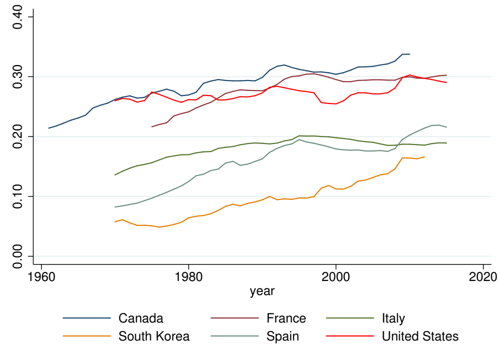
(c) High-Tech Industry



(d) Unskilled Services



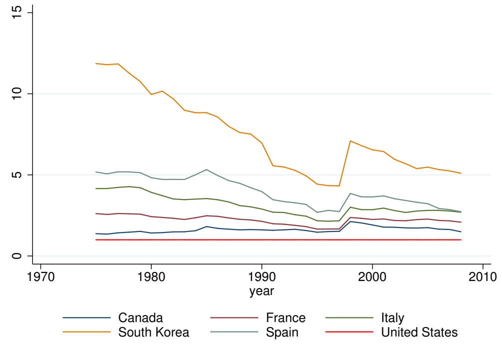
(e) Skilled Market Services



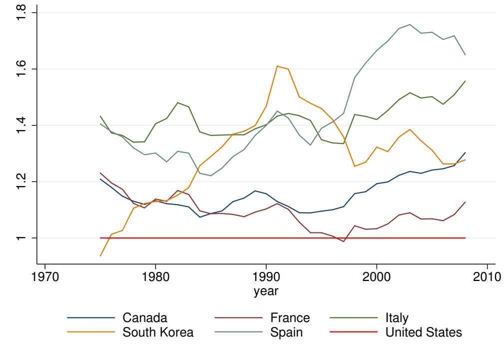
(f) Skilled Non-Market Services

Figure 2A4: Share of Labor, by Sectors

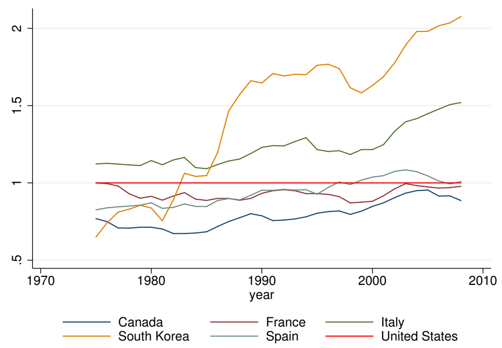
Source: EU KLEMS and WORLD KLEMS Databases.



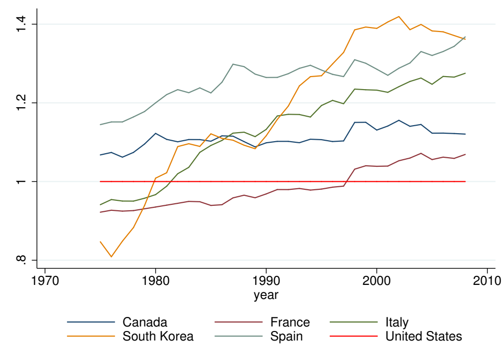
(a) Agriculture



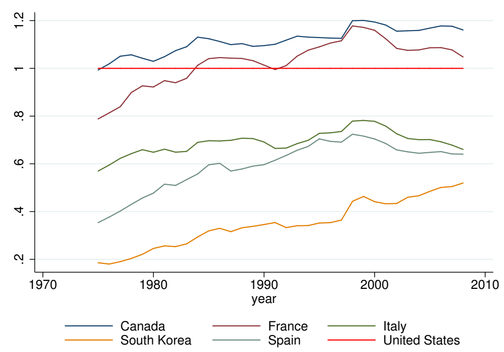
(b) Low-Tech Industry



(c) High-Tech Industry



(d) Unskilled Services



(e) Skilled Non-Market Services

Figure 2A5: Share of Labor Compared to the U.S., by Sectors

Source: EU KLEMS and WORLD KLEMS Databases.

Figure 2A6 plots the share of capital over time for Canada, France, Italy, South Korea, Spain and the U.S. Figure 2A7 plots the share of capital of all sectors relative to the U.S.

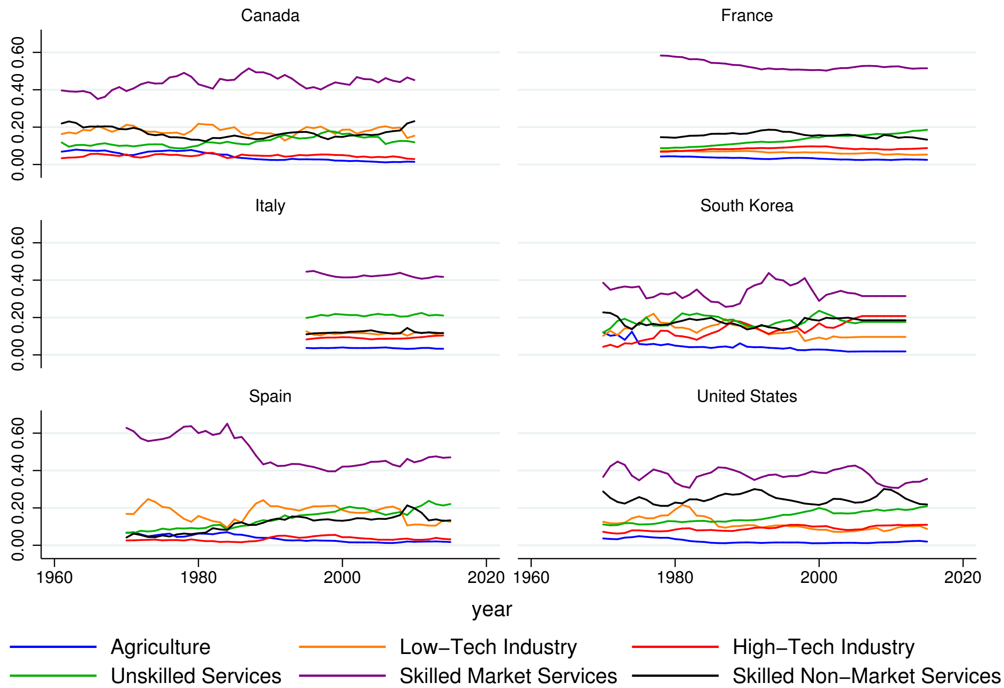
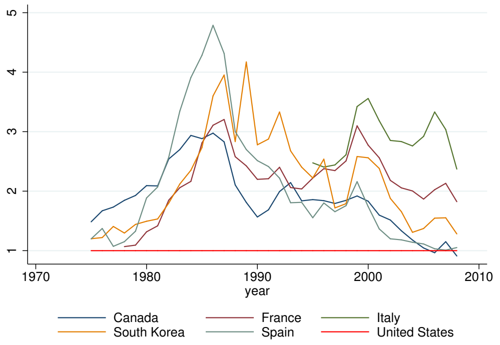
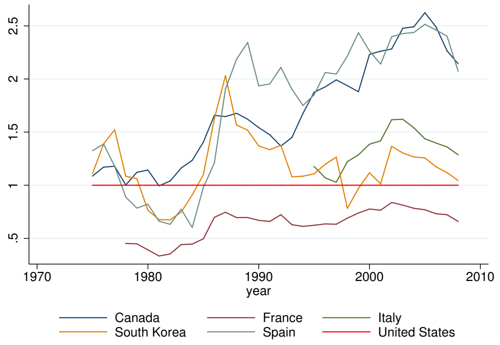


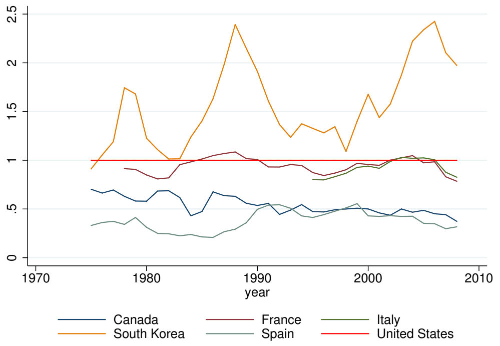
Figure 2A6: Share of Capital, by Countries
Source: EU KLEMS and WORLD KLEMS Databases.



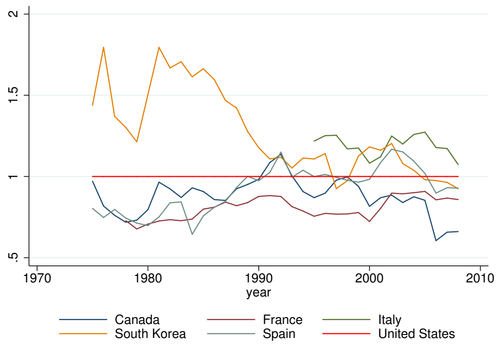
(a) Agriculture



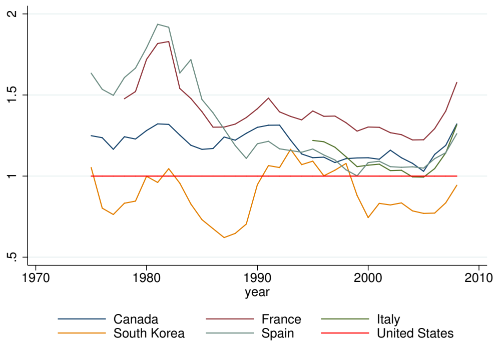
(b) Low-Tech Industry



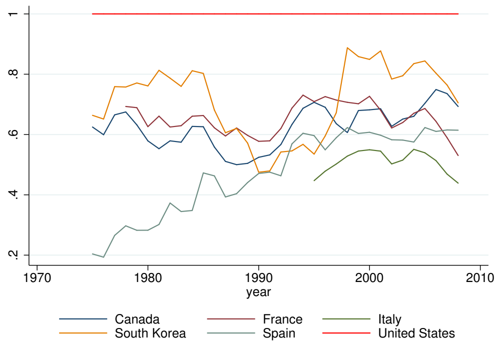
(c) High-Tech Industry



(d) Unskilled Services



(e) Skilled Market Services

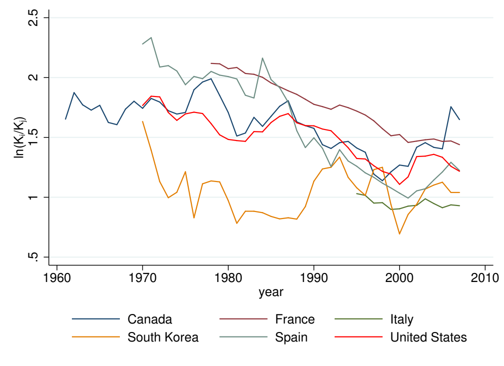


(f) Skilled Non-Market Services

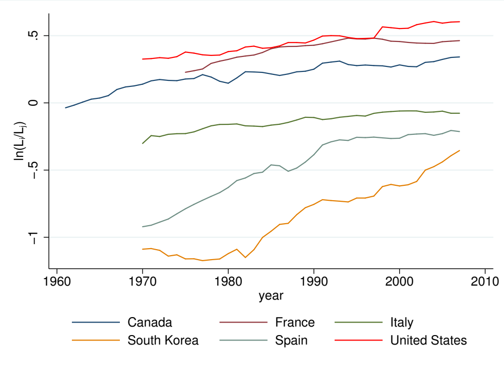
Figure 2A7: Share of Capital Compared to the U.S., by Sectors

Source: EU KLEMS and WORLD KLEMS Databases.

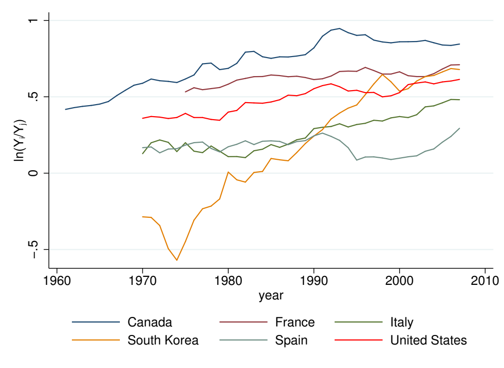
Figures 2A8 to 2A11 plot the relative capital, labor, value added and TFP of skilled sectors vs unskilled sectors. Specifically, Figure 2A8 plots skilled services (Skilled Market and Skilled Non-Market) relative to the Unskilled Services sector. Figure 2A9 plots the Skilled Market Services relative to the Unskilled Services. Figure 2A10 plots the High-Tech Industry, Skilled Market and Skilled Non-Market Services relative to the Low-Tech Industry and Unskilled Services. Finally, Figure 2A11 plots the High-Tech Industry and Skilled Market Services relative to the Low-Tech Industry and Unskilled Services.



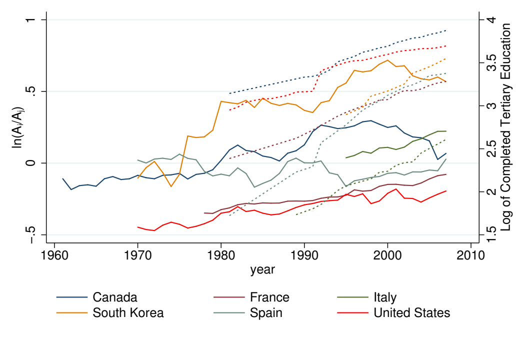
(a) Capital



(b) Labor

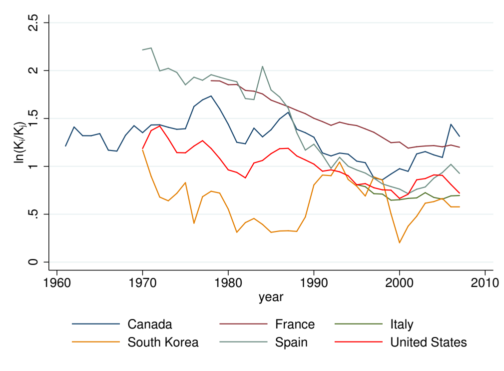


(c) Value Added

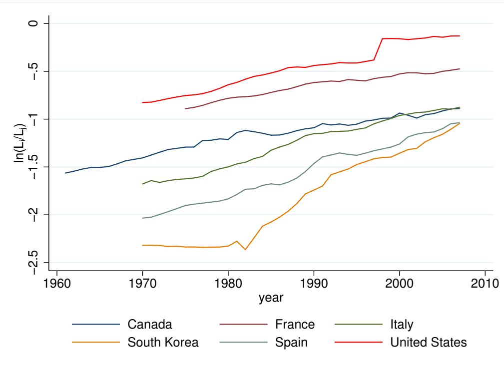


(d) TFP

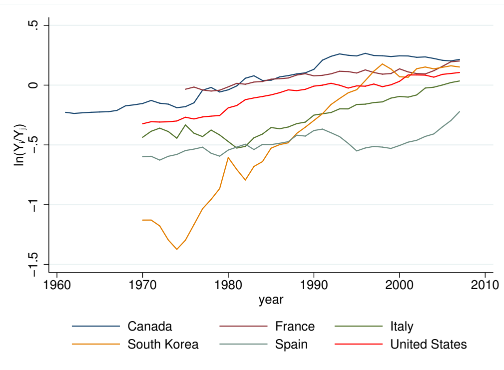
Figure 2A8: Services



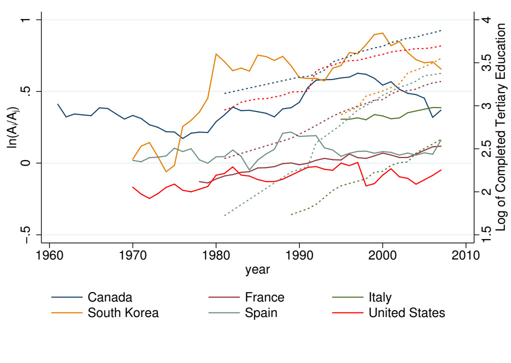
(a) Capital



(b) Labor

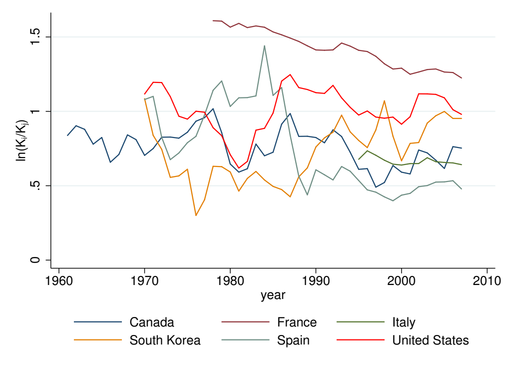


(c) Value Added

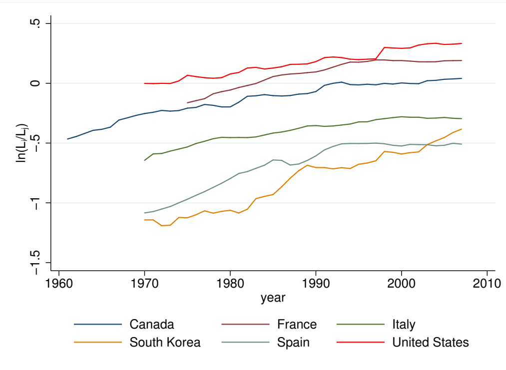


(d) TFP

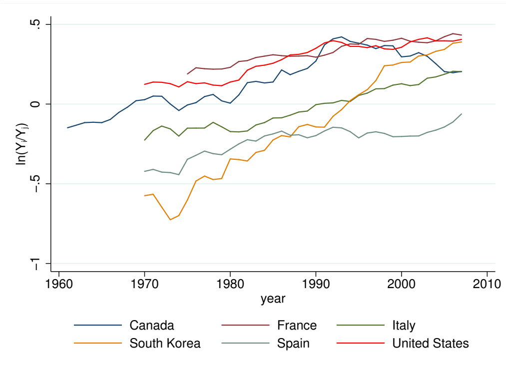
Figure 2A9: Market Services



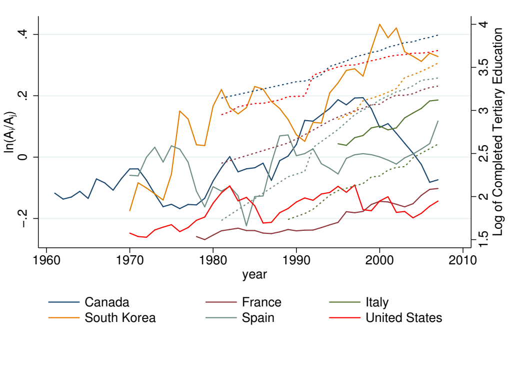
(a) Capital



(b) Labor

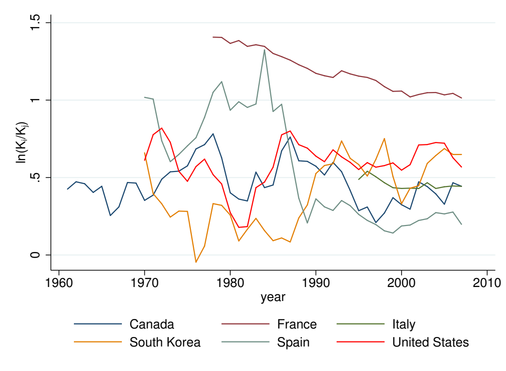


(c) Value Added

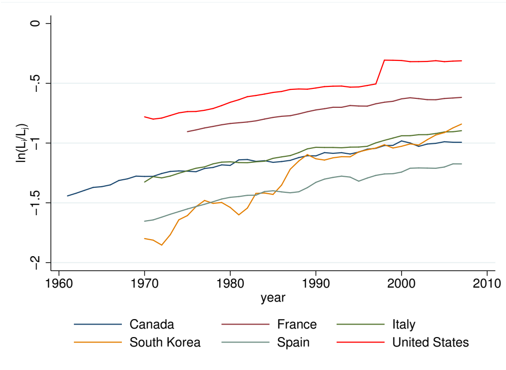


(d) TFP

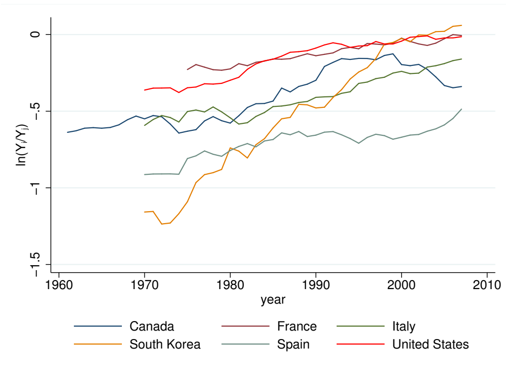
Figure 2A10: Industry and Services



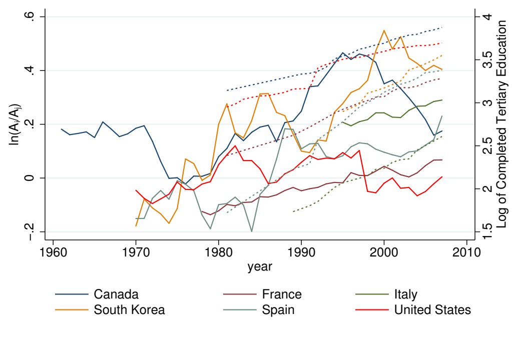
(a) Capital



(b) Labor



(c) Value Added



(d) TFP

Figure 2A11: Industry and Market Services

Tables

Macrodata Evidence

Table 2A1: Linear Regression of the Share of Value Added of Skilled Sectors and the Share of Completed Tertiary Educated Population

	U.S.	South Korea	France	Italy	Spain	Canada
Share of Completed Tertiary Educated Population	0.219***	0.385***	0.291***	0.672***	0.718***	-0.155***
	(0.025)	(0.022)	(0.037)	(0.052)	(0.076)	(0.039)
Constant	0.510***	0.440***	0.519***	0.450***	0.270***	0.627***
	(0.008)	(0.007)	(0.010)	(0.007)	(0.021)	(0.015)
Observations	35	16	19	18	19	19
R-squared	0.702	0.957	0.785	0.914	0.841	0.479
LR χ^2	77.57	311.59	61.91	169.80	89.59	15.61
Prob<χ^2	0.000	0.000	0.000	0.000	0.000	0.000
RMSE	0.012	0.006	0.007	0.006	0.016	0.011

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: EU KLEMS, KLEMS and OECD.

Table 2A2: Linear Regression of the Share of Value Added of Unskilled Sectors and the Share of Completed Tertiary Educated Population

	U.S.	South Korea	France	Italy	Spain	Canada
Share of Completed Tertiary Educated Population	-0.198***	-0.233***	-0.195***	-0.628***	-0.563***	0.235***
	(0.022)	(0.026)	(0.031)	(0.051)	(0.082)	(0.043)
Constant	0.468***	0.472***	0.435***	0.519***	0.654***	0.320***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.023)	(0.017)
Observations	35	16	19	18	19	19
R-squared	0.699	0.850	0.697	0.904	0.737	0.642
LR χ^2	76.47	79.55	39.07	151.10	47.58	30.53
Prob<χ^2	0.000	0.000	0.000	0.000	0.000	0.000
RMSE	0.011	0.007	0.006	0.006	0.017	0.012

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: EU KLEMS, KLEMS and OECD.

Microdata Evidence

Additional to the observations we made in Section 2.4, it is important to note that information on age in the Labor Force Survey of Canada is a categorical variable and, then, we group the data according to the OECD classification[25]. Tables 2A3 to 3A1 show the results of GLS panel data estimations for the U.S., South Korea, France, Canada, Italy, and Spain using the Unskilled Services as the category of reference. Regarding other results of the GLS estimation for each country, we see that firms in Regions 1 and 3 in the U.S. pay more than those in Region 4 [26]. In South Korea, firms located in areas producing more than 25% of total GDP pay more but their coefficients are not significant[27]. In France, firms located in regions that produce more than 25% of the total GDP pay more[28]. In Canada, firms located in regions that produce over 25% of total GDP pay more[29]. In Italy, firms

[25]See https://data.oecd.org/emp/employment-rate-by-age-group.htm.

[26]Examples are: New York for Region 1, Texas for Region 2, California for Region 3, and Ohio for Region 4.

[27]Examples are: Seoul for Region 1, Incheon for Region 2, Daegu for Region 3, and Gwangju for Region 4.

[28]Examples are: Paris for Region 1, Haute-Savoie for Region 2, Yvelines for Region 3, and Doubs for Region 4.

[29]Examples are: Montreal for Region 1, Toronto for Region 2, Vancouver for Region 3, and Québec for Region 4.

located in Region 1 and 3 pay more[30]. Finally, Tables 3A3 to 2A13 show the results of GLS panel data estimations for the U.S., South Korea, France, Canada, and Italy using the Agriculture sector as the category of reference and we obtain the same conclusions for the existence of directed technical change.

Table 2A3: GLS Estimation of Wages of U.S. (Category of Reference: Unskilled Services).

	(1)	(2)	(3)
Age	0.141***	0.140***	0.132***
	(0.000)	(0.000)	(0.000)
Age^2	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Gender (Female)	-0.312***	-0.310***	-0.422***
	(0.001)	(0.001)	(0.000)
Education (Tertiary)	0.995***	0.997***	0.542***
	(0.002)	(0.002)	(0.001)
Agriculture	-0.153***	-0.180***	-0.242***
	(0.003)	(0.003)	(0.001)
Low-Tech Industry	-0.177***	-0.172***	0.181***
	(0.001)	(0.001)	(0.001)
High-Tech Industry	-0.211***	-0.186***	0.349***
	(0.002)	(0.002)	(0.001)
Skilled Market Services	0.308***	0.310***	0.226***
	(0.001)	(0.001)	(0.001)
Skilled Non-Market Services	0.013***	0.012***	0.140***
	(0.001)	(0.001)	(0.001)
Agriculture $*$ Education (Tertiary)	-0.053***	-0.043***	0.065***
	(0.010)	(0.010)	(0.004)
Low-Tech Industry $*$ Education (Tertiary)	0.039***	0.039***	0.039***
	(0.004)	(0.004)	(0.002)
High-Tech Industry $*$ Education (Tertiary)	0.377***	0.359***	0.127***
	(0.004)	(0.004)	(0.002)
Skilled Market Services $*$ Education (Tertiary)	0.176***	0.177***	0.128***
	(0.003)	(0.003)	(0.001)
Skilled Non-Market Services $*$ Education (Tertiary)	-0.122***	-0.120***	-0.053***
	(0.003)	(0.003)	(0.001)
Region 1	-	-0.053***	0.056***
		(0.001)	(0.000)
Region 2	-	0.152***	-0.021***
		(0.001)	(0.000)
Region 3	-	0.214***	0.044***
		(0.001)	(0.000)
Constant	5.687***	5.606***	4.953***
	(0.003)	(0.003)	(0.002)
Geographic Controls	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	21,557,941	21,557,941	21,557,941
R-squared	0.133	0.136	0.853
LR χ^2	2.361e+05	1.989e+05	5.192e+06
Prob<χ^2	0.000	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: IPUMS International.

[30]Examples are: Trentino alto Adige for Region 1, Toscana for Region 2, Lombardia for Region 3, and Abruzzo for Region 4.

Table 2A4: GLS Estimation of Wages of South Korea (Category of Reference: Unskilled Services).

	(1)	(2)	(3)
Age	0.071***	0.072***	0.072***
	(0.003)	(0.003)	(0.003)
Age^2	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Gender (Female)	-0.465***	-0.465***	-0.440***
	(0.012)	(0.012)	(0.011)
Education (Tertiary)	0.147***	0.147***	0.129***
	(0.022)	(0.023)	(0.022)
Agriculture	-0.164***	-0.165***	-0.128***
	(0.035)	(0.035)	(0.034)
Low-Tech Industry	0.002	0.002	0.037***
	(0.015)	(0.015)	(0.014)
High-Tech Industry	-0.001	0.001	-0.003
	(0.028)	(0.028)	(0.027)
Skilled Market Services	0.222***	0.222***	0.234***
	(0.020)	(0.020)	(0.019)
Skilled Non-Market Services	0.279***	0.278***	0.257***
	(0.027)	(0.027)	(0.026)
Agriculture ∗ Education (Tertiary)	0.357*	0.360*	0.284
	(0.212)	(0.212)	(0.204)
Low-Tech Industry ∗ Education (Tertiary)	0.123***	0.121***	0.080**
	(0.036)	(0.036)	(0.035)
High-Tech Industry ∗ Education (Tertiary)	0.588***	0.589***	0.537***
	(0.057)	(0.057)	(0.055)
Skilled Market Services ∗ Education (Tertiary)	0.307***	0.305***	0.275***
	(0.038)	(0.038)	(0.036)
Skilled Non-Market Services ∗ Education (Tertiary)	0.246***	0.246***	0.230***
	(0.040)	(0.040)	(0.039)
Region 1	-	0.007	0.036*
		(0.021)	(0.020)
Region 2	-	-0.050*	0.006
		(0.026)	(0.025)
Region 3	-	-0.002	0.026
		(0.024)	(0.023)
Constant	-6.261***	-6.265***	-6.581***
	(0.058)	(0.061)	(0.068)
Geographic Controls	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	9,625	9,625	9,625
R-squared	0.308	0.309	0.365
LR χ^2	306	253	162
Prob<χ^2	0.000	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Korea Labor Institute.

Table 2A5: GLS Estimation of Wages of France (Category of Reference: Unskilled Services).

	(1)	(2)	(3)
Age	0.079***	0.079***	0.079***
	(0.001)	(0.001)	(0.001)
Age^2	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Gender (Female)	-0.326***	-0.318***	-0.318***
	(0.002)	(0.002)	(0.002)
Education (Tertiary)	0.392***	0.374***	0.372***
	(0.004)	(0.004)	(0.004)
Agriculture	-0.147***	-0.137***	-0.134***
	(0.009)	(0.009)	(0.009)
Low-Tech Industry	0.059***	0.070***	0.072***
	(0.003)	(0.003)	(0.003)
High-Tech Industry	-0.030***	-0.002	0.003***
	(0.003)	(0.004)	(0.004)
Skilled Market Services	0.080***	0.067***	0.072***
	(0.003)	(0.003)	(0.003)
Skilled Non-Market Services	0.013***	0.015***	0.015***
	(0.003)	(0.003)	(0.003)
Agriculture $*$ Education (Tertiary)	-0.053**	-0.048**	-0.048**
	(0.024)	(0.024)	(0.024)
Low-Tech Industry $*$ Education (Tertiary)	0.020***	0.025***	0.026***
	(0.007)	(0.007)	(0.007)
High-Tech Industry $*$ Education (Tertiary)	0.180***	0.163***	0.162***
	(0.007)	(0.007)	(0.007)
Skilled Market Services $*$ Education (Tertiary)	0.079***	0.084***	0.083***
	(0.006)	(0.006)	(0.006)
Skilled Non-Market Services $*$ Education (Tertiary)	0.030***	0.037***	0.038***
	(0.005)	(0.005)	(0.005)
Region 1	-	0.178***	0.178***
		(0.002)	(0.002)
Region 2	-	0.086***	0.086***
		(0.003)	(0.003)
Region 3	-	0.129***	0.129***
		(0.002)	(0.002)
Constant	0.990***	0.879***	0.852***
		(0.011)	(0.012)
Geographic Controls	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	416,896	416,896	416,896
R-squared	0.230	0.241	0.241
LR χ^2	8892	7775	2369
Prob<χ^2	0.000	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: National Institute of Statistics and Economic Studies.

Table 2A6: GLS Estimation of Wages of Canada (Category of Reference: Unskilled Services).

	(1)	(2)	(3)
Age (25-54 years old)	0.794***	0.792***	0.796***
	(0.001)	(0.001)	(0.001)
Age (55-64 years old)	0.713***	0.711***	0.704***
	(0.001)	(0.001)	(0.001)
Gender (Female)	-0.349***	-0.350***	-0.350***
	(0.000)	(0.000)	(0.000)
Education (Tertiary)	0.277***	0.276***	0.271***
	(0.001)	(0.001)	(0.001)
Agriculture	0.130***	0.134***	0.136***
	(0.002)	(0.002)	(0.002)
Low-Tech Industry	0.392***	0.393***	0.394***
	(0.001)	(0.001)	(0.001)
High-Tech Industry	0.457***	0.457***	0.464***
	(0.001)	(0.001)	(0.001)
Skilled Market Services	0.264***	0.261***	0.263***
	(0.001)	(0.001)	(0.001)
Skilled Non-Market Services	0.211***	0.213***	0.216***
	(0.001)	(0.001)	(0.001)
Agriculture $*$ Education (Tertiary)	-0.080***	-0.079***	-0.078***
	(0.003)	(0.003)	(0.003)
Low-Tech Industry $*$ Education (Tertiary)	-0.110***	-0.109***	-0.110***
	(0.001)	(0.001)	(0.001)
High-Tech Industry $*$ Education (Tertiary)	-0.096***	-0.095***	-0.096***
	(0.002)	(0.002)	(0.002)
Skilled Market Services $*$ Education (Tertiary)	0.040***	0.039***	0.037***
	(0.001)	(0.001)	(0.001)
Skilled Non-Market Services $*$ Education (Tertiary)	0.111***	0.111***	0.109***
	(0.001)	(0.001)	(0.001)
Region 1	-	0.091***	0.091***
		(0.001)	(0.001)
Region 2	-	0.095***	0.095***
		(0.001)	(0.001)
Region 3	-	0.042***	0.041***
		(0.001)	(0.001)
Constant	7.166***	7.118***	7.044***
	(0.001)	(0.001)	(0.003)
Geographic Controls	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	11,728,036	11,728,036	11,728,036
R-squared	0.364	0.365	0.368
LR χ^2	478356	396184	27932
Prob<χ^2	0.000	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Statistics Canada.

Table 2A7: GLS Estimation of Wages of Italy (Category of Reference: Unskilled Services).

	(1)	(2)	(3)
Age	0.039***	0.038***	0.038***
	(0.000)	(0.000)	(0.000)
Age^2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Gender (Female)	-0.283***	-0.290***	-0.290***
	(0.001)	(0.001)	(0.001)
Education (Tertiary)	0.240***	0.234***	0.236***
	(0.002)	(0.002)	(0.002)
Agriculture	-0.227***	-0.202***	-0.203***
	(0.002)	(0.002)	(0.002)
Low-Tech Industry	0.115***	0.112***	0.111***
	(0.001)	(0.001)	(0.001)
High-Tech Industry	0.199***	0.183***	0.182***
	(0.001)	(0.001)	(0.001)
Skilled Market Services	0.084***	0.082***	0.081***
	(0.001)	(0.001)	(0.001)
Skilled Non-Market Services	0.199***	0.207***	0.205***
	(0.001)	(0.001)	(0.001)
Agriculture * Education (Tertiary)	0.115***	0.104***	0.102***
	(0.012)	(0.012)	(0.012)
Low-Tech Industry * Education (Tertiary)	0.068***	0.065***	0.067***
	(0.004)	(0.004)	(0.004)
High-Tech Industry * Education (Tertiary)	0.073***	0.082***	0.081***
	(0.003)	(0.003)	(0.003)
Skilled Market Services * Education (Tertiary)	0.111***	0.112***	0.111***
	(0.003)	(0.003)	(0.003)
Skilled Non-Market Services * Education (Tertiary)	0.006***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)
Region 1	-	0.008***	0.008***
		(0.002)	(0.002)
Region 2	-	-0.020***	-0.020***
		(0.002)	(0.002)
Region 3	-	0.078***	0.078***
		(0.001)	(0.001)
Constant	6.111***	6.095***	6.130***
	(0.004)	(0.004)	(0.005)
Geographic Controls	NO	YES	YES
Time Fixed Effects	NO	NO	YES
Observations	1,503,181	1,503,181	1,503,181
R-squared	0.263	0.272	0.275
LR χ^2	38269	33033	10552
Prob<χ^2	0.000	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: National Institute of Statistics.

Table 2A8: GLS Estimation of Wages of Spain (Category of Reference: Unskilled Services).

	(1)	(2)
Age (20-49 years old)	0.072***	0.071***
	(0.004)	(0.004)
Age (50-60 years old)	0.285***	0.286***
	(0.005)	(0.005)
Gender (Female)	-0.321***	-0.321***
	(0.002)	(0.002)
Education (Tertiary)	0.476***	0.470***
	(0.003)	(0.003)
Low-Tech Industry	0.177***	0.173***
	(0.003)	(0.003)
High-Tech Industry	0.343***	0.343***
	(0.005)	(0.005)
Skilled Market Services	-0.003	-0.004
	(0.003)	(0.003)
Skilled Non-Market Services	0.233***	0.235***
	(0.004)	(0.004)
Low-Tech Industry $*$ Education (Tertiary)	-0.104***	-0.103***
	(0.006)	(0.006)
High-Tech Industry $*$ Education (Tertiary)	-0.090***	-0.090***
	(0.008)	(0.008)
Skilled Market Services $*$ Education (Tertiary)	0.196***	0.199***
	(0.006)	(0.006)
Skilled Non-Market Services $*$ Education (Tertiary)	-0.111***	-0.111***
	(0.005)	(0.005)
Constant	5.020***	5.049***
	(0.004)	(0.005)
Geographic Controls	NO	NO
Time Fixed Effects	NO	YES
Observations	426,205	426,205
R-squared	0.210	0.212
LR χ^2	9444	8807
Prob$<\chi^2$	0.000	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: National Institute of Statistics.

Table 2A9: GLS Estimation of Wages of U.S. (Category of Reference: Agriculture).

VARIABLES	(3)
Age	0.132***
	(0.000)
Age^2	-0.001***
	(0.000)
Gender (Female)	-0.422***
	(0.000)
Education (Tertiary)	0.607***
	(0.004)
Low-Tech Industry	0.423***
	(0.001)
High-Tech Industry	0.591***
	(0.001)
Unskilled Services	0.242***
	(0.001)
Skilled Market Services	0.469***
	(0.001)
Skilled Non-Market Services	0.382***
	(0.001)
Low-Tech Industry * Education (Tertiary)	-0.025***
	(0.004)
High-Tech Industry * Education (Tertiary)	0.063***
	(0.004)
Unskilled Services * Education (Tertiary)	-0.065***
	(0.004)
Skilled Market Services * Education (Tertiary)	0.063***
	(0.004)
Skilled Non-Market Services * Education (Tertiary)	-0.118***
	(0.004)
Region 1	0.056***
	(0.000)
Region 2	-0.021***
	(0.000)
Region 3	0.044***
	(0.000)
Constant	4.710***
	(0.002)
Observations	21,557,941
R-squared	0.853
LR χ^2	5.192e+06
Prob<χ^2	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: IPUMS International.

Table 2A10: GLS Estimation of Wages of South Korea (Category of Reference: Agriculture).

VARIABLES	(3)
Age	0.072***
	(0.003)
Age^2	-0.001***
	(0.000)
Gender (Female)	-0.440***
	(0.011)
Education (Tertiary)	0.413**
	(0.203)
Low-Tech Industry	0.165***
	(0.033)
High-Tech Industry	0.125***
	(0.041)
Unskilled Services	0.128***
	(0.034)
Skilled Market Services	0.362***
	(0.036)
Skilled Non-Market Services	0.385***
	(0.040)
Low-Tech Industry $*$ Education (Tertiary)	-0.204
	(0.205)
High-Tech Industry $*$ Education (Tertiary)	0.253
	(0.209)
Unskilled Services $*$ Education (Tertiary)	-0.284
	(0.204)
Skilled Market Services $*$ Education (Tertiary)	-0.009
	(0.205)
Skilled Non-Market Services $*$ Education (Tertiary)	-0.054
	(0.205)
Region 1	0.036*
	(0.020)
Region 2	0.006
	(0.025)
Region 3	0.026
	(0.023)
Constant	-6.709***
	(0.068)
Observations	9,625
R-squared	0.365
LR χ^2	162.2
Prob$<\chi^2$	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Korea Labor Institute.

Table 2A11: GLS Estimation of Wages of France (Category of Reference: Agriculture).

VARIABLES	(3)
Age	0.079***
	(0.001)
Age^2	-0.001***
	(0.000)
Gender (Female)	-0.318***
	(0.002)
Education (Tertiary)	0.324***
	(0.024)
Low-Tech Industry	0.206***
	(0.009)
High-Tech Industry	0.137***
	(0.009)
Unskilled Services	0.134***
	(0.009)
Skilled Market Services	0.206***
	(0.009)
Skilled Non-Market Services	0.149***
	(0.009)
Low-Tech Industry $*$ Education (Tertiary)	0.074***
	(0.024)
High-Tech Industry $*$ Education (Tertiary)	0.210***
	(0.024)
Unskilled Services $*$ Education (Tertiary)	0.048**
	(0.024)
Skilled Market Services $*$ Education (Tertiary)	0.132***
	(0.024)
Skilled Non-Market Services $*$ Education (Tertiary)	0.087***
	(0.024)
Region 1	0.178***
	(0.002)
Region 2	0.086***
	(0.003)
Region 3	0.129***
	(0.002)
Constant	5.323***
	(0.014)
Observations	416,896
R-squared	0.241
LR χ^2	2369
Prob<χ^2	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: National Institute of Statistics and Economic Studies.

Table 2A12: GLS Estimation of Wages of Canada (Category of Reference: Agriculture).

VARIABLES	(3)
Age (25-54 years old)	0.796***
	(0.001)
Age (55-64 years old)	0.704***
	(0.001)
Gender (Female)	-0.350***
	(0.000)
Education (Tertiary)	0.193***
	(0.003)
Low-Tech Industry	0.258***
	(0.002)
High-Tech Industry	0.327***
	(0.002)
Unskilled Services	-0.136***
	(0.002)
Skilled Market Services	0.126***
	(0.002)
Skilled Non-Market Services	0.080***
	(0.002)
Low-Tech Industry ∗ Education (Tertiary)	-0.032***
	(0.003)
High-Tech Industry ∗ Education (Tertiary)	-0.018***
	(0.004)
Unskilled Services ∗ Education (Tertiary)	0.078***
	(0.003)
Skilled Market Services ∗ Education (Tertiary)	0.115***
	(0.003)
Skilled Non-Market Services ∗ Education (Tertiary)	0.187***
	(0.003)
Region 1	0.091***
	(0.001)
Region 2	0.095***
	(0.001)
Region 3	0.041***
	(0.001)
Constant	7.181***
	(0.004)
Observations	11,728,036
R-squared	0.368
LR χ^2	27932
Prob<χ^2	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Statistics Canada.

Table 2A13: GLS Estimation of Wages of Italy (Category of Reference: Agriculture).

VARIABLES	(3)
Age	0.038***
	(0.000)
Age^2	-0.000***
	(0.000)
Gender (Female)	-0.290***
	(0.001)
Education (Tertiary)	0.338***
	(0.012)
Low-Tech Industry	0.313***
	(0.002)
High-Tech Industry	0.384***
	(0.002)
Unskilled Services	0.203***
	(0.002)
Skilled Market Services	0.283***
	(0.002)
Skilled Non-Market Services	0.408***
	(0.002)
Low-Tech Industry $*$ Education (Tertiary)	-0.036***
	(0.012)
High-Tech Industry $*$ Education (Tertiary)	-0.021*
	(0.012)
Unskilled Services $*$ Education (Tertiary)	-0.102***
	(0.012)
Skilled Market Services $*$ Education (Tertiary)	0.009
	(0.012)
Skilled Non-Market Services $*$ Education (Tertiary)	-0.091***
	(0.012)
Region 1	0.008***
	(0.002)
Region 2	-0.020***
	(0.002)
Region 3	0.078***
	(0.001)
Constant	5.928***
	(0.005)
Observations	1,503,181
R-squared	0.275
LR χ^2	10552
Prob<χ^2	0.000

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: National Institute of Statistics.

Chapter 3

Understanding Women: the Preference for the Skilled Non-Market Services Sector

3.1 Introduction

The gender composition of labor markets has changed over time. In the U.S., women constituted 35.86% and men 64.14% of the total labor force in 1970, while in 2010 this number increased for women to 47.33% and decreased for men to 52.67%[1]. Additionally, human capital investment has increased over time due to an increase in the college premium; see Acemoglu (1998). As a consequence, more women have acquired tertiary education and decided to participate in the labor market. In the U.S., 10.44% of the female workers had completed tertiary education in 1970 while in 2010 this number increased to 33.80%. This increase in skilled female participation has come together with a smaller gender wage gap. In 1970, skilled men had on average an hourly compensation 1.65 times higher than skilled women while in 2010 this number decreased to 1.30 in the U.S. In spite of the rise in skilled female workforce and the decrease of the skilled gender wage gap, the gender composition within economic sectors has not reversed yet. Skilled men share is still higher than skilled women share in all economic sectors, except in the Skilled Non-Market Services sector —education, health, public administration, and defense—[2]. Hence, it is essential to understand how skilled women are allocated among sectors during structural transformation and why they end up working mostly in the Skilled Non-Market Services sector. In order to do this we identify important factors that explain this phenomenon.

First, structural transformation has been accompanied by both an increase in skilled labor supply and an increase in the college premium of skilled versus unskilled workers; see Acemoglu (1998, 2002). This path of structural transformation has inspired to a vast number of studies that analyze the impact of education on the labor force participation, specially

[1]Section 3.1 and Section 3.2 present evidence on the evolution of labor force using data from the U.S. Labor Input File published by the WORLD KLEMS consortium.

[2]We consider a wider division of the economy within six sectors: Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services, Skilled Market Services, and Skilled Non-Market Services; see Chapter 2 for this classification. As the Agriculture sector has become very small, we make little references to this sector.

for women; see Guvenen and Rendall (2015), Chiappori et al. (2017) and Zhang (2021). What these studies suggest is that the increase in college premium has motivated women to complete tertiary education and participate in the labor market since the opportunity cost of not going to the university —and staying at home—became very high. In point of fact the Skilled Non-Market Services sector not only shows the highest increase in labor participation of skilled women —the number of skilled women in the Skilled Non-Market Services sector represented 39.94% of total skilled labor force in 1970 while in 2010 it was 61.82% —but also shows the lowest and decreasing skilled gender wage gap: in 1970 a skilled man earned on average 1.17 times more than a skilled woman in this sector in the U.S. while in 2010 this number decreased to 1.13. This important fact certainly shapes the preference of skilled women to end up working in a sector with less gender inequality and, therefore, it encourages women to choose a career that leads them to end up working in the Skilled Non-Market Services sector.

The second factor is the provision of government services. It has replaced household work and has motivated women to participate in the labor market; see Rogerson (2007) and Cavalcanti and Tavares (2011). What is more important, government is not only a provider of those services but also has become an important employer for women; see Chassamboulli and Gomes (2018). In fact, in 1970, in the U.S. 37.29% of women participating in the labor market was allocated in the Skilled Non-Market Services sector while in 2010 this number increased to 48.72%. Then, the allocation of women in services would be explained by the existence of a government and the services it provides.

Third, the increase in female participation has come together with some demographic issues: the decrease in the number of children and marriages and fecundity rates; see Greenwood et al. (2016), Greenwood et al. (2017) and Goussé et al. (2017). However, in 2010 skilled women had more children on average than in 1971 in the Skilled Non-Market Services sector —from 0.88 in 1971 to 1.10 in 2010—. Also, the percentage of married skilled women increased in this sector —from 58.44% in 1971 to 68.27% in 2010—. We then see increasing demographic indicators for those women that have tertiary education and work in the Skilled Non-Market Services sector.

Finally, on the one hand, as we refer to a sector within services, previous findings about the creation of jobs where women have a comparative advantage might explain why skilled women end up working in this sector. Previous literature suggests that differences in skill intensities within sectors have favored women to participate in the labor market. The shift in the demand of physical ("brawn") skills for intellectual ("brain") skills has characterized the structural transformation of economies from industry to services; see Rendall (2013), Olivetti and Petrongolo (2014), Kucera and Tejani (2014), Rendall (2017) and Ngai and Petrongolo (2017). In fact, in 1970 28.75% of the total labor force were women working in services while in 2010 this number rose to 44.03%, in the U.S. Moreover, in 1970 13.37% of the total labor force were women working in the Skilled Non-Market Services while in 2010 this number rose to 23.05%[3], which explains 63.35% of the total increase in services. On the other hand, in Chapter 2 we argue that the increase in the supply of skilled labor force and the existence of a directed technical change have induced a skilled-biased structural transformation towards high TFP sectors—High-Tech Industry, Skilled Market Services and Skilled Non-Market Services —. They argue that it is the existence of directed technical change what determines where skilled labor force ends up working. Following this analysis,

[3]In 1970 4.06% of the total labor force were women working in the Skilled Market Services and 11.32% in the Unskilled Services. In 2010 these numbers rose to 9.05% and 11.93%, respectively.

we argue that technological advances have overcome the comparative advantage in "brawn" tasks for men over women. Then, there are similar opportunities for both a skilled woman and a skilled man to be hired in any sector. In other words, skilled women might end up working in industry during structural transformation and not necessarily in services as well as skilled men might end up working in services and not necessarily in industry. In point of fact, the number of skilled women relative to the number of skilled men has increased over time in all sectors, being the High-Tech Industry sector the one with the highest increase—in 2010 the number of skilled women relative to the number of skilled men was around 5 times higher than in 1970 in this sector—. Additionally, the share of skilled men relative to total skilled labor force is still higher than the share of skilled women in almost all sectors, although it is decreasing over time. The Skilled Non-Market Services sector is the only sector where the number of skilled women is higher than the number of skilled men—the number of skilled women in the Skilled Non-Market Services sector represented 39.94% of total skilled labor force in this sector in 1970 while in 2010 it was 61.82%—.

In this chapter, we study the allocation of skilled women during structural transformation. We suggest there are forces, different from the "brain" versus "brawn" comparative advantage, that drive their allocation specially in the Skilled Non-Market Services sector. The increase in college premium and the subsequent decrease in skilled gender wage gap, the existence of directed technical change during structural transformation, the huge importance of government as employer of women, and the balanced trade-off between marriage, having children and participating in the labor market are main drivers of the allocation of skilled women during structural transformation, specially in the Skilled Non-Market Services sector. We propose a "new" comparative advantage defined as the opportunity cost of staying working in other sectors different from the analyzed one. We show that a skilled woman has a higher opportunity cost than a skilled man when she stays working in any sector different from the Skilled Non-Market Services sector. In other words, a skilled woman has a comparative advantage over a skilled man in the Skilled Non-Market Services sector since she faces higher losses than him when she works in any other sector. As a consequence, skilled women end up working mainly in the Skilled Non-Market Services sector during structural transformation.

We build a theoretical model that is not based on the "brain" versus "brawn" assumption but focuses on the preferences of an empowered woman[4]. She decides whether to acquire tertiary education or not—and, therefore, where to work—, how much to consume —personal consumption and family consumption—, how many hours to devote to leisure and whether and how many children to have. We find that "own" leisure and family consumption account for the largest weight on our empowered woman utility. We show that as gender wage gap increases the fraction of her wage mass devoted to satisfy family consumption decreases while it increases if she decides to be tertiary educated. We also find that this fraction

[4]We want to emphasize on the empowerment of women because they have earned different rights over time that allow them to participate in activities that only men were supposed to do before, such as voting and participating in any sector of the labor market. They also have been liberated from the strings of religion that forced them to get married before sex, to stay married even when they faced violence or betrayal at home —no divorce—, and to have their children even when they could not afford them—no abortion—. In this sense, they now have more available tools to make decisions regarding work and family based on their own preferences. They can decide now whether to study or not, where to work, how much to consume, whether to get married, and also, through the power of contraceptives and the pill, whether and how many children to have; see Goldin and Katz (2002), Barham et al. (2009), and Greenwood et al. (2017). Moreover, as women are the ones who can carry a baby biologically, we assume that the family's decision about whether and how many children to have is determined only by them not their husband.

increases when she works more hours, however, it comes together with a high cost: a lower number of children. As Skilled Non-Market Services sector offers skilled women the smallest gender wage gap, requires the smallest hours to work per, offers a compensation per hour worked as large as the average compensation among sectors, and shows higher demographic indicators for skilled women we conclude that our empowered woman's optimal decisions lead her to work in this sector.

Additionally, we present a microdata approach using data from Current Population Survey where we identify relevant characteristics of the Skilled Non-Market Services sector. These characteristics are work stability in the older ages, job flexibility or less hours worked, a small gender wage gap, and better family indicators. We then confirm women have strong preferences to end up working in this sector. First, we perform a logit estimation of the probability of an individual to end up working in the Skilled Non-Market Services sector. We find that this probability is higher for those with tertiary education. Moreover, it is higher for individuals in the older ages—work stability in the older ages—. Furthermore, it decreases when hours worked increases and increases when the individual has a full-time type of contract—job flexibility or less hours worked —. We find that as income of the individual increases, this probability increases if the individual is a female, while it decreases for males. Finally, we find that it increases as the number of own children increases, for females —better family indicators —. Second, we emphasize the role of tertiary education in the allocation of females in this sector. Then, we estimate the probability of a woman to end up working in the Skilled Non-Market Services sector. We find that this probability is higher for women with tertiary education in every group of age —work stability in the older ages—. It also increases regardless the type of contract when she has tertiary education —job flexibility—. Finally, we find that it increases when she has tertiary education and decides to have babies—better family indicators —. These findings support our claims about strong preferences of skilled women to end up working in the Skilled Non-Market Services sector.

This chapter is organized as follows. Section 3.2 reports historical gender composition of labor markets and defines a "new" comparative advantage. Section 3.3 reports a theoretical model based on the preferences of an empowered woman and not on the usual "brain" versus "brawn" comparative advantage. The calibration for this model is also included in this section. Section 3.4 reports a microdata approach that supports our findings about strong preferences of women to end up working in the Skilled Non-Market Services sector. Finally, Section 3.5 concludes.

3.2 Skilled Female Labor Participation and Comparative Advantage

Gender composition of labor markets has changed over time. This change has been characterized by the increase in female participation across countries. Previous literature suggests that working women are mainly allocated in services due to their "brain" versus "brawn" comparative advantage. However, we argue that when we consider more economic sectors rather than the three usual —agriculture, industry, and services—it is possible to identify even wider reasons for the labor allocation of skilled women. In this section, we show the evolution of the labor market for skilled women and skilled men considering six economic sectors: Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services, Skilled Market Services, and Skilled Non-Market Services.

3.2.1 Evolution of the Labor Force

In the U.S., women represented the 35.86% of labor force in 1970 while in 2010 this number increased to 47.33%. Additionally, in the U.S., 10.44% of female workers and 14.18% of male workers had completed tertiary education in 1970 while in 2010 these numbers rose to 33.80% and 31.81%, respectively. When we analyze this evolution considering a wider division of economic sectors rather than the three usual —agriculture, industry, and services—, we can observe remarkable facts. In Figure 3.1 we plot the evolution of the labor force by gender in the U.S. The top of this figure plots the share of women and the share of men relative to the total labor force in each sector and the bottom of this figure plots the share of skilled labor force by gender relative to the total labor force in each sector.

First, on the one hand, we see in the top of Figure 3.1 that female workforce has been mainly allocated in services, as previous literature suggests. We see an increase in the female labor share in the Unskilled Services, Skilled Market Services, and Skilled Non-Market Services sectors. In 1970 41.03% of the total labor force in the Unskilled Services sector were women while in 2010 this number increased to 43.46%. In the Skilled Market Services sector this number was 41.63% in 1970 and 46.80% in 2010. While in the Skilled Non-Market Services sector this number was 43.62% in 1970 and 61.28% in 2010.

On the other hand, it is important to note that the share of women in industry remains constant due to the increase in female labor share in the High-Tech Industry and the decrease in the Low-Tech Industry —see Kucera and Tejani (2014) for references about the defeminization experienced in the Low-Tech Industry—. In 1970 23.64% of the total labor force in the Low-Tech Industry were women while in 2010 this number decreased to 19.14%. While in the High-Tech Industry this number was 24.24% in 1970 and increase to 27.94% in 2010.

Second, we see in the bottom of Figure 3.1 that skilled labor force —female and male —has been allocated mainly in high TFP sectors —High-Tech Industry, Skilled Market Services, and Skilled Non-Market Services—, as shown in Chapter 2. They argue it is the existence of directed technical change during structural transformation that allows to allocate skilled workers into high TFP sectors and they reveal it is the case for the U.S. We indeed see that in 1970 the share of skilled female share relative to the total labor force was 0.67% in High-Tech Industry, 2.83% in Skilled Market Services and 9.78% in Skilled Non-Market Services while in 2010 these numbers rose to 9.33%, 17.85% and 25.61%, respectively [5].

From Figure 3.1 we then identify relevant facts for women. First, the increase in college premium has motivated women to complete tertiary education and participate in the labor market. Remarkably, when we consider a wider division of the economy we see that Skilled Non-Market Services sector shows the highest participation of skilled women over time —government is the most important employer of women—. Second, their allocation during structural transformation has happened not only towards services but also towards industry, more specifically, into high TFP sectors—High-Tech Industry, Skilled Market Services, and Skilled Non-Market Services—.

[5] In 1970 the share of skilled male share relative to the total labor force was 9.66% in High-Tech Industry, 15.44% in Skilled Market Services and 14.70% in Skilled Non-Market Services while in 2010 these numbers rose to 27.11%, 26.60% and 15.82%, respectively.

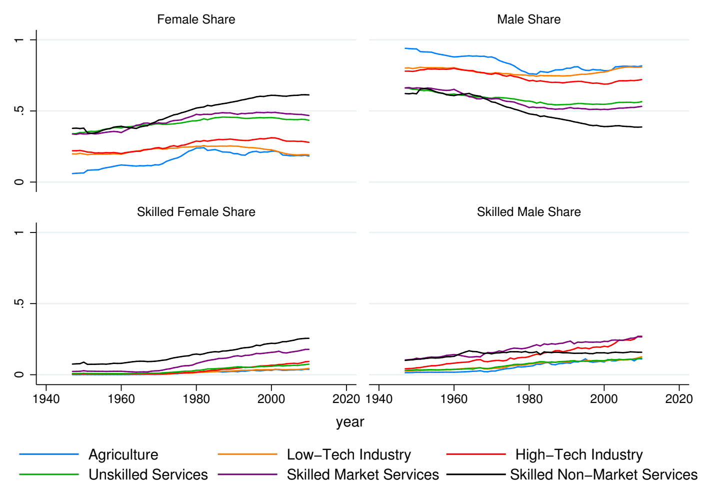


Figure 3.1: Evolution of the Labor Force
Source: WORLD KLEMS Database.

Moreover, in Figure 3.2 we analyze the share of skilled men and skilled women relative to total skilled labor force within sectors. We see that the gap between these shares has reduced over time in all sectors. More importantly, the share of skilled women has become higher than the share of skilled men in the Skilled Non-Market Services sector —it was 39.94% in 1970 while it was 61.82% in 2010—. It is the only sector that shows this phenomenon, although the share of skilled men has decreased over time in all sectors. From this figure we emphasize the role of the Skilled Non-Market Services sector regarding allocation of skilled women during structural transformation but more importantly we highlight the fact that it is the only sector where skilled women outnumber skilled men.

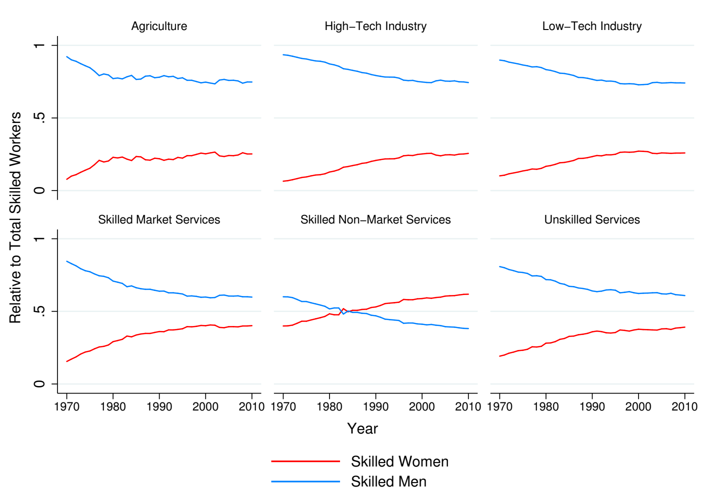


Figure 3.2: Share of Skilled Women and Skilled Men relative to Total Skilled Labor Force
Source: WORLD KLEMS Database.

Finally, in Figure 3.3 we plot the number of skilled women relative to the number of skilled men within sectors (left) and the growth of this ratio (right) in the U.S.[6] In the left

[6] We drop the Agriculture sector in Figure 3.2 since the share of workers in this sector is almost zero.

we see that this ratio has increased over time in all sectors, not only in services. Moreover, in the right we see that the High-Tech Industry shows the highest growth in this ratio: in 2010 this ratio was around 5 times higher than in 1970 in this sector[7]. In this figure we then identify another relevant fact for women. The ratio of skilled women relative to skilled men within sectors has increased over time in all sectors but the High-Tech Industry shows the highest growth.

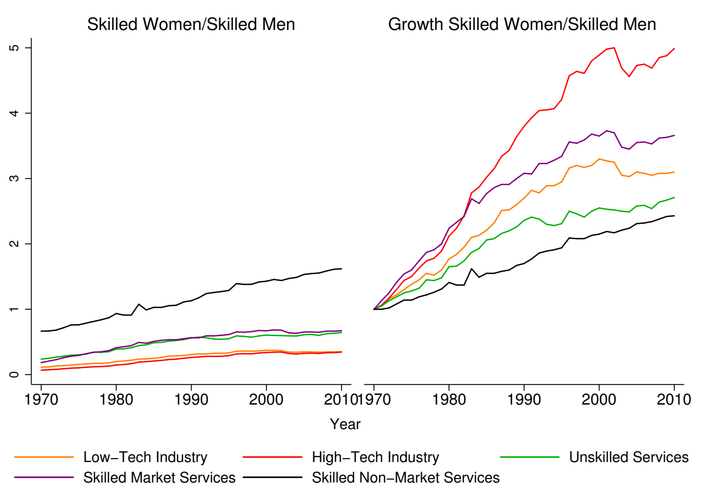


Figure 3.3: Ratio of Skilled Women Relative to Skilled Men and Its Growth, Within Sectors
Source: WORLD KLEMS Database.

This evidence suggests that it is not only the "brain" vs "brawn" comparative advantage that determines the allocation of skilled labor force during structural transformation. If it was the case, we would not see the high growth of skilled women participation in the High-Tech Industry. We would not see either that the share of skilled men relative to total skilled labor force is higher than the share of skilled women in services —the share of skilled women relative to total skilled labor force is higher only in the Skilled Non-Market Services sector—. Evidence shows first that government is the most important employer of women. Second, skilled women have been allocated mainly into high TFP sectors —High-Tech Industry, Skilled Market Services, and Skilled Non-Market Services—in line with the findings in Chapter 2 where we argue that it is the existence of directed technical change during structural transformation that determines to allocate skilled workers into high TFP sectors. We next study the behavior of some family indicators as a result of the rise in female participation.

3.2.2 Family Indicators

The increase in female participation has come together with some demographic issues: the decrease in the number of children and marriages and fecundity rates. Using data from the IPUMS-CPS and considering a wider division of the economy we identify differences in these family indicators for unskilled and skilled women among sectors. We drop those observations without information about sex, education, income and type of industry in which

[7]The growth in this ratio in the other sectors was 3.66 in the Skilled Market Services sector, 3.10 in the Low-Tech Industry, 2.71 in the Unskilled Services sector, and 2.43 in the Skilled Non-Market Services sector.

the person performed his or her primary occupation. We use the following variables: *"Educational attainment recode"* to categorize individuals into two groups, skilled —with at least a bachelor degree—and unskilled—without tertiary education—; *"Industry, 1990 basis"* to divide the economy into Agriculture, Low-Tech Industry, High-Tech Industry, Unskilled Services, Skilled Market Services and Skilled Non-Market Services[8]; *"Age"* to group individuals into 4 groups —25-34, 35-44, 45-54 and 55-65—; *"Marital status"* to identify those married individuals; and *"Number of own children in household"* in order to compute the average number of children. In Table 3.1 we present data for women regarding the average number of own children in household and the percentage of marriage among sectors in 1971 and 2010. We group women into skilled and unskilled and categorize them according to the economic sector they work in and their group of age.

We identify differences between unskilled and skilled women. First, unskilled women indeed show a decrease in the number of own children and the percentage of marriage, regardless the economic sector. However, these family indicators behave differently for skilled women according to the economic sector they work in. Specifically, we see that those skilled women in high TFP sectors —High-Tech Industry, Skilled Market Services and Skilled Non-Market Services—have more children in 2010 than in 1971 and the percentage of marriage has also increased. Second, when we control for age, these family indicators for unskilled women behave differently depending on the economic sector they work in and their group of age. While for skilled women we point out a relevant fact. The two family indicators have increased in the Skilled Non-Market Services sector, regardless the group of age. We then argue that the trade-off between marriage, having children and participating in the labor market depends not only in the level of education of women but also in the economic sector they decide to work in. Women, who decide to have a family and work, get tertiary education not only because the cost of not doing so has increased over time but allows them to end up working in a sector such as the Skilled Non-Market Services sector that offers skilled women a more favorable trade-off between family and working life. We next study sector specific working characteristics that help us to enhance the preference of skilled women to end up working in this sector.

[8]We do not make any reference to Agriculture since it has become the sector with the smallest share or workers engaged.

Table 3.1: Demographic Indicators: Number of Own Children and Percentage of Marriage.

Categories	Number of own children				% of married women			
	Skilled		Unskilled		Skilled		Unskilled	
	1971	2010	1971	2010	1971	2010	1971	2010
By sector								
Low-Tech Industry	1.27	1.03	1.38	1.24	36.36	64.58	70.61	63.60
High-Tech Industry	0.50	1.14	1.32	1.12	50.00	67.47	69.19	58.56
Unskilled Services	0.95	0.99	1.44	1.23	68.42	62.91	73.17	55.48
Skilled Market Services	0.62	1.10	1.22	1.21	48.65	67.59	68.71	62.98
Skilled Non-Market Services	*0.88*	*1.10*	1.46	1.25	*58.44*	*68.27*	70.58	59.75
By group of age								
25-34								
Low-Tech Industry	0.57	0.66	1.83	1.51	28.57	51.56	71.79	54.49
High-Tech Industry	0.50	0.95	1.74	1.42	25.00	56.73	73.37	45.88
Unskilled Services	0.92	0.69	1.87	1.38	75.00	48.57	74.35	43.73
Skilled Market Services	0.31	0.72	1.31	1.44	30.77	56.66	66.85	52.61
Skilled Non-Market Services	*0.54*	*0.82*	1.56	1.55	*57.22*	*58.79*	70.61	47.81
35-44								
Low-Tech Industry	3.50	1.54	2.13	1.76	50.00	71.72	77.23	62.96
High-Tech Industry	0.00	1.43	1.77	1.72	100.00	75.14	69.45	58.62
Unskilled Services	0.90	1.46	2.29	1.69	70.00	70.23	79.52	59.70
Skilled Market Services	0.29	1.58	1.94	1.66	28.57	75.53	77.07	65.21
Skilled Non-Market Services	*1.60*	*1.64*	2.44	1.80	*63.13*	*74.97*	80.37	62.23
45-54								
Low-Tech Industry	3.00	1.14	0.91	0.99	100.00	68.99	72.33	68.53
High-Tech Industry	1.00	1.13	0.88	0.91	100.00	68.91	73.33	61.05
Unskilled Services	1.27	1.16	1.02	1.01	63.64	71.33	73.75	60.87
Skilled Market Services	2.13	1.27	1.01	1.01	75.00	72.40	71.46	67.59
Skilled Non-Market Services	*1.10*	*1.23*	1.27	1.09	*68.39*	*72.32*	73.74	65.01
55-65								
Low-Tech Industry	0.00	0.36	0.30	0.44	-	65.57	55.50	65.23
High-Tech Industry	-	0.66	0.34	0.31	-	61.02	52.38	65.88
Unskilled Services	0.40	0.47	0.30	0.44	60.00	66.98	61.33	60.11
Skilled Market Services	0.00	0.41	0.27	0.37	66.67	62.94	54.78	66.74
Skilled Non-Market Services	*0.18*	*0.43*	0.31	0.40	*41.18*	*65.26*	53.02	61.23

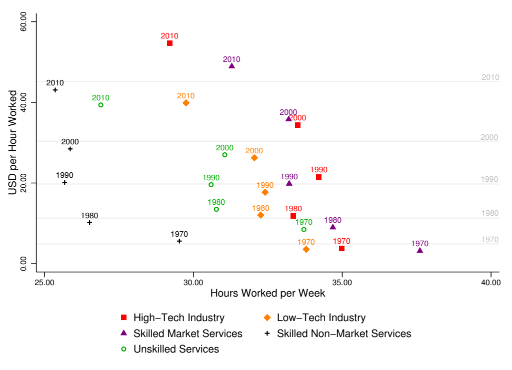
Source: Current Population Survey.

3.2.3 Hours Worked vs Compensation per Hour

The decrease in hours worked per week and the rise in compensation per hour worked —in constant U.S. dollars—characterize the evolution of industry and services in the U.S. Figure 3.4 describes this evolution for skilled women and skilled men considering a wider division of the economy[9]. In this figure we see a similar behavior for both skilled men and skilled women in all sectors. Although hours worked per week differed among sectors, compensation per hour worked was very similar for skilled workers in 1970, 1980 and 1990. Since 2000 hours worked per week still differ among sectors but compensation per hour worked now is also different. Specifically, skilled workers earn considerably more than the average compensation per hour worked in the Skilled Market Services and the High-Tech Industry sectors. Regarding skilled women, note that in the Skilled Non-Market Services sector they earn as much as the average compensation per hour worked and work less hours per week. As a consequence, skilled women working in the Skilled Non-Market Services sector have more hours for leisure or to share with family while earning as much as the average compensation per hour worked for skilled women among sectors. This difference surely explains the increase in family indicators for skilled women in this sector.

[9]Horizontal lines in Figure 3.4 indicate the average compensation for skilled women and skilled men in 1970, 1980, 1990, 2000 and 2010, respectively.

Skilled Female Workers



Skilled Male Workers

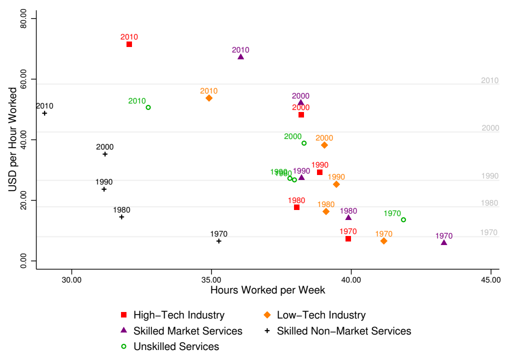


Figure 3.4: Hours Worked per Week vs Compensation per Hour Worked
Source: U.S. Labor Input File - WORLD KLEMS Database.

The evidence in this figure shows that when we consider a wider division of the economy we can identify deeper reasons that explain the allocation of skilled women in the Skilled Non-Market Services sector. This sector offers them the best trade-off between hours worked per week and compensation per hour worked. They work less hours and earn as much the average compensation per hour worked for skilled women among sectors. It is a key reason for the increase of family indicators discussed previously. Through a low number of hours worked at a relatively high compensation per hour worked, the Skilled Non-Market Services sector allows skilled women to have a balanced working family life, different from the other economic sectors. In order to find another key factor that explains the allocation of skilled women in the Skilled Non-Market Services sector, we next analyze the evolution of gender wage gap.

3.2.4 Gender Wage Gap

It is a known fact that gender wage gap within skilled labor force has declined over time. However, when we classify the economy in more sectors, we identify some differences. In Figure 3.5 we plot the skilled gender wage gap by groups of age and consider a wider division on the economy. We see that the skilled gender wage gap is the smallest in the Skilled Non-Market Services sector for every group of age. It is also interesting to note that in younger ages —the two upper graphs—the skilled gender wage gap is the lowest and very similar in high TFP sectors —High-Tech Industry, Skilled Market Services and Skilled Non-Market Services—. It suggests that a young woman might choose a degree that leads her to work in these sectors due to a more "equal" salary relative to a young man. Nonetheless, when we analyze older ages —the two lower graphs—we see that the skilled gender wage gap in the Skilled Non-Market Services sector is distant from the other sectors. It suggests that when a skilled woman considers her later stages of working life she would face a more valuable situation relative to a skilled man when she ends up working in the Skilled Non-Market Services sector.

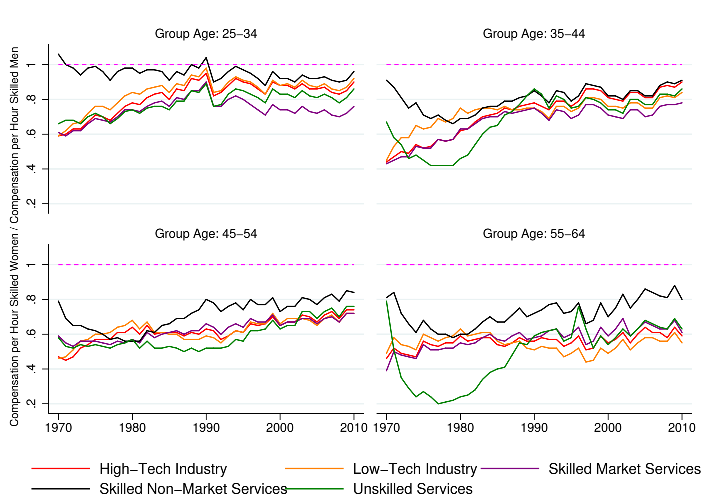


Figure 3.5: Compensation per Hour Worked Skilled Women vs Skilled Men by Group of Age
Source: WORLD KLEMS Database.

The evidence given in this figure suggests that gender wage gap is a key driver for women to be allocated into the Skilled Non-Market Services sector during structural transformation. The small gender wage gap experienced in this sector shapes the preferences of women to end up working on it. This small gender wage gap not only motivates young women to choose a career that leads them to end up working in the Skilled Non-Market Services sector but also offers a more valuable situation relative to men when they reach older ages. We then explore an alternative explanation different from the "brain" vs "brawn" comparative advantage as the key assumption to explain the allocation of women towards services. We refer to this alternative as a "new" comparative advantage. It refers to the opportunity cost of staying working a certain amount of hours in one sector instead of another one. Specifically, we argue that a skilled woman has a "new" comparative advantage over a skilled man if her opportunity cost is higher than the opportunity cost of a skilled man.

3.2.5 Comparative Advantage

Consider w^S as the compensation per hour worked in sector S and L^S as the total hours worked per week in sector S. Assume that industry requires L^I hours to work per week. We then compute the opportunity cost of staying working L^I hours in industry instead of working L^I hours in services. The weekly compensation if a worker decides to work L^I hours per week in industry is $\omega^{I,I} = w^I L^I$ while in services is $\omega^{I,s} = w^s L^I$. Then, the opportunity cost of working in industry instead of services is given by the ratio $\omega^{I,s}/\omega^{I,I}$, i.e., the sector premium[10]. Given the differences in hours worked per week and in compensation per hour worked between women and men, we compute this opportunity cost for both separately and compare the results[11]. We name this comparison as a "new" comparative advantage and argue that a woman has a comparative advantage if her opportunity cost is higher than the opportunity cost of a man. Figures 3.6 to 3.8 show the evolution of this "new" comparative advantage for skilled women —red line—over skilled men —blue line—[12]. We expect to see the red line above the blue line in these figures if skilled women have comparative advantage in services. It would imply skilled women have a higher opportunity cost —or higher losses—than skilled men if they decide to work in industry instead of services.

We first analyze this "new" comparative advantage within high TFP sectors—High-Tech Industry, Skilled Market Services and Skilled Non-Market Services—. In Figure 3.6 we see that the opportunity cost of staying working in the High-Tech Industry instead of moving towards the Skilled Market Services is similar for both skilled men and skilled women. This opportunity cost is even slightly higher for skilled men. It means that if a skilled woman stays working in the High-Tech Industry instead of working the same hours in the Skilled Market Services, she loses slightly less than a skilled man. In other words, skilled men would have a small comparative advantage over skilled women in the Skilled Market Services. Note that this opportunity cost is increasing over time and, then, not moving towards this sector has become very costly for both skilled women and skilled men.

In Figure 3.7 we plot the opportunity cost of staying working in the High-Tech Industry instead of moving towards the Skilled Non-Market Services. We see that it is clearly higher for skilled women than for skilled men, although it is decreasing over time. It implies that if a skilled woman stays working in the High-Tech Industry instead of working the same hours in the Skilled Non-Market Services, she has higher losses than a skilled man. Then, we argue that skilled would women have a comparative advantage over skilled men in the Skilled Non-Market Services sector and, therefore, skilled women would make decisions that lead them to end up working in this sector.

Second, we compare this "new" comparative advantage within low TFP sectors—Low-Tech Industry and Unskilled Services—. In Figure 3.8 we see that the opportunity cost of staying working in the Low-Tech Industry instead of moving towards the Unskilled Services is decreasing over time and it is clearly higher for skilled men before 1990. It means that before 1990 if a skilled woman stayed working in the Low-Tech Industry instead of working the same hours in the Unskilled Services, her losses were lower than those of a skilled man. Therefore, before 1990 skilled men would have had a comparative advantage over skilled women in the Unskilled Services. However, it changed after 1990. This opportunity cost became slightly higher for skilled women. Then, the Unskilled Services sector does not show a clear comparative advantage for skilled women or skilled men.

Finally, we make this analysis for a skilled worker moving from a low TFP sector in industry —Low-Tech Industry—to a high TFP sector in services —Skilled Market Services and Skilled Non-Market Services—and we obtain similar results; see Figures 3A1 and 3A2 in Appendix A. Skilled women show a similar opportunity cost than skilled men if they move from the Low-Tech Industry towards the Skilled Market Services and it is slightly higher for skilled men. While the opportunity cost of staying working in the Low-Tech Industry instead of moving towards the Skilled Non-Market Services is clearly higher for

[10]If we build it from services to industry we would have the opposite interpretation.
[11]See section 3.2.3.
[12]We make the same analysis considering also unskilled women and find the same conclusions.

skilled women. Then, skilled women would have a comparative advantage over skilled men in the Skilled Non-Market Services sector.

Figure 3.6: Opportunity Cost of Skilled Market Services vs High-Tech Industry
Source: WORLD KLEMS Database.

Figure 3.7: Opportunity Cost of Skilled Non-Market Services vs High-Tech Industry
Source: WORLD KLEMS Database.

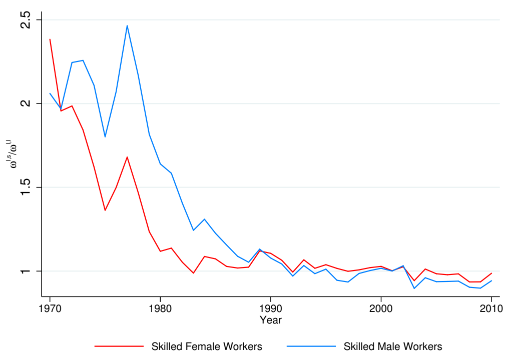


Figure 3.8: Opportunity Cost of Unskilled Services vs Low-Tech Industry
Source: WORLD KLEMS Database.

Because of the evidence shown in this section, we argue that the "brain" versus "brawn" comparative advantage is not enough to explain the allocation of the skilled female labor force in services. We argue that because of different forces —such as a directed technical change, lower hours worked at a relatively high compensation per hour, a small gender wage gap, better family indicators—a skilled woman has stronger preferences to work in the Skilled Non-Market Services sector. In the next section, we propose a theoretical approach used to explain why a skilled woman is allocated mainly in the Skilled Non-Market Services sector during structural transformation. This model does not assume the usual comparative advantage of gender literature and, instead, focuses on the empowerment of women and their preferences.

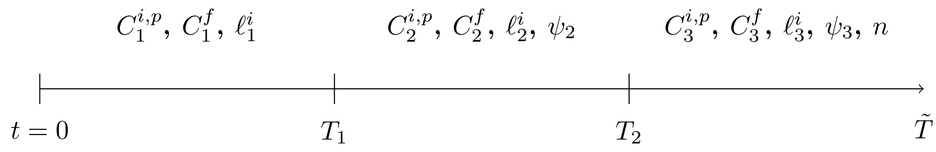
3.3 Model and Calibration

In previous sections we described different factors that might shape the preferences of a skilled woman related to her working and family life. In this section we build a theoretical model that explain why some of these factors make a skilled woman have strong preferences to work in the Skilled Non-Market Services sector.

Over time, there has existed critical changes—such as the legal use of the pill and divorce laws—that have favored women to truly decide over her body and, therefore, over her desired balance between working and family life. We focus then on the preferences of these empowered women. More precisely, we focus on their decisions about where and how many hours to work, how many hours to share with family, their consumption, and whether and how many children to have. We implicitly assume that if a woman decides to have tertiary education, she chooses a degree that leads her to end up working in the sector she prefers. We also assume that if a woman decides to have tertiary education, she starts with a higher human capital. Moreover, we assume that a woman that does not decide to be tertiary educated in her first period of time cannot get a degree in later periods. In our model we also assume a discount factor of zero and, then, there are no savings in our model. Finally, we do not consider taxes nor transfers from government.

3.3.1 Decisions of An Empowered Woman

The lifetime period of an empowered woman is divided into three periods of time: from the moment she starts to work ($t = 0$)[13] until the moment she decides to get married ($t = T_1$), from the moment she decides to get married until the moment she decides to have children ($t = T_2$), and from the moment she decides to have children until retirement ($t = \tilde{T}$). Since we assume there are no savings nor taxes in our model, we do not analyze any kind of pension system nor public policies related to it. As a consequence, the lifetime period of our empowered woman —and her family —ends exactly at $t = \tilde{T}$.



In each period of time she makes decisions on consumption and leisure. We assume two different types of consumption: personal and family consumption. We refer to personal consumption ($C_1^{i,p}$, $C_2^{i,p}$ and $C_3^{i,p}$) to the one that satisfies own necessities or personal likes,

[13] Across OECD countries, the average age of first-time entrants to tertiary education was 22 years old in 2018. Moreover, a bachelor's programme allows students to obtain a first degree qualification over three to four years; see OECD (2020). We assume that any individual with tertiary education starts to work ($t = 0$) at the age of 25, on average.

such as clothes. We refer to family consumption (C_1^f, C_2^f and C_3^f) to the one that satisfies general or common necessities to live, such as housing. She is endowed with one unit of time each period. The share of time she devotes to "own" leisure (ℓ_1^i, ℓ_2^i and ℓ_3^i) does not only depend on the share of hours worked in sector s ($L^{i,s}$) but also on the share of time spent with the other members of the family. Specifically, in the second period of time it also depends on the share of time spent with her husband (ψ_2). In the third period of time it also depends on the time spent with her husband (ψ_3) and the time spent with each child (θ^i). We assume a fixed $L^{i,s}$ in the three periods since it is the sector s who determines the total number of hours to work. The share of time devoted to "own" leisure in each period of time is then given by

$$\ell_1^i = \left(1 - L^{i,s}\right), \tag{3.1}$$

$$\ell_2^i = \left(1 - L^{i,s} - \psi_2\right), \tag{3.2}$$

$$\ell_3^i = \left(1 - L^{i,s} - \psi_3 - \theta^i n\right), \tag{3.3}$$

where n in equation (3.3) refers to the number of children in household which is decided only by our empowered woman. She accumulates utility in each period of time as follows:

$$u_1^i = \alpha_1^p ln\left(\int_0^{T_1} C_1^{i,p} dt\right) + \alpha_1^f ln\left(\int_0^{T_1} C_1^f dt\right) + \alpha_1^\ell ln\left(\int_0^{T_1} \ell_1^i dt\right), \tag{3.4}$$

$$u_2^i = \alpha_2^p ln\left(\int_{T_1}^{T_2} C_2^{i,p} dt\right) + \alpha_2^f ln\left(\int_{T_1}^{T_2} C_2^f dt\right) + \alpha_2^\ell ln\left(\int_{T_1}^{T_2} \ell_2^i dt\right) + \alpha_2^\psi ln\left(\int_{T_1}^{T_2} \psi_2 dt\right), \tag{3.5}$$

$$u_3^i = \alpha_3^p ln\left(\int_{T_2}^{\tilde{T}} C_3^{i,p} dt\right) + \alpha_3^f ln\left(\int_{T_2}^{\tilde{T}} C_3^f dt\right) + \alpha_3^\ell ln\left(\int_{T_2}^{\tilde{T}} \ell_3^i dt\right) + \alpha_3^\psi ln\left(\int_{T_2}^{\tilde{T}} \psi_3 dt\right) + \alpha_3^n ln\left(\int_{T_2}^{\tilde{T}} t^\phi f(\theta^i, n) dt\right), \tag{3.6}$$

where the last term of equation (3.6) refers to the utility our empowered woman gets from the number of children and the share of time she devotes to them[14]. We define

$$f(\theta^i, n) = \left(\theta^i + \theta^j\right)\left(\bar{n} + n\right), \tag{3.7}$$

where θ^j refers to the share of time her husband devotes to children and $\bar{n}$ is defined as in Guner et al. (2019)[15]. $\alpha_t^p > 0$, $\alpha_t^f > 0$, $\alpha_t^\ell > 0$, for $t = 1, 2, 3$, $\alpha_t^\psi > 0$ for $t = 2, 3$, and $\alpha_3^n > 0$ are the preferences' parameters for personal and family consumption, "own" leisure, time with other members of family, and children, respectively. We assume that in each period of time the preferences' parameters for accumulated consumption and accumulated leisure sum up to one and impose $\alpha_3^n > 0$ in order to have a positive utility from the number of children.

[14]Similar to Guner et al. (2019) we assume that utility from the number of children is increasing in parents age. However, the growth rate of this utility declines with age, captured by t^ϕ with $0<\phi<1$.

[15]It is an exogenously given number of children from which parents get utility, independent of the number of children they have. It is a standard feature of models with fertility, which allows us to pin down the fraction of childless females.

She devotes a fraction of time $L^{i,s}$ to work in sector s and gets paid a wage $w^{i,s}$ per efficiency unit of work. She accumulates human capital h^i which does not only captures her education but also her learning by doing at her job. The growth rate of her human capital is high at earlier stages of her working life; however, it declines with age, given by $\int t^\rho dt$, with $0 < \rho < 1$. Considering that $L^{i,s}h^i$ are the total efficiency units of labor offered, $w^{i,s}L^{i,s}h^i$ is the wage mass of the female. She devotes a fraction ξ_t^i of her wage mass to satisfy personal consumption and a fraction $(1-\xi_t^i)$ to family consumption, with $0 < \xi_t^i < 1$. Childcare costs are a part of family consumption in the third period of time. The interest rate of the intertemporal budget constraints is zero[16]. There are no taxes nor transfers from government. Then, accumulated personal consumption, family consumption and leisure, in the first period of time, satisfy

$$\int_0^{T_1} C_1^{i,p} dt = \int_0^{T_1} \xi_1^i w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.8}$$

$$\int_0^{T_1} C_1^{i,f} dt = \int_0^{T_1} (1-\xi_1^i) w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.9}$$

$$\int_0^{T_1} \ell_1^i dt = \left(1 - L^{i,s}\right) T_1, \tag{3.10}$$

in the second period of time

$$\int_{T_1}^{T_2} C_2^{i,p} dt = \int_{T_1}^{T_2} \xi_2^i w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.11}$$

$$\int_{T_1}^{T_2} C_2^{i,f} dt = \int_{T_1}^{T_2} (1-\xi_2^i) w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.12}$$

$$\int_{T_1}^{T_2} \ell_2^i dt = \left(1 - L^{i,s} - \psi_2\right)(T_2 - T_1), \tag{3.13}$$

$$\int_{T_1}^{T_2} \psi_2 dt = \psi_2 (T_2 - T_1), \tag{3.14}$$

and in the third period of time

$$\int_{T_2}^{\tilde{T}} C_3^{i,p} dt = \int_{T_2}^{\tilde{T}} \xi_3^i w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.15}$$

$$\int_{T_2}^{\tilde{T}} C_3^{i,f} dt = \int_{T_2}^{\tilde{T}} (1-\xi_3^i) w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.16}$$

$$\int_{T_2}^{\tilde{T}} \ell_3^i dt = \left(1 - L^{i,s} - \psi_3 - \theta^i n\right)(\tilde{T} - T_2), \tag{3.17}$$

$$\int_{T_2}^{\tilde{T}} \psi_i dt = \psi_3 (\tilde{T} - T_2). \tag{3.18}$$

Her husband faces the same decisions about the two types of consumption and leisure

[16] For a positive interest rate, we have a discount factor of $\frac{1}{1+r}$ in the intertemporal buget constraint. As a consequence, in the third period, where our empowered woman works some years more than her husband, we should include the discounted rent that she earns.

along his lifetime cycle, see Appendix B[17]. He is endowed with one unit of time each period. He devotes a fraction of time L^j to work and gets paid a wage w^j per efficiency unit of work. He also accumulates human capital h^j. A skilled man starts with a higher human capital than an unskilled man. He devotes a fraction ξ_t^j of his wage mass to personal consumption and $(1-\xi_t^j)$ to family consumption.

As in the first period of time there is only one member in household, family consumption satisfies

$$\int_0^{T_1} C_1^f dt = \int_0^{T_1} (1-\xi_t^i) w^{i,s} L^{i,s} h^i t^\rho dt, \tag{3.19}$$

while in the second and third period of time family consumption is decided simultaneously by the female and her husband. In these periods family consumption in household satisfies

$$\int_{T_1}^{T_2} C_2^f dt = \frac{\int_{T_1}^{T_2} C_2^{i,f} dt + \int_{T_1^j}^{T_2^j} C_2^{j,f} dt}{\Omega_2(n)}, \tag{3.20}$$

$$\int_{T_2}^{\tilde{T}} C_3^f dt = \frac{\int_{T_2}^{\tilde{T}} C_3^{i,f} dt + \int_{T_2^j}^{\tilde{T}^j} C_3^{j,f} dt}{\Omega_3(n)}, \tag{3.21}$$

where $\Omega_2(n) = 1 + 0.5$ and $\Omega_3(n) = 1 + 0.5 + 0.3n$ refer to household equivalence scale, as defined by the OECD[18]. Moreover, accumulated utility from children in the third period of time is given by

$$\int_{T_2}^{\tilde{T}} t^\phi \left(\theta^i + \theta^j\right) (\bar{n} + n)\, dt = \left(\theta^i + \theta^j\right) (\bar{n} + n) \left(\frac{\tilde{T}^{\phi+1} - T_2^{\phi+1}}{\phi + 1}\right). \tag{3.22}$$

We replace equations (3.8) to (3.22) into utility functions (3.4) to (3.6) and determine the accumulated utility that our empowered woman gets over her lifetime cycle

$$u^i = u_1^i + u_2^i + u_3^i, \tag{3.23}$$

which is then maximized. In order to find closed forms optimal solutions we use $\max(u^i) \leq \max(u_1^i) + \max(u_2^i) + \max(u_3^i)$[19]. We then maximize utility functions (3.8) with respect to ξ_1^i and $L^{i,s}$, (3.9) with respect to ξ_2^i, $L^{i,s}$ and ψ_2, and (3.10) with respect to ξ_3^i, $L^{i,s}$, ψ_3 and n and assume these first order conditions solve the maximization problem of our empowered woman over her lifetime cycle. Since the decision of the female becomes an externality to her husband and vice versa, as we can see in restrictions (3.20) and (3.21), her husband maximizes his accumulated utility u^j over ξ_t^j and L^j[20], simultaneously. We emphasize it is only the female who decides whether and how many children to have and the share of time spent with the partner. The first order conditions of utility maximization imply:

[17] $T_2^j = T_1^j + T_2 - T_1$. Whether and how many children to have is determined only by the woman in household. Also, $\tilde{T}$=$\tilde{T^j}$ since women and men usually retire at the same age in the U.S. The 2018 average normal retirement age in the U.S. for an individual with a full career and who entered the labour market at age 22 was equal to 66 years; see OECD (2019).

[18] Equivalence scales capture how the needs of a household grow with each additional member but – due to economies of scale in consumption– not in a proportional way. Needs for housing space, electricity, and others are not three times as high for a household with three members than for a single person.

[19] See Appendix 3.6.2

[20] See Appendix 3.6.2.

$$\alpha_1^p = \xi_1^i L^{i,s}, \tag{3.24}$$

$$\alpha_1^f = (1-\xi_1^i)L^{i,s}, \tag{3.25}$$

$$\alpha_1^l = 1 - L^{i,s}, \tag{3.26}$$

$$\alpha_2^p = \frac{(\rho^j+1)\xi_2^i w^{i,s} L^{i,s} h^i (T_2^{\rho+1} - T_1^{\rho+1})}{(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})(1 - L^{i,s} + L^{i,s}\xi_2^i) + \kappa_2}, \tag{3.27}$$

$$\alpha_2^f = \frac{\kappa_2}{(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})(1 - L^{i,s} + L^{i,s}\xi_2^i) + \kappa_2}, \tag{3.28}$$

$$\alpha_2^l = \frac{(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})(1 - L^{i,s} - \psi_2)}{(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})(1 - L^{i,s} + L^{i,s}\xi_2^i) + \kappa_2}, \tag{3.29}$$

$$\alpha_2^\psi = \frac{\psi_2(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})}{(\rho^j+1)w^{i,s}h^i(T_2^{\rho+1} - T_1^{\rho+1})(1 - L^{i,s} + L^{i,s}\xi_2^i) + \kappa_2}, \tag{3.30}$$

with $\kappa_2 = (\rho^j+1)(1-\xi_2^i)w^{i,s}L^{i,s}h^i(T_2^{\rho+1}-T_1^{\rho+1})+(\rho+1)(1-\xi_2^j)w^jL^jh^j\left[\left(T_1^j+T_2-T_1\right)^{\rho^j+1} - T_1^{j^{\rho^j+1}}\right]$,

$$\alpha_3^p = \frac{(\rho^j+1)\xi_3^i w^{i,s}L^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)}{(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \theta^i n + L^{i,s}\xi_3^i) + \kappa_3}, \tag{3.31}$$

$$\alpha_3^f = \frac{\kappa_3}{(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \theta^i n + L^{i,s}\xi_3^i) + \kappa_3}, \tag{3.32}$$

$$\alpha_3^l = \frac{(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \psi_3 - \theta^i n)}{(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \theta^i n + L^{i,s}\xi_3^i) + \kappa_3}, \tag{3.33}$$

$$\alpha_3^\psi = \frac{\psi_3(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)}{(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \theta^i n + L^{i,s}\xi_3^i) + \kappa_3} \tag{3.34}$$

and

$$\alpha_3^n = \frac{(\bar{n}+n)\left[\Omega_3'(n)\kappa_3 + \theta^i\Omega_3(n)(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)\right]}{\Omega_3(n)\left[(\rho^j+1)w^{i,s}h^i\left(\tilde{T}^{\rho+1} - T_2^{\rho+1}\right)(1 - L^{i,s} - \theta^i n + L^{i,s}\xi_3^i) + \kappa_3\right]}, \tag{3.35}$$

with $\kappa_3 = (\rho^j+1)(1-\xi_3^i)w^{i,s}L^{i,s}h^i(\tilde{T}^{\rho+1}-T_2^{\rho+1})+(\rho+1)(1-\xi_3^j)w^jL^jh^j\left[\tilde{T}^{\rho^j+1} - \left(T_1^j+T_2-T_1\right)^{\rho^j+1}\right]$.
Hence, $\alpha_t^\psi < \alpha_t^p < \alpha_t^f < \alpha_t^l$ for $t = 1, 2, 3$ meaning that our empowered woman prefers to work in a sector where she can devote more time to "own" leisure and from which she can earn the most in order to satisfy common necessities of her household. Consequently with previous sections, we expect this is true when she works in the Skilled Non-Market Services sector. Therefore, we consider this sector as our benchmark model and calibrate preference parameters (3.24) to (3.35).

3.3.2 Calibration

We use the National Survey of Family Growth (NSFG) 2002 to target T_1, T_2, T_1^j, and n for a skilled individual. The Multinational Time Use Study (MTUS) 2003 is used to target θ^i for a skilled woman in the public sector, θ^j for a skilled man, and ψ_2 and ψ_3 for skilled individuals in the public sector. With the information of the Labor Input Data File of WORLD KLEMS we compute the following values in 2002: the average share of hours worked in a week in the Skilled Non-Market Services for a skilled woman ($L^{i,s}$), the average share of hours worked in a week for a skilled man (L^j), the average compensation per hour worked in the Skilled Non-Market Services for a skilled woman ($w^{i,s}h^i$), the average compensation per hour worked for a skilled man ($w^j h^j$), and the growth rate of compensation per hour worked, for a skilled woman in the Skilled Non-Market Services and for a skilled man (ρ, ρ^j). Additionally, from the Consumer Expenditure Surveys (CE) 2002, we compute the average share of income spent in personal consumption for a skilled woman and for a skilled man (ξ_t^i, ξ_t^j), see Table 3.2. Note that we assume our empowered woman marries an average skilled man due to assortative matching. Note also that she marries this skilled man regardless the economic sector he works in. Using these targets we calibrate preference parameters (3.24) to (3.35) and show them in Table 3.3.

Table 3.2: Model Targets.

Target	Description
Time	
$T_1 = 3.84$	Years between age of 25 and average age of getting married, for a skilled woman. NSFG 2002.
$T_1^j = 4.35$	Years between age of 25 and average age of getting married, for a skilled man. NSFG 2002.
$T_2 = 8.17$	Years between average age of getting married and average age of having children, for a skilled woman. NSFG 2002.
$\tilde{T} = \tilde{T}^j = 41$	Years between of 25 and 66 (retirement).
$\psi_2 = 0.05$	Average share of time spent in the family, for skilled individuals with no children in the public sector. MTUS 2003.
$\psi_3 = 0.04$	Average share of time spent in the family, for skilled individuals with children n the public sector. MTUS 2003.
Children	
$n = 1.04$	Number of own children for a skilled woman, on average. NSFG 2002.
$\bar{n} = 2.20$, $\phi = 0.36$	Preferences for children. Guner et al. (2019).
$\theta^i = 0.03$	Average share of time spent with the children, for a skilled woman in the public sector. MTUS 2003.
$\theta^j = 0.02$	Average share of time spent with the children, for a skilled man. MTUS 2003.
Employment and Consumption	
$L^{i,s} = 0.23$	Average share of hours worked in a week in the SNMS, for a skilled woman. WORLD KLEMS.
$L^j = 0.35$	Average share of hours worked in a week, for a skilled man. WORLD KLEMS.
$w^{i,s}h^i = 30.63$	Average compensation per hour worked in the SNMS, for a skilled woman. WORLD KLEMS.
$w^j h^j = 42.02$	Average compensation per hour worked, for a skilled man. WORLD KLEMS.
$\rho = 0.05$	Growth rate of compensation per hour worked, for a skilled woman in the SNMS. WORLD KLEMS.
$\rho^j = 0.05$	Growth rate of compensation per hour worked, for a skilled man. WORLD KLEMS.
$\xi_1^i = 0.27$, $\xi_2^i = 0.28$, $\xi_3^i = 0.27$	Average share of income spent in personal consumption, for a skilled woman, single, married with no children, and married with children, respectively. CE 2002.
$\xi_1^j = 0.26$, $\xi_2^j = 0.28$, $\xi_3^j = 0.29$	Average share of income spent in personal consumption, for a skilled man, single, married with no children, and married with children, respectively. CE 2002.

Table 3.3: Preference Parameters Calibration.

Parameter	Value
Personal Consumption	
α_1^p	0.062
α_2^p	0.048
α_3^p	0.047
Family Consumption	
α_1^f	0.167
α_2^f	0.380
α_3^f	0.387
Leisure	
α_1^ℓ	0.771
α_2^ℓ	0.536
α_3^ℓ	0.537
Time spent with partner	
α_2^ψ	0.036
α_3^ψ	0.029
Children	
α_3^n	0.277

From first order conditions of utility maximization we know that

$$\xi_2^{i^*} = \frac{\alpha_2^p}{\alpha_2^p + \alpha_2^f}\left[1 + \left(\frac{\rho+1}{\rho^j+1}\right)\left(1-\xi_2^j\right)\left(\frac{L^j}{L^{i,s}}\right)\left(\frac{w^j h^j}{w^{i,s}h^i}\right)\left(\frac{\left[T_1^j + T_2 - T_1\right]^{\rho^j+1} - T_1^{j^{\rho^j+1}}}{T_2^{\rho+1} - T_1^{\rho+1}}\right)\right], \tag{3.36}$$

$$\xi_3^{i^*} = \frac{\alpha_3^p}{\alpha_3^p + \alpha_3^f}\left[1 + \left(\frac{\rho+1}{\rho^j+1}\right)\left(1-\xi_3^j\right)\left(\frac{L^j}{L^{i,s}}\right)\left(\frac{w^j h^j}{w^{i,s}h^i}\right)\left(\frac{\tilde{T}^{\rho^j+1} - \left[T_1^j + T_2 - T_1\right]^{\rho^j+1}}{\tilde{T}^{\rho+1} - T_2^{\rho+1}}\right)\right] \tag{3.37}$$

and

$$n^* = \frac{-\left[0.3\bar{n}\theta^i(\alpha_3^f - \alpha_3^\ell) - 0.3(1 - L^{i,s} - \psi_3)(\alpha_3^f - \alpha_3^n) - 1.5\theta^i(\alpha_3^\ell + \alpha_3^n)\right] - (\kappa_n)^{\frac{1}{2}}}{0.6\theta^i(\alpha_3^f - \alpha_3^\ell - \alpha_3^n)}, \tag{3.38}$$

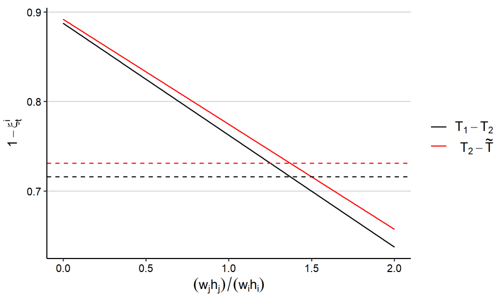
with

$$\kappa_n = \left[0.3\bar{n}\theta^i(\alpha_3^f - \alpha_3^\ell) - 0.3(1 - L^{i,s} - \psi_3)(\alpha_3^f - \alpha_3^n) - 1.5\theta^i(\alpha_3^\ell + \alpha_3^n)\right]^2 \\ - 1.2\theta^i(\alpha_3^f - \alpha_3^\ell - \alpha_3^n)\left[(1 - L^{i,s} - \psi_3)(1.5\alpha_3^n - 0.3\alpha_3^f\bar{n}) - 1.5\alpha_3^\ell\theta^i\bar{n}\right].$$

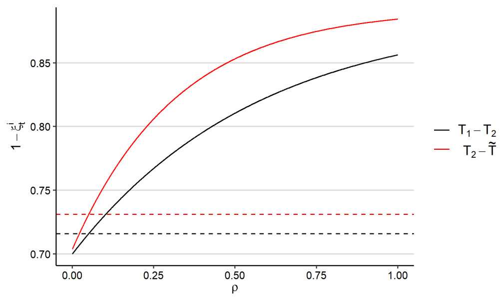
In equations (3.36) and (3.37) we see that as gender wage gap $\left(\frac{w^j h^j}{w^{i,s}h^i}\right)$ increases the fraction of her wage mass devoted to satisfy personal consumption (ξ_t^i) increases, i.e. the fraction of her wage mass devoted to satisfy family consumption $(1 - \xi_t^i)$ decreases, see Figure 3.9a. From first order conditions we also know that $\alpha_t^p < \alpha_t^f$ meaning that our empowered woman has stronger preferences to satisfy family consumption rather than personal consumption. Therefore, she decides to work in an economic sector with a low gender wage gap so she can satisfy family consumption more likely. Recall that h^i refers to our empowered woman human capital. From equations (3.36) and (3.37) we also see that if she decides to have tertiary education, i.e. start with a higher human capital than one without it, she would also have a higher fraction of her wage mass devoted to satisfy family consumption. Then, our empowered woman optimally decides to be tertiary educated and chooses a career that leads her to end up working in the Skilled Non-Market Services sector. In Figure 3.9b we additionally observe how the fraction of her wage mass devoted to satisfy family consumption $(1 - \xi_t^i)$ increases as the growth rate of compensation per hour worked (ρ) increases. Thus, our empowered woman would like to move to other sectors with higher ρ such as the High-Tech Industry and the Skilled Market Services. However, it implies to move to other sectors that require a higher number of hours worked as explained in Section 3.2. It is true that moving towards sectors with higher number of hours worked ($L^{i,s}$) allows women to have a higher ρ and, therefore, a higher fraction of her wage mass devoted to satisfy family consumption but it also comes together with a high cost for her: a decrease in the number of children, see equation (3.38) and Figure 3.9c. Finally, as the share of time devoted to childcare increases (θ^i) the number of children decreases, see Figure 3.9d. It means that women with a high number of children devote very little time to each child. This latter case might explain why skilled women in general decide to have a low number of children[21].

As described in Section 3.2, Skilled Non-Market Services offers skilled women the smallest gender wage gap among economic sectors, regardless their age. It also requires the smallest hours to work per week and compensation per hour worked is as much as the average compensation per hour worked among sectors. The number of own children has increased over time for skilled women in this sector. We then conclude that our empowered woman's optimal decisions lead her to work in the Skilled Non-Market Services sector. This sector offers her a balanced trade-off between marriage, having children and participating in the labor market. Finally, we confirm our findings identifying relevant characteristics of this sector through a microdata approach. These characteristics strengthen our claims about the allocation of skilled women into this sector.

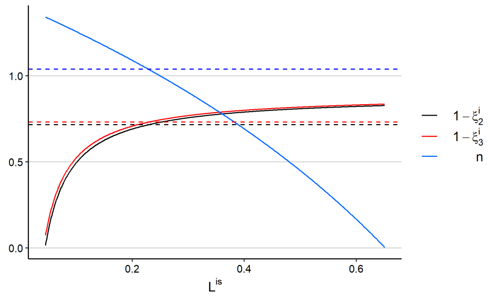
[21] See Table 3.1.



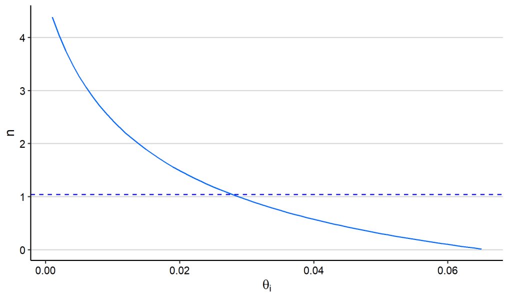
(a) Gender Wage Gap



(b) Growth Rate of Compensation per Hour Worked



(c) Share of Time Devoted to Work



(d) Share of Time Devoted to Children

Figure 3.9: Fraction of Wage Mass Devoted to Satisfy Family Consumption and Number of Own Children

3.4 Microdata Approach

We use information from IPUMS-CPS database. Specifically, we use the Annual Social and Economic (ASEC) supplement to the Current Population Survey (CPS) from 1976 to 2018. We consider those individuals with valid entries for those variables that we use in the estimation. We use the variable "*Educational attainment recode*" to determine if the individual has tertiary education or not[22]. We use the variable "*Industry, 1990 basis*" to identify the six economic sectors described in the previous sections. We use the variable "*Wage and salary income*" since it indicates each respondent's total pre-tax wage and salary income for the previous calendar year. We adjust it for inflation to be able to make results comparable over time[23]. Similar to Section 3.2, we categorize the age of the individual into four groups: from 25 to 34, from 35 to 44, from 45 to 54 and from 55 to 65. Finally, we use the variable "*Annual Social and Economic Supplement Weight*" as our weighting variable.

First, we perform a logit estimation of the probability of an individual to end up working in the Skilled Non-Market Services, i.e. we define

$$y_i = \begin{cases} 1, & \text{if } i \text{ works in the Skilled Non-Market Services sector} \\ 0, & \text{otherwise.} \end{cases}$$

and estimate

$$Pr[y_i = 1|\mathbf{x}] = F(\mathbf{x}_i'\beta), \tag{3.39}$$

[22] We consider that an individual has tertiary education if she has a Bachelor's degree or higher.
[23] We adjust for 1999 inflation; see Flood et al. (2020).

where $\mathbf{x}_i$ is a set of characteristics of individuals[24]. Specifically, we use sex and age of the individual as regressors in Model (1). In Model (2) we include work characteristics such as hours worked, income wage (in logs), and part-time or full-time employment status of the individual. In Model (3) we capture the impact of fertility rate with variables such us the number of children and whether the individual has babies or not[25]. In Model (4) we introduce a geographic control since government activities are usually more concentrated in big cities and, therefore, we would face a problem of omitted variable bias. Finally, in Model (5) we include time-fixed effects. Table 3.4 shows the results for this estimation and we only describe the results of this last model since it considers the same variables than the others but also controls for time-fixed effects.

We see that the sex of individual is not significant to estimate the probability of ending up working in the Skilled Non-Market Services sector. However, we have seen in Section 3.2 that the evolution of the Skilled Non-Market Services sector has been characterized by a higher participation of women over men. Moreover, when we consider age, we see that individuals in the older ages have higher probability to end up working in this sector than those in the youngest ages. It is specially true for a woman in the older ages—e.g. an increase of 0.196 is expected in the log odds of our dummy with respect to a male in all groups of age and females in the 25-34 group—. These results depict a work stability in the older ages for individuals in this sector, specially for women.

As expected, if the individual has tertiary education the probability of ending up working in the Skilled Non-Market Services sector also increases —an increase of 1.106 is expected in the log odds of our dummy with respect to an individual with less than tertiary education—. This result supports the importance of tertiary education in the allocation of the labor force in this sector.

Moreover, when we consider work characteristics such as hours worked, income wage, and part-time or full-time employment status of the individual, we identify relevant facts. On the one hand, we see that as the number of hours worked increases the probability for the individual to end up working in the Skilled Non-Market Services sector decreases. It is true for both, males and females—a higher decrease is expected in the log odds of our dummy for a male (0.021 compared to 0.010)—. Moreover, regarding the income of the individual, we see that its increase has a positive impact on the analyzed probability for females while it is negative for males[26]. These results support the evidence shown in Section 3.2. On the other hand, when we consider the individual's type of contract, we see that the probability of working in the Skilled Non-Market Services sector increases if it is a full time contract and the individual is a female—an increase of 0.126 is expected in the log odds of our dummy with respect to individuals with part time contract—. With this result, we argue that there exists an "unobserved" stability offered by this sector to females.

Finally, when we consider those variables related to family indicators we see that as the number of own children increases, the probability to end up working in the Skilled Non-Market Services sector increases for females while it decreases for males—an increase of 0.121 is expected in the log odds of our dummy if the individual is a female—. But when we consider the presence of a baby in the household we see that this probability decreases for

[24]See Cameron and Trivedi (2005). In Appendix 3.6.3 we perform a logit estimation of the probability to end up working in the other economic sectors.

[25]We use the variable of number of children under age 5 as a dummy to identify if there is a baby or not in household. We do this assumption since the CPS does not include the age of every children in household.

[26]Results on Appendix 3.6.3 show that this phenomenon happens only the Skilled Non-Market Services sector.

females—a decrease of 0.071 is expected in the log odds of our dummy—. As discussed in Section 3.2, we believe this result can be explained when we consider the level of education of the individual and, therefore, we next perform an additional analysis where we emphasize the role of tertiary education.

We now define

$$y_i^1 = \begin{cases} 1, & \text{if } i \text{ is a woman and works in the Skilled Non-Market Services sector} \\ 0, & \text{otherwise.} \end{cases}$$

and estimate

$$Pr[y_i^1 = 1|\mathbf{x}] = F(\mathbf{x}_i'\beta). \tag{3.40}$$

Table 3.5 shows the results for this estimation. Additional to the age of the individual, in Model (1) we create an interaction term between age and education of the individual and use it as another regressor. In Model (2) we include work characteristics such as hours worked, income wage, and part-time or full-time employment status of the individual. Due to collinearity problems we do not use the interaction term created in Model (1). Instead, we create interaction terms between the work-related characteristics and the education of the individual. In Model (3) we take into account variables regarding fertility rate such as the number of own children and if the individual has babies or not. Due to collinearity problems we do not use the interaction terms created for the first two models. Instead, we consider interaction terms between the variables regarding fertility rate and the education of the individual. In Model (4), (5), and (6) we perform the same analysis of Model (1), (2), and (3), respectively, but introducing a geographic control and time-fixed effects. We describe mainly the results of models (4) to (6) since they consider a geographic control and time-fixed effects.

Model (4) suggest that women in the older ages have higher probability to end up working in this sector than those in the youngest ages. More importantly, due to the interaction term between age and level of education, we see that skilled women in every group of age have higher probability to end up working in this sector than unskilled individuals and it is even higher in the first group of age—an increase of 0.909 is expected in the log odds of our dummy—. This result suggests that women that decide to have tertiary education might choose a career that leads them to end up working in this sector.

Different from the results in Table 3.4, in Model (5) we can see that full-time contracts would reduce the analyzed probability—a decrease of 0.029 is expected in the log odds of our dummy with respect to individuals working with a part-time contract—. However, when we take into account the level of education, those with tertiary education actually have higher probability to end up working in the Skilled Non-Market Services sector regardless the type of contract—an increase of 2.311(2.495) is expected in the log odds of our dummy with respect to individuals without tertiary education working with a part(full)-time contract—. This result suggests that job flexibility might be an important characteristic offered to skilled women in this sector.

Finally, the results of Model (6) show that indeed there exists a difference between skilled and unskilled women regarding the decision of whether to have babies. Different from results in Table 3.4, we now see that skilled women that decide to have babies make increase the probability to end up working in the Skilled Non-Market Services sector—an increase of 1.253 is expected in the log odds of our dummy with respect to individuals without tertiary education that have babies—.

The results of this section allow us not only to confirm our findings in previous sections but also to point out other relevant characteristics of Skilled Non-Market Services sector, specially for skilled women. We have identified they experience a long run stability and job flexibility in this sector. These characteristics might strengthen the preferences of women regarding acquiring education or not, participating in the labor force or having a family, or both. We have seen that Skilled Non-Market Services seems to be the sector that offers skilled women a balanced life between work and family.

Table 3.4: Logit Estimation of Equation (3.39).

	(1)	(2)	(3)	(4)	(5)
Sex					
Female	1.118***	0.200***	-0.035	-0.049	-0.069
	(0.009)	(0.052)	(0.052)	(0.052)	(0.052)
Age					
35-44	0.040***	0.103***	0.115***	0.114***	0.121***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
45-54	0.174***	0.257***	0.269***	0.268***	0.276***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
55-65	0.282***	0.349***	0.352***	0.349***	0.353***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
35-44 (Female)	0.146***	0.109***	0.018	0.017	0.018
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
45-54 (Female)	0.169***	0.133***	0.099***	0.099***	0.100***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
55-65 (Female)	0.160***	0.147***	0.193***	0.193***	0.196***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Education					
Tertiary	1.021***	1.080***	1.091***	1.091***	1.106***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Work					
Hours Worked (Male)		-0.021***	-0.021***	-0.021***	-0.021***
		(0.000)	(0.000)	(0.000)	(0.000)
Hours Worked (Female)		-0.011***	-0.010***	-0.010***	-0.010***
		(0.000)	(0.000)	(0.000)	(0.000)
Income Wage (Male)		-0.032***	-0.034***	-0.032***	-0.034***
		(0.004)	(0.004)	(0.004)	(0.004)
Income Wage (Female)		0.001	0.010**	0.013**	0.013**
		(0.004)	(0.004)	(0.004)	(0.004)
Full Time (Male)		0.004	0.008	0.002	0.002
		(0.016)	(0.016)	(0.016)	(0.016)
Full Time (Female)		0.117***	0.132***	0.124***	0.126***
		(0.010)	(0.010)	(0.010)	(0.010)
Children					
Number of Own Children (Male)			-0.017***	-0.016***	-0.017***
			(0.003)	(0.003)	(0.003)
Number of Own Children (Female)			0.121***	0.121***	0.121***
			(0.003)	(0.003)	(0.003)
Babies (Male)			0.022**	0.022**	0.024*
			(0.010)	(0.010)	(0.010)
Babies (Female)			-0.074***	-0.074***	-0.071***
			(0.009)	(0.009)	(0.009)
Constant	-2.070***	-0.864***	-0.857***	-0.827***	-0.595***
	(0.007)	(0.040)	(0.040)	(0.041)	(0.048)
Individual Income	NO	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES
Observations	1,774,884	1,684,313	1,684,313	1,684,313	1,684,313
Wald χ^2	120919.83	118982.80	122392.30	123003.90	123545.50
Prob< χ^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

Table 3.5: Logit Estimation of Equation (3.40).

	(1)	(2)	(3)	(4)	(5)	(6)
Age						
35-44	0.226***	0.232***	0.148***	0.232***	0.234***	0.151***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
45-54	0.392***	0.411***	0.337***	0.391***	0.409***	0.335***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
55-65	0.493***	0.412***	0.383***	0.482***	0.401***	0.374***
	(0.010)	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)
25-34 (Tertiary Education)	0.907***			0.909***		
	(0.009)			(0.010)		
35-44 (Tertiary Education)	0.692***			0.692***		
	(0.008)			(0.008)		
45-54 (Tertiary Education)	0.613***			0.620***		
	(0.009)			(0.009)		
55-65 (Tertiary Education)	0.485***			0.490***		
	(0.012)			(0.012)		
Work						
Income Wage		-0.177***	-0.251***		-0.176***	-0.250***
		(0.004)	(0.003)		(0.004)	(0.003)
Hours Worked		-0.035***	-0.031***		-0.035***	-0.031***
		(0.000)	(0.000)		(0.000)	(0.000)
Type of Contract (Full Time)		-0.025*	0.046		-0.029*	0.039***
		(0.012)	(0.009)		(0.012)	(0.009)
Income Wage (Tertiary Education)		-0.182***			-0.183***	
		(0.007)			(0.007)	
Hours Worked (Tertiary Education)		0.008***			0.009***	
		(0.001)			(0.001)	
Type of Contract (Partial Time) (Tertiary Education)		2.303***			2.311***	
		(0.060)			(0.060)	
Type of Contract (Full Time) (Tertiary Education)		2.493***			2.495***	
		(0.068)			(0.068)	
Children						
Number of Own Children			0.124***			0.126***
			(0.003)			(0.003)
Babies			-0.349***			-0.347***
			(0.011)			(0.011)
Number of Own Children (Tertiary Education)			-0.094***			-0.098***
			(0.004)			(0.004)
No babies (Tertiary Education)			1.008***			1.014***
			(0.007)			(0.007)
Babies (Tertiary Education)			1.251***			1.253***
			(0.016)			(0.016)
Constant	-1.962***	1.210***	1.684***	-1.858***	1.252***	1.707***
	(0.006)	(0.034)	(0.027)	(0.030)	(0.045)	(0.040)
Individual Income	NO	YES	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES	YES
Year Fixed Effects	NO	NO	NO	YES	YES	YES
Observations	1,774,884	1,684,313	1,684,313	1,774,884	1,684,313	1,684,313
Wald χ^2	24499.10	57462.94	58641.78	26526.72	59062.19	60220.64
Prob< χ^2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

3.5 Conclusions

The opportunity cost of staying working in a sector different from the Skilled Non-Market Services sector is clearly higher for skilled women than for skilled men and, then, we argue that skilled women show a ("new") comparative advantage in this sector. However, this behavior is not identified within other services sectors and, therefore, we do not consider the usual "brain" versus "brawn" comparative advantage in our theoretical model. Instead, our model focuses on the preferences of an empowered woman.

We find that "own" leisure and family consumption account for the largest weight on our empowered woman utility. We show that as gender wage gap increases the fraction of her wage mass devoted to satisfy family consumption decreases while it increases if she decides to be tertiary educated. We also find that this fraction increases when she works more hours, however, it comes together with a high cost: a lower number of children. As Skilled Non-Market Services sector offers skilled women the smallest gender wage gap, requires the smallest hours to work per, offers a compensation per hour worked as large as the average compensation among sectors, and shows higher demographic indicators for skilled women we conclude that our empowered woman's optimal decisions lead her to work in this sector.

We also present a microdata approach using data from Current Population Survey where we identify relevant characteristics of the Skilled Non-Market Services sector. These characteristics are work stability in the older ages, job flexibility or less hours worked, a small gender wage gap, and better family indicators. We then confirm women preferences match the characteristics of the Skilled Non-Market Services sector and, as a consequence, they are more likely allocated in this sector during structural transformation.

3.6 Appendix

3.6.1 From Low TFP to High TFP Sectors

Figures 3A1 and 3A2 show the comparative advantage defined in Section 3.2 if workers move from low TFP sectors to high TFP sectors.

Figure 3A1: Opportunity Cost of Skilled Market Services vs Low-Tech Industry
Source: WORLD KLEMS Database.

Figure 3A2: Opportunity Cost of Skilled Non-Market Services vs Low-Tech Industry
Source: WORLD KLEMS Database.

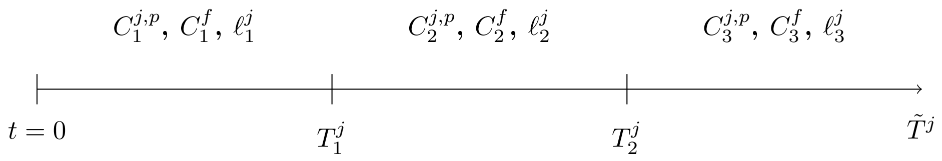
3.6.2 Utility Maximization

Definition

Let $x^* = \arg\max f(x) + g(x)$, $x^a = \arg\max f(x)$ and $x^b = \arg\max g(x)$. As $f(x^a) \geq f(x^*)$ and $g(x^b) \geq g(x^*)$, we have that $f(x^*) + g(x^*) \leq f(x^a) + g(x^b)$.

Male Utility Maximization Problem

Similar to our empowered woman, the lifetime cycle of her husband is shown in the following plot.



In each period of time he makes decisions on consumption and leisure. He decides on his personal consumption ($C_1^{j,p}$, $C_2^{j,p}$ and $C_3^{j,p}$) and family consumption (C_1^f, C_2^f and C_3^f). He is endowed with one unit of time each period. The share of time he devotes to leisure (ℓ_1^j, ℓ_2^j and ℓ_3^j) does not only depend on the share of hours worked (L^j) but also on the share of time spent with the other members of the family. Specifically, in the second period of time it also depends on the share of time spent with his wife (ψ_2). In the third period of time it also depends on the time spent with his wife (ψ_3) and the time spent with each child (θ^j):

$$\ell_1^j = \left(1 - L^j\right), \tag{3.41}$$

$$\ell_2^j = \left(1 - L^j - \psi_2\right), \tag{3.42}$$

$$\ell_3^j = \left(1 - L^j - \psi_3 - \theta^j n\right). \tag{3.43}$$

His accumulated utility functions in each period of time are

$$u_1^j = \alpha_1^{j,p} ln \left(\int_0^{T_1^j} C_1^{j,p} dt \right) + \alpha_1^{j,f} ln \left(\int_0^{T_1^j} C_1^f dt \right) + \alpha_1^{j,\ell} ln \left(\int_0^{T_1^j} \ell_1^j dt \right), \tag{3.44}$$

$$u_2^j=\alpha_2^{j,p}ln\left(\int_{T_1^j}^{T_2^j}C_2^{j,p}dt\right)+\alpha_2^{j,f}ln\left(\int_{T_1^j}^{T_2^j}C_2^{f}dt\right)+\alpha_2^{j,\ell}ln\left(\int_{T_1^j}^{T_2^j}\ell_2^{j}dt\right)+\alpha_2^{\psi}ln\left(\int_{T_1^j}^{T_2^j}\psi_2 dt\right), \tag{3.45}$$

$$u_3^j=\alpha_3^{j,p}ln\left(\int_{T_2^j}^{\tilde{T}^j}C_3^{j,p}dt\right)+\alpha_3^{j,f}ln\left(\int_{T_2^j}^{\tilde{T}^j}C_3^{f}dt\right)+\alpha_3^{j,\ell}ln\left(\int_{T_2^j}^{\tilde{T}^j}\ell_3^{j}dt\right)+\alpha_3^{\psi}ln\left(\int_{T_2^j}^{\tilde{T}^j}\psi_3 dt\right)+$$
$$\alpha_3^{j,n}ln\left(\int_{T_2^j}^{\tilde{T}^j}t^{\phi}f(\theta^j,n)dt\right), \tag{3.46}$$

where $f(\theta^j,n)=f(\theta^i,n)$.

Additionally, in the first period of time, his accumulated personal consumption, family consumption and leisure satisfy

$$\int_0^{T_1^j}C_1^{j,p}dt=\int_0^{T_1^j}\xi_1^j w^j L^j h^j t^{\rho^j}dt, \tag{3.47}$$

$$\int_0^{T_1^j}C_1^{j,f}dt=\int_0^{T_1^j}(1-\xi_1^j)w^j L^j h^j t^{\rho^j}dt, \tag{3.48}$$

$$\int_0^{T_1^j}\ell_1^j dt=\left(1-L^j\right)T_1^j, \tag{3.49}$$

in the second period of time

$$\int_{T_1^j}^{T_2^j}C_2^{j,p}dt=\int_{T_1^j}^{T_2^j}\xi_2^j w^j L^j h^j t^{\rho^j}dt, \tag{3.50}$$

$$\int_{T_1^j}^{T_2^j}C_2^{j,f}dt=\int_{T_1^j}^{T_2^j}(1-\xi_2^j)w^j L^j h^j t^{\rho^j}dt, \tag{3.51}$$

$$\int_{T_1^j}^{T_2^j}\ell_2^j dt=\left(1-L^j-\psi_2\right)(T_2^j-T_1^j), \tag{3.52}$$

and in the third period of time

$$\int_{T_2^j}^{\tilde{T}^j}C_3^{j,p}dt=\int_{T_2^j}^{\tilde{T}^j}\xi_3^j w^j L^j h^j t^{\rho^j}dt, \tag{3.53}$$

$$\int_{T_2^j}^{\tilde{T}^j}C_3^{j,f}dt=\int_{T_2^j}^{\tilde{T}^j}(1-\xi_3^j)w^j L^j h^j t^{\rho^j}dt, \tag{3.54}$$

$$\int_{T_2^j}^{\tilde{T}^j}\ell_3^j dt=\left(1-L^j-\psi_3-\theta^j n\right)(\tilde{T}^j-T_2^j). \tag{3.55}$$

As in the first period of time there is only one member in household, family consumption satisfies

$$\int_0^{T_1^j}C_1^{f}dt=\int_0^{T_1^j}(1-\xi_1^j)w^j L^j h^j t^{\rho^j}dt, \tag{3.56}$$

while in the second and third period of time family consumption is decided simultaneously by the female and her husband and is defined as in equations (3.20) and (3.21). Moreover, accumulated utility from children in the third period of time is given by

$$\int_{T_2^j}^{\tilde{T}^j} t^{\phi} f(\theta^j, n)dt = \left(\theta^i + \theta^j\right)(\bar{n} + n)\left[\frac{\tilde{T^j}^{\phi+1} - \left(T_1^j + T_2 - T_1\right)^{\phi+1}}{\phi + 1}\right]. \tag{3.57}$$

We replace equations (3.47) to (3.57) into utility functions (3.44) to (3.46) and determine his accumulated utility over his lifetime cycle

$$u^j = u_1^j + u_2^j + u_3^j. \tag{3.58}$$

3.6.3 Logit Estimation for Other Economic Sectors

Table 3A1: Probability for an Individual To End Up Working in the High-Tech Industry Sector.

	(1)	(2)	(3)	(4)	(5)
Sex					
Female	-0.721***	0.953***	0.984***	0.929***	0.706***
	(0.015)	(0.116)	(0.116)	(0.117)	(0.118)
Age					
35-44	0.198***	0.093***	0.082***	0.084***	0.094***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
45-54	0.251***	0.128***	0.120***	0.118***	0.157***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
55-65	0.169***	0.102***	0.104***	0.103***	0.161***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
35-44 (Female)	-0.035*	0.053**	0.089***	0.089***	0.085***
	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)
45-54 (Female)	-0.088***	-0.014	0.013	0.011	0.016
	(0.020)	(0.021)	(0.022)	(0.022)	(0.023)
55-65 (Female)	-0.160***	-0.092***	-0.088***	-0.090***	-0.073***
	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
Education					
Tertiary	-0.149***	-0.392***	-0.392***	-0.381***	-0.329***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Work					
Hours Worked (Male)		-0.007***	-0.007***	-0.007***	-0.008***
		(0.000)	(0.000)	(0.000)	(0.000)
Hours Worked (Female)		0.020***	0.020***	0.020***	0.020***
		(0.001)	(0.001)	(0.001)	(0.001)
Income Wage (Male)		0.430***	0.428***	0.420***	0.417***
		(0.007)	(0.007)	(0.007)	(0.007)
Income Wage (Female)		0.190***	0.186***	0.178***	0.194***
		(0.010)	(0.010)	(0.010)	(0.010)
Full Time (Male)		1.056***	1.055***	1.072***	1.060***
		(0.037)	(0.037)	(0.037)	(0.037)
Full Time (Female)		0.895***	0.894***	0.936***	0.938***
		(0.029)	(0.029)	(0.029)	(0.029)
Children					
Number of Own Children (Male)			0.016***	0.011**	0.007
			(0.004)	(0.004)	(0.004)
Number of Own Children (Female)			-0.028***	-0.031***	-0.026***
			(0.006)	(0.006)	(0.006)
Babies (Male)			-0.014	-0.011	-0.005
			(0.013)	(0.013)	(0.013)
Babies (Female)			0.070***	0.069***	0.084***
			(0.021)	(0.021)	(0.021)
Constant	-2.304***	-7.325***	-7.313***	-6.995***	-6.555***
	(0.009)	(0.071)	(0.071)	(0.073)	(0.081)
Individual Income	NO	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES
Observations	1,774,884	1,684,313	1,684,313	1,684,313	1,684,313
Wald χ^2	12370.35	21663.85	22009.02	29712.07	32642.30
Prob< χ^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

Table 3A2: Probability for an Individual To End Up Working in the Low-Tech Industry Sector.

	(1)	(2)	(3)	(4)	(5)
Sex					
Female	-1.425***	-1.964***	-2.008***	-2.066***	-2.163***
	(0.012)	(0.080)	(0.081)	(0.081)	(0.082)
Age					
35-44	0.056***	0.042***	0.004	0.003	0.003
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
45-54	0.003	-0.007	-0.021*	-0.023*	-0.010
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
55-65	-0.091***	-0.076***	-0.052***	-0.054***	-0.029*
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
35-44 (Female)	0.034*	0.052**	0.095***	0.095***	0.092***
	(0.016)	(0.017)	(0.018)	(0.018)	(0.018)
45-54 (Female)	0.048**	0.041*	0.061**	0.062**	0.062**
	(0.017)	(0.018)	(0.019)	(0.019)	(0.019)
55-65 (Female)	0.035	0.039	0.019	0.021	0.027
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Education					
Tertiary	-1.198***	-1.187***	-1.183***	-1.176***	-1.158***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Work					
Hours Worked (Male)		0.000	0.000	-0.001	-0.001*
		(0.000)	(0.000)	(0.000)	(0.000)
Hours Worked (Female)		0.013***	0.013***	0.012***	0.012***
		(0.001)	(0.001)	(0.001)	(0.001)
Income Wage (Male)		-0.043***	-0.052***	-0.046***	-0.048***
		(0.005)	(0.005)	(0.005)	(0.005)
Income Wage (Female)		-0.018*	-0.019*	-0.007	-0.002
		(0.008)	(0.008)	(0.008)	(0.008)
Full Time (Male)		0.613***	0.607***	0.599***	0.590***
		(0.020)	(0.020)	(0.020)	(0.020)
Full Time (Female)		0.507***	0.508***	0.492***	0.490***
		(0.021)	(0.021)	(0.021)	(0.021)
Children					
Number of Own Children (Male)			0.070***	0.071***	0.071***
			(0.003)	(0.003)	(0.003)
Number of Own Children (Female)			-0.004	-0.003	-0.001
			(0.005)	(0.005)	(0.005)
Babies (Male)			-0.006	-0.007	-0.007
			(0.010)	(0.010)	(0.010)
Babies (Female)			0.020	0.015	0.019
			(0.019)	(0.019)	(0.019)
Constant	-1.039***	-1.226***	-1.177***	-1.309***	-1.117***
	(0.006)	(0.043)	(0.043)	(0.045)	(0.054)
Individual Income	NO	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES
Observations	1,774,884	1,684,313	1,684,313	1,684,313	1,684,313
Wald χ^2	68237.97	64663.75	66731.30	67740.87	69154.98
Prob< χ^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

Table 3A3: Probability for an Individual To End Up Working in the Unskilled Services Sector.

	(1)	(2)	(3)	(4)	(5)
Sex					
Female	-0.118***	0.814***	1.034***	1.063***	1.144***
	(0.008)	(0.053)	(0.054)	(0.054)	(0.054)
Age					
35-44	-0.143***	-0.091***	-0.061***	-0.060***	-0.068***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
45-54	-0.182***	-0.118***	-0.110***	-0.107***	-0.124***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
55-65	-0.171***	-0.121***	-0.143***	-0.140***	-0.159***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
35-44 (Female)	-0.067***	-0.101***	-0.105***	-0.105***	-0.103***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
45-54 (Female)	-0.138***	-0.168***	-0.197***	-0.198***	-0.200***
	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)
55-65 (Female)	-0.183***	-0.228***	-0.269***	-0.270***	-0.275***
	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)
Education					
Tertiary	-0.795***	-0.704***	-0.713***	-0.716***	-0.739***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Work					
Hours Worked (Male)		0.016***	0.016***	0.016***	0.016***
		(0.000)	(0.000)	(0.000)	(0.000)
Hours Worked (Female)		0.005***	0.005***	0.005***	0.005***
		(0.000)	(0.000)	(0.000)	(0.000)
Income Wage (Male)		-0.190***	-0.182***	-0.182***	-0.179***
		(0.004)	(0.004)	(0.004)	(0.004)
Income Wage (Female)		-0.280***	-0.286***	-0.287***	-0.291***
		(0.004)	(0.004)	(0.004)	(0.004)
Full Time (Male)		-0.536***	-0.531***	-0.530***	-0.529***
		(0.015)	(0.015)	(0.015)	(0.015)
Full Time (Female)		-0.241***	-0.252***	-0.253***	-0.253***
		(0.011)	(0.011)	(0.011)	(0.011)
Children					
Number of Own Children (Male)			-0.057***	-0.057***	-0.055***
			(0.003)	(0.003)	(0.003)
Number of Own Children (Female)			-0.071***	-0.070***	-0.071***
			(0.003)	(0.003)	(0.003)
Babies (Male)			-0.015	-0.015	-0.017
			(0.009)	(0.009)	(0.009)
Babies (Female)			-0.048***	-0.046***	-0.052***
			(0.010)	(0.010)	(0.010)
Constant	-0.560***	1.193***	1.147***	1.054***	0.776***
	(0.005)	(0.038)	(0.038)	(0.039)	(0.047)
Individual Income	NO	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES
Observations	1,774,884	1,684,313	1,684,313	1,684,313	1,684,313
Wald χ^2	31740.46	43289.25	44180.93	45486.61	46759.97
Prob< χ^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

Table 3A4: Probability for an Individual To End Up Working in the Skilled Market Services Sector.

	(1)	(2)	(3)	(4)	(5)
Sex					
Female	0.151***	1.740***	1.881***	1.901***	1.977***
	(0.009)	(0.072)	(0.073)	(0.073)	(0.073)
Age					
35-44	0.015*	-0.122***	-0.092***	-0.092***	-0.096***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
45-54	-0.016*	-0.213***	-0.188***	-0.187***	-0.199***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
55-65	-0.015	-0.219***	-0.219***	-0.218***	-0.236***
	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
35-44 (Female)	-0.078***	-0.001	0.011	0.012	0.014
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
45-54 (Female)	-0.127***	-0.022*	-0.023	-0.023	-0.024*
	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)
55-65 (Female)	-0.161***	-0.049***	-0.057***	-0.058***	-0.063***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Education					
Tertiary	0.502***	0.269***	0.262***	0.258***	0.237***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Work					
Hours Worked (Male)		-0.004***	-0.004***	-0.003***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)
Hours Worked (Female)		0.001**	-0.002**	-0.001**	-0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Income Wage (Male)		0.429***	0.436***	0.433***	0.436***
		(0.006)	(0.006)	(0.006)	(0.006)
Income Wage (Female)		0.255***	0.250***	0.246***	0.242***
		(0.005)	(0.005)	(0.005)	(0.005)
Full Time (Male)		-0.207***	-0.206***	-0.204***	-0.200***
		(0.019)	(0.019)	(0.019)	(0.019)
Full Time (Female)		-0.003	-0.010	-0.009	-0.008
		(0.012)	(0.012)	(0.012)	(0.012)
Children					
Number of Own Children (Male)			-0.045***	-0.044***	-0.043***
			(0.003)	(0.003)	(0.003)
Number of Own Children (Female)			-0.056***	-0.056***	-0.057***
			(0.003)	(0.003)	(0.003)
Babies (Male)			0.044***	0.045***	0.044***
			(0.010)	(0.010)	(0.010)
Babies (Female)			0.075***	0.078***	0.074***
			(0.011)	(0.011)	(0.011)
Constant	-1.554***	-5.522***	-5.574***	-5.533***	-5.874***
	(0.006)	(0.057)	(0.057)	(0.058)	(0.066)
Individual Income	NO	YES	YES	YES	YES
Work-related Characteristics	NO	YES	YES	YES	YES
Geographic Controls	NO	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	NO	YES
Observations	1,774,884	1,684,313	1,684,313	1,684,313	1,684,313
Wald χ^2	12688.42	17362.919	17864.244	18695.146	19489.862
Prob< χ^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: IPUMS-CPS.

Chapter 4

The Role of Intangible Capital in Structural Transformation

4.1 Introduction

One of the most interesting trends among developed and developing countries has been the rising importance of the services sector in the last 60 years. The implications of this sector growth have not been only reflected in relevant phenomena of economy, e.g. the growth in the skill premium in wages despite an increasing relative supply of high skilled workers[1], but also as an essential contribution as input for production in other sectors. Regarding this latter aspect, the domestic services value added share of gross exports accounts for around 22% in the High-Tech Industry sector in the U.S. by 2016, 18% in UK, 22% in France, 23% in Japan, and 17% in India. While in the Low-Tech Industry sector it accounts for around 34% in the U.S. by 2016, 27% in UK, 33% in France and Japan, and 16% in India. Note that this indicator is higher in the Low-Tech Industry sector than in the High-Tech Industry sector in almost all countries, except India[2].

This chapter provides a theoretical framework for understanding why the High-Tech Industry sector uses less services from other sectors as inputs than the Low-Tech Industry sector. Specifically, I focus my analysis on the elasticity of substitution between skilled workers and those characteristic services of industry: software and databases capital services, R&D capital services, and other intellectual property products (OIPP) capital services —known as intangible capital—.

In the last decades, the contribution of intangible capital to value added growth has been stable and, therefore, has become important for most economies; see Corrado et al. (2018) and Haskel and Westlake (2018). On average, intangible capital accounts for around 0.05% of contribution to value added growth in Japan and the U.S., 0.04% in EU11[3], and 0.01% in UK. The importance of intangible capital is not only shown in terms of contribution to value added growth but also in terms of its weight in gross fixed capital formation. Intangible capital account for around 21% of GFCF in Japan by 2015, 26% in the U.S., 23% in EU11[4],

[1]See Buera et al. (2019).

[2]See Armas and Sánchez-Losada (2021) for the importance of considering a wider classification of economic sectors.

[3]EU11 includes Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Italy, Netherlands and Sweden.

[4]This average does not include Belgium since GFCF is not classified in tangible and intangible capital in

and 22% in UK. Similarly, considering a multisector analysis, the weight of this type of capital in GFCF is clearly higher than tangible capital in those firms within the High-Tech Industry sector in all countries. It accounts for around 56% of GFCF in those firms in this sector in Japan by 2015, 66% in the U.S., 54% in EU11[5], and 52% in UK.

This rising importance of intangible capital has been subject of many studies although there is little research on the impact it has on the allocation of labor force. Given the nature of intangible capital, the need for skilled workers might increase as firms decide to invest in this type of capital[6]. In this article, through the theoretical framework mentioned above, I study how the elasticity of substitution between intangibles and skilled workers determines whether a sector is skill-biased. I find that intangibles and skilled workers are complements in high TFP sectors —High-Tech Industry—while they are substitutes in low TFP sectors —Low-Tech Industry—. Then, as investment in intangible capital increases, allocation of skilled workers rises in high TFP sectors. This finding is in line with those in Marrocu et al. (2009) and Chiavari and Goraya (2021) and argue that firms within high TFP sectors are those who decide to produce intangible capital internally, i.e. they decide to hire skilled workers instead of using services of other sectors as inputs in their production. Opposite results are found for firms in low TFP sectors.

I begin by providing general evidence on the evolution of the domestic services value added share of gross exports and the contribution of intangible capital to value added growth. After, I focus my analysis on the investment in intangibles and the allocation of skilled labor force in Japan. The main reasons for the use of this country is that, first, investment in intangibles has risen over time making its contribution to GPD important in this country and, second, because the share of people with completed tertiary education among those between 25 and 64 years old is higher than 50% by 2016, a phenomenon shown only in countries such as Canada, Israel and Russia. The insights of this general evidence allow me to construct a theoretical framework that explains why in some sectors the investment in intangible capital rises the number of skilled workers also increases.

Second, I provide a microdata approach that shows that this phenomenon might be different in India. Specifically, I perform a linear and a quantile regression to analyze the impact of R&D units on firm' total cost of production. Results suggest that those firms in the highest quantile (90%) actually face lower total cost of production if they do not have a R&D unit and are firms in the High-Tech Industry. Moreover, I find that as the number of workers increases those firms in the highest quantile (90%) also face higher total cost of production if they are firms in the High-Tech Industry. Then, I argue that large firms in India might decide not to invest in R&D units and, as a consequence, they might neither hire skilled workers if they are in the High-Tech Industry sector. This finding might explain why the domestic services value added share of gross exports in the High-Tech Industry sector is higher than in the Low-Tech Industry sector in India, different from other countries.

This chapter is organized as follows. Section 4.2 summarizes the literature and give relevant macroevidence regarding the importance of intangible capital on structural transformation. Section 4.3 contains the theoretical framework that describes hhow the elasticity of substitution between intangibles and skilled workers determines whether a sector is skill-biased. Section 4.4 presents a microdata approach that analyzes the impact of the existence of a R&D unit on firm' total cost of production in India. Finally, Section 4.5 concludes.

Statistical Capital file - EUKLEMS for this country.

[5]See footnote 4.

[6]Skilled workers are those with completed tertiary education.

4.2 Literature Review and Macroeconomic Evidence

4.2.1 Literature Review

The rising importance of intangible capital has been analyzed by many studies. First, intangible capital has been described as a key source of productivity growth. Nakamura (2000) explains how the rising value of U.S. equities are explained by a rising investment in intangible assets. Also, Bontempi and Mairesse (2008) show that intangible capital is at least as productive as tangible capital using a large panel of Italian firms in manufacture. Later, Corrado et al. (2009) and Corrado and Hulten (2010) show how the inclusion of intangible capital to sources-of-work framework explains the patterns of U.S. economic growth. McGrattan and Prescott (2010) also build an extended growth model and show that accounting for the production of intangible investment explains the puzzling boom of the U.S. economy in the 1990s. Finally, regarding the analysis of intangible capital in other regions, Suriñach and Moreno (2011) analyze the role of intangible on European growth while Corrado et al. (2013) and Corrado et al. (2018) produce harmonized estimates of intangibles in a growth framework for Europe and compare how intangible capital has played an important role in growth for these economic regions.

Second, McGrattan and Prescott (2005), Conesa and Domínguez (2013), and Conesa and Domínguez (2019) find that it is crucial to consider different types of capital, tangible and intangible, for a better taxation policy.

Third, many studies have built frameworks that relate intangible capital and firms' market value. Jorgenson (1963) shows that R&D and patents effectiveness determine the market's valuation of a firm. Klock and Megna (2000) show that intangibles explain the variation in Tobin's q in the wireless telecommunication industry. Through a similar approach, Gleason and Klock (2006) explains the impact of R&D and advertising in the pharmaceutical and chemical industry. Also, Brynjolfsson et al. (2002) and Brynjolfsson et al. (2021) analyze how computerization is related to intangible assets and argues that those computer-intensive firms have higher valuation in markets. Moreover, Delgado-Gomez et al. (2004) argue that intangible resources have a direct impact on the international diversification of Spanish firms while Villalonga (2004) finds that intangibles are linked to a firm's comparative advantage. Later, Abowd et al. (2005) use micro-level data to address how firm-level heterogeneity accounts for productivity, growth, and value. By analyzing R&D intensive industries, Bernstein and Mamuneas (2006) find that investment in R&D contributed to productivity growth. Using data for the Italian manufacturing sector, Arrighetti et al. (2014) find that initial investment in intangible capital depends on the firm's heterogeneity. Lastly, Crouzet and Eberly (2019) show that investment in intangible capital not only explains the weakness in physical capital investment but also the rising industry concentration.

This vast literature on the rising importance of intangible capital does not address the impact it has on the allocation of labor force. The main contribution of this chapter is to build a theoretical and empirical framework in this regard. I begin by describing the macrodata evidence that rises this research question. Next, I build a theoretical model that explains how skilled workers are complements to intangible capital in high TFP sectors, at least in developed countries. Finally, I perform a microdata approach that analyzes the impact of a R&D unit on firm' total cost of production in India.

4.2.2 Macroeconomic Evidence

Economies have moved from agriculture to industry and, then, from industry to services in the process of growth. This phenomenon of structural transformation has been experienced in many developing and developed countries in the last 60 years. The rising importance of the services sector has bring together different relevant phenomena of economy such as the growth in the skill premium in wages despite an increasing relative supply of high skilled workers[7]. But also services have become an essential input for production in other sectors. Figure 4.1 shows how the domestic services value added share of gross exports has evolved over time in different countries. It accounts for around 22% in the High-Tech Industry sector in the U.S. by 2016, 18% in UK, 22% in France, 23% in Japan, and 17% in India. While in the Low-Tech Industry sector it accounts for around 34% in the U.S. by 2016, 27% in UK, 33% in France and Japan, and 16% in India. Note that this indicator is higher in the Low-Tech Industry sector than in the High-Tech Industry sector in almost all countries, except India.

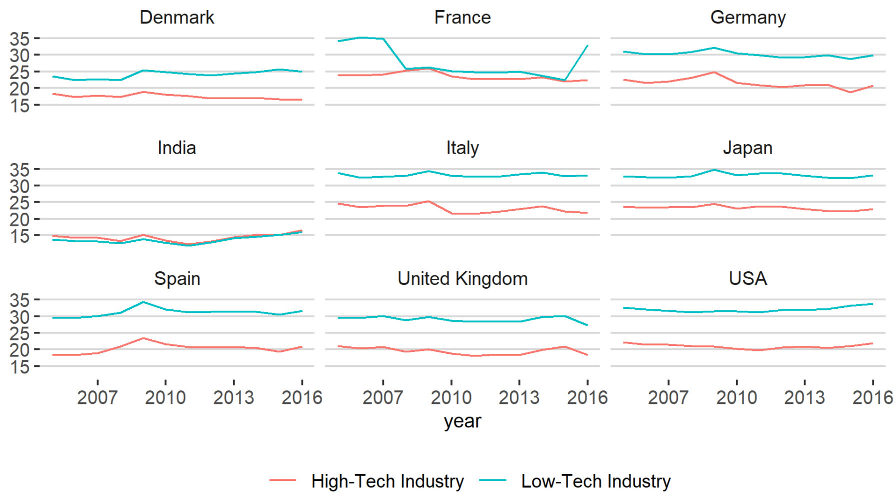


Figure 4.1: Share of Services in Exports, by Sector
Source: TiVA - OECD.

[7]See Buera et al. (2019).

In this chapter I provide insights for understanding why the High-Tech Industry sector uses less services from other sectors as inputs than the Low-Tech Industry sector. Specifically, I focus my analysis on those characteristic services of industry: software and databases capital services (SoftDB), R&D capital services (R&D), and other intellectual property products (OIPP) capital services —known as intangible capital—. Investment in intangible capital has risen in the last decades and has become a main driver of economic growth. In Figure 4.2 I plot the contribution of intangible and tangible capital to value added growth using the EUKLEMS Growth Accounts Statistical Database[8]. In this figure OIPP, R&D and SoftDB refer to intangibles while ICT and Non-ICT refer to tangibles[9]. On the one hand, note that the contribution of tangible capital to growth has been large in all countries, in almost all sectors. However, it has been unstable and has been reduced after the Great Recession. On the other hand, the contribution of intangibles to value added growth has been stable even after the Great Recession. The highest contribution to value added growth among intangibles is that of R&D capital services, specially in the High-Tech Industry. This contribution in the High-Tech Industry sector in the period 1995-1999 was 0.44% on average in the U.S., -0.08% in UK and 0.47% in Japan. In the period 2000-2006 this contribution was 0.18% on average in the U.S., 0.19% in EU11, -0.03% in UK and 0.25% in Japan. In the period 2007-2010 it was 0.20% in the U.S., 0.27% in EU11%, -0.17% in UK and 0.18% in Japan. Finally, in the period 2011-2017 it was 0.38% on average in the U.S., 0.24% in EU11, -0.04% in UK and 0.22% in Japan.

I argue that this rising importance in investment in intangible capital has had implications on the allocation of skilled workers among sectors. Using data from RIETI JIP database I plot this relationship in Figure 4.3 for Japan. The main reasons for the use of this country is that, first, investment in intangibles has risen over time making its contribution to GPD important in this country[10] and, second, because the share of people with completed tertiary education among those between 25 and 64 years old is higher than 50% by 2016, a phenomenon shown only in countries such as Canada, Israel and Russia[11]. Figure 4.3 tells us that as the investment in intangible capital increases, the share of skilled workers in the High-Tech Industry sector increases, while it decreases for the Low-Tech Industry sector. This finding might explain why the High-Tech Industry sector uses less services from other sectors as inputs and is in line with those of Marrocu et al. (2009) and Chiavari and Goraya (2021) who argue that intangible capital is produced internally rather than acquired externally.

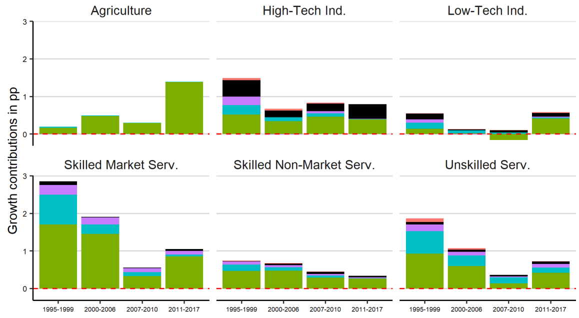
Based on this evidence I next build a theoretical framework that explains how the elasticity of substitution between skilled workers and intangible capital determines whether an economic sector is skill-biased.

[8] Note that I do not include TFP which is a "'classical" growth driver. Then, values in the vertical axis do not account for the total economy value added growth.

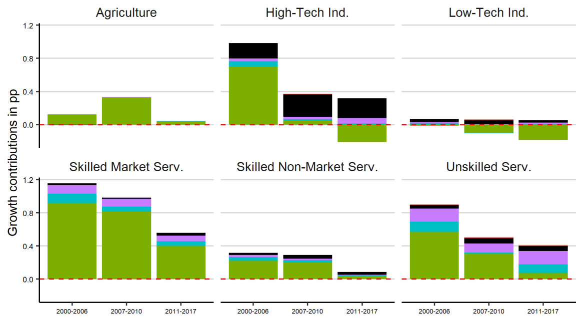
[9] ICT assets: tangible information and communication capital and intangible software and databases. Non-ICT assets: buildings and construction, machinery, transport equipment and cultivated assets.

[10] Fukao et al. (2009) find that the ratio of intangible investment to GDP in Japan has risen during the past 20 years and stands at 11.1% by 2005.

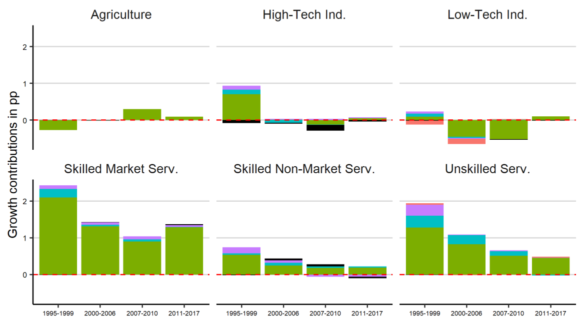
[11] See OECD (2018).



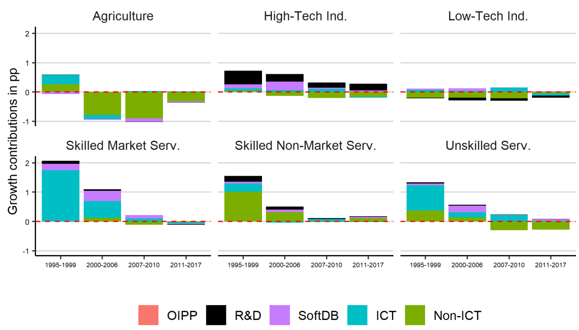
(a) United States



(b) EU11



(c) United Kingdom



(d) Japan

Figure 4.2: Contribution to value added growth in %
Source: Growth Accounts File - EU KLEMS.

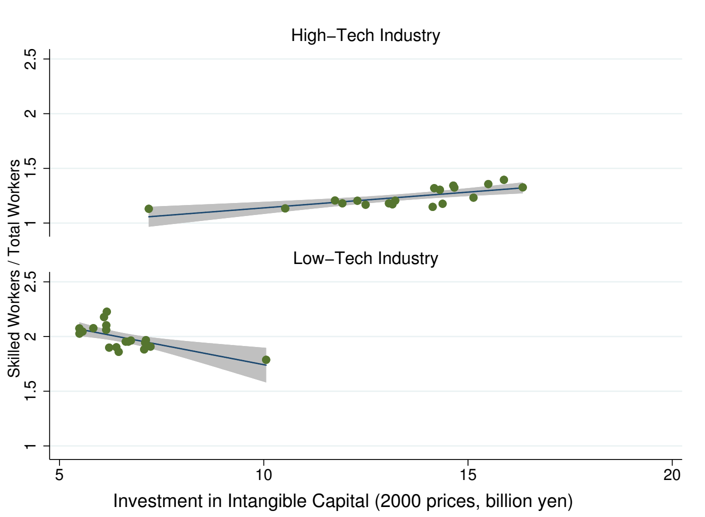


Figure 4.3: Share of Skilled Workers vs Investment in Intangible Capital, by Sector
Source: RIETI JIP Database 2018.

4.3 Theoretical Framework

My analysis focuses on how skilled workers are allocated among sectors during structural transformation considering a rising investment in intangible capital. In order to capture this interaction I propose a standard structural transformation model extended to allow for two labor inputs that are distinguished by skill and two capital inputs that are distinguished by their nature.

4.3.1 Production Technology

There are multiple sectors in the economy that are distinguished by their skill-intensity. To facilitate this analysis I follow Armas and Sánchez-Losada (2021) and assume that firms are either in high TFP sectors or in low TFP sectors. I denote these sectors as HT and LT. Each of the two production sectors has a constant returns to scale production function that uses unskilled and skilled labor and tangible and intangible capital as inputs. I assume that each of these production functions is CES:

$$Y_e = K_e^{(1-\alpha_1-\alpha_2)} L_{e,l}^{\alpha_1} \left[\left[\gamma_e \left(A_{L_h} L_{e,h} \right)^{\rho} + (1-\gamma_e) \left(A_I I_e \right)^{\rho} \right]^{\frac{1}{\rho}} \right]^{\alpha_2} \quad e = HT, LT, \tag{4.1}$$

where $L_{e,l}$ and $L_{e,h}$ are inputs of unskilled and skilled labor in sector e, respectively, and K_e and I_e are inputs of tangible and intangible capital in sector e, respectively. The parameter γ_e dictates the importance of skilled workers and intangible capital in each sector. Moreover, $\gamma_e \in (0,1)$ and $\rho \leq 1$ and the time subscripts in (4.1) have been eliminated to keep notation simple. Note that

$$\frac{\frac{\partial Y_e}{\partial I_e}}{\frac{\partial Y_e}{\partial L_{e,h}}} = \frac{1-\gamma_e}{\gamma_e} \left(\frac{A_I}{A_{L_h}} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{I_e}{L_{e,h}} \right)^{-\frac{1}{\sigma}}, \tag{4.2}$$

where $\sigma = \frac{1}{1-\rho}$ is the elasticity of substitution between $L_{e,h}$ and I_e. The relative marginal product of I_e is decreasing in the relative abundance of I_e, $\frac{I_e}{L_{e,h}}$. This is the usual substitution effect, leading to a downward sloping relative demand curve. Moreover, when $\sigma > 1$ these factors are substitutes while they are complements when $\sigma < 1$. In the case of complements, an increase in A_I (relative to A_{L_h}) makes the relative marginal product of I_e decrease. While in the case of substitutes, an increase in A_I (relative to A_{L_h}) increases the relative marginal product of I_e. In the case of complements, an increase in the productivity of I_e increases the demand for the other factor, $L_{e,h}$, by more than the demand of I_e, effectively creating excess demand for $L_{e,h}$. Because of evidence shown in Section 4.2, I suspect this is the case of those firms in the high TFP sector.

4.3.2 Households

Households in the economy are distinguished by their skill level. I normalize to one the total mass of households and denote the fraction of unskilled and skilled households as h_{LT} and h_{HT}, respectively where $h_{LT} + h_{HT} = 1$. All households have identical preferences over the two goods produced in the economy, independently of their skill level. I assume these preferences take the form:

$$\theta_{LT} c_{LT_i}^{\frac{\epsilon-1}{\epsilon}} + (1-\theta_{LT})(c_{HT_i} + \bar{c}_{HT})^{\frac{\epsilon-1}{\epsilon}}, \tag{4.3}$$

where c_{LT_i} and c_{HT_i} are consumption of the good produced by the low TFP sector and the good produced by the high TFP sector by an individual of skill level i, $0 < \theta_{LT} < 1$, $\bar{c}_{HT} \geq 0$ and $\epsilon > 0$. In the case that $\bar{c}_{HT} > 0$ preferences are non-homothetic and, then, as income increases the expenditure share on the good produced by the high TFP sector increases[12]. Note that households do not value leisure in this model.

4.3.3 Equilibrium

The competitive equilibrium of the above economy features six markets: four factor markets (unskilled and skilled labor and tangible and intangible capital), and two output markets (the good produced by high TFP sectors and the good produced by low TFP sectors), with prices denoted as $w_{e,l}$, $w_{e,h}$, R_K, R_I, p_{HT}, and p_{LT}. The competitive equilibrium results from the household's consumption maximization problem and firm's profits maximization problem. The characterization of the competitive equilibrium and the calibration of the model are a work in progress. For now, it is important to note that the elasticity of substitution between skilled workers and intangible capital is a key parameter that characterizes the competitive equilibrium.

The competitive equilibrium might also be a result of the primal form of firm's optimization problem. With this approach the competitive equilibrium equilibrium is also characterized by the elasticity of substitution between skilled workers and intangible capital. But now I can provide microdata evidence on the role of intangible capital and the number of workers in firms on total cost of production. In the next section, I provide a microdata evidence on the total cost of production in Indian firms.

[12]See Buera et al. (2018).

4.4 The Impact of a R&D Unit on a Firm

4.4.1 Database

A microdata approach for the primal form of firm's optimization problem is analyzed in this section. Specifically, I evaluate the impact of a R&D unit on total cost of production within firm[13]. I use data from the Annual Survey of Industries (ASI) in India which is the principal source of industrial statistics. This database is conducted by the National Statistical Office and published by the Ministry of Statistics & Programme Implementation. It focuses on the perform of manufacturing sector regarding growth, composition and structures. The primary unit of enumeration in this survey is a factory, workshop, undertaking (or license), and establishment in the case of manufacturing industries, repair services, electricity, gas and water supply undertakings, and bidi and cigar industries, respectively. Industries are classified according to NIC 2008 developed on the basis of UNISIC Rev 4. This survey consists of fourteen blocks, although only ten are published[14]. Given that it is not possible to identify firms across different years of survey, I use the most recent available database, i.e. I use the database corresponding to the financial year 2018 - 2019[15]. I use Block A that collects descriptive identification of the sample unit. I classify firms into High-Tech Industry and Low-Tech Industry sector; see Armas and Sánchez-Losada (2021). I use the variable "*A8: District Code*" to group sample units into five different geographic locations, according to GDP per capita[16]. I use Block B to identify those firms with a R&D unit. Finally, I also use Block E where information on employment is given. Note that information on workers' education level is not recorded in this survey and, then, I can not distinguish between skilled and unskilled workers.

Table 4.1 shows some descriptive statistics of the sample before and after cleaning, disaggregating the data by economic sectors. The initial database consists of 501,615 firms, 25.49% of which are in the High-Tech Industry and 4.15% have a R&D unit. I consider only open firms that are not joint returns[17]. Also, I exclude those firms with zero total cost of production, zero number of workers and zero wages. As a result, the database I use to evaluate the impact of a R&D unit on the total cost of production consists of 286,093 firms, 26.97% of which are in the High-Tech Industry and 3.79% have a R&D unit.

[13] I use the existence of a R&D unit as a proxy for intangible capital since ASI database does not include information about this type of capital.

[14] Published blocks do not have all the information is asked during the survey.

[15] ASI databases with R&D unit information are only those corresponding to the financial year 2017 - 2018 onward.

[16] Low Income —districts with a GDP per capita less than 150 thousand Indian rupees—, Middle-Low Income —between 150 and 200—, Middle-High Income —200 and 250—, High Income —higher than 250—, and Others —with no GDP per capita information—; see `https://www.statista.com/statistics/1027998/india-per-capita-income-by-state/`. Then, districts are grouped as follows. **Low Income:** Jammu and Kashmir, Tripura, Nagaland, Rajasthan, West Bengal, Odisha, Chhattisgarh, Madhya Pradesh, Meghalaya, Assam, Manipur, Jharkhand, Uttar Pradesh, and Bihar, **Middle-Low Income:** Himachal Pradesh, Arunachal Pradesh, Andhra Pradesh, and Punjab, **Middle-High Income** Uttrakhand, Haryana, Telangana, Karnataka, Kerala, Puducherry, A and N Islands, Tamil Nadu, Gujarat, and Maharashtra, **High Income** Goa, Sikkim, Delhi, and Chandigarh(U.T.), and **Others:** Daman and Diu and Dadra and Nagar Haveli.

[17] Joint returns are those units with the same state code, management, combined accounts, their resources are not identifiable, and that are of the same industry group.

Table 4.1: Summary statistics before and after data-cleaning.

	Sample before cleaning (N = 501,615)						Sample used (N = 286,093)					
	Mean	SD	10%	25%	75%	90%	Mean	SD	10%	25%	75%	90%
High-Tech Industry												
No. Workers	12.31	33.36	0	0	12	32	19.90	38.21	2	4	21	48
Total Cost of Production	0.13	0.47	0.001	0.007	0.097	0.287	0.148	0.32	0.004	0.011	0.120	0.327
N High-Tech Industry	127,872						77,149					
Low-Tech Industry												
No. Workers	99.48	505.01	0	0	71	223	96.08	368.88	3	7	103	239
Total Cost of Production	1.50	18.43	0.004	0.022	0.741	2.300	0.55	0.88	0.007	0.029	0.650	1.648
N Low-Tech Industry	373,743						208,944					
R&D Unit												
High-Tech Industry												
Yes	1,467						1,013					
No. Workers	24.75	46.41	0	0	30	68	35.76	52.23	3	7	42	87
Total Cost of Production	0.33	0.60	0.015	0.037	0.274	0.895	0.34	0.62	0.019	0.040	0.274	0.920
No	126,405						76,136					
No. Workers	12.16	33.15	0	0	11	32	19.69	37.94	2	3	21	48
Total Cost of Production	0.13	0.47	0.001	0.006	0.095	0.282	0.13	0.32	0.004	0.010	0.118	0.324
Low-Tech Industry												
Yes	19,350						9,829					
No. Workers	307.42	1,387.26	0	3	221	644.5	166.77	278.56	9	24	192	404
Total Cost of Production	6.02	26.38	0.123	0.364	3.386	10.317	1.13	1.16	0.100	0.261	1.617	2.957
No	354,393						199,115					
No. Workers	88.12	401.75	0	0	65	206	92.59	372.42	3	7	100	229
Total Cost of Production	1.25	17.86	0.004	0.019	0.658	2.036	0.52	0.85	0.007	0.026	0.604	1.553

Total cost of production in billions of rupees. High-Tech Industry includes alcohol production, nuclear fuels, oil refining, coke, chemical products, machinery and equipment, office, accounting and computing machinery, electrical machinery and apparatus, radio, television and communications equipment, medical, precision and optical instruments, motor vehicles, trailers and semi-trailers, and other transportation equipment. Low-Tech Industry includes food and beverage, tobacco products, textiles, apparel, leather products and footwear, wood products, paper, cellulose, paper products, editing and printing, rubber and plastic products, non-metallic mineral products, basic metals, fabricated metal products (except machinery and equipment), furniture, and recycling.

4.4.2 Linear Regression

I want to emphasize the role of intangible capital in the optimal decision of firms regarding total cost minimization. Using the existence of a R&D unit in a firm as a proxy for intangible capital, I first perform an OLS regression of total cost of production. If the existence of a R&D unit helps firms to reduce costs they might produce intangible capital internally rather than acquire it externally and, then, the share of skilled workers might increase. Sections 4.2 and 4.3 show it is the case for those firms in the High-Tech Industry, at least for developed countries such as Japan. I presume there might be differences in the case of India since the domestic services value added share of gross exports is higher in the High-Tech Industry than in the Low-Tech Industry, different from other countries. The general form of a linear regression is:

$$y_i = \boldsymbol{x}_i' \boldsymbol{\beta} + u_i, \tag{4.4}$$

with $\mathbb{E}[u] = 0$ and $\text{Cov}[\boldsymbol{x}, u] = 0$; see Cameron and Trivedi (2005). I consider total cost of production (in logs) as the endogenous variable (y) and different sets of exogenous variables ($\boldsymbol{x}$). The set of exogenous variables in model (1) consists of the following variables: number of workers (in logs), whether there is any R&D unit in the firm and the economic sector of the firm. Due to possible omitted variables, I consider different interaction terms in the following specifications. I add an interaction term between the economic sector of the firm and whether there is any R&D unit in the firm in model (2). In model (3) I add an interaction term between the number of workers and whether there is any R&D unit in the firm. In model (4) I add an interaction term between the number of workers and the economic sector of the firm. Finally, in model (5) I include an interaction term between whether there is any R&D unit in the firm, the economic sector and the number of workers in the firm. Models (1) to (5) control for the geographic location of the firm[18]. Table 4.2 shows the results for each specification.

In general, results suggest that as the number of workers increases, total cost of production also increases. Moreover, those firms without a R&D unit face a lower total cost of production with respect to those that do have a R&D unit. Also, a firm in the High-Tech Industry sector has lower total cost of production than those in the Low-Tech Industry sector. More importantly, when I consider the interaction terms described before I get relevant insights. First, a firm in the High-Tech Industry sector that does not have a R&D unit has a higher cost of production than a firm that has one. This result might suggest that those firms within this sector have a R&D unit in order to reduce costs, but the absolute value of this coefficient is much smaller than the coefficient analyzing the existence of a R&D unit solely, e.g. in model specification (5) the coefficient of the interaction term between the existence of a R&D unit and the economic sector is 0.958 which is smaller than the coefficient of the existence of a R&D unit, 1.970 (in absolute values). Then, firms in this sector would not invest necessarily in a R&D unit. Additionally, as the number of workers increases firms in the High-Tech Industry sector without a R&D unit face higher costs than those in the Low-Tech Industry sector having a R&D unit. It is also true for those firms in the Low-Tech Industry without a R&D unit. These results of the interaction terms of R&D units suggest that firms in industry in India might not invest in R&D units and if they do, they are more likely to be firms in the Low-Tech Industry. Lastly, note in model specification (4) that as the number of workers in the firm increases, total cost of production decreases for firms in the High-Tech Industry sector. This result implies that firms in this sector might be more willing to hire workers than those firms in the Low-Tech Industry. I presume these workers might be skilled but since I do not have information of the workers' education level, I can not make any certain conclusion.

As described in previous sections, the domestic services value added share of gross exports is lower in the High-Tech Industry sector than in the Low-Tech Industry sector, at least for developed countries. This fact might suggest that industrial firms produce their required services —intangible capital—internally. It also suggests that those firms that decide to acquire them externally might do it even in other countries. Following Denekamp (1995), I argue that it is crucial to consider the role of foreign investment in my analysis in order to identify other relevant insights. Similar to before, I perform an OLS regression on the total cost of production (in logs) considering different sets of independent variables. These sets include now a dummy that indicates whether the share of capital of the company includes

[18]The category of reference of the geographic area is "Low Income". See footnote 16.

share of foreign entities. Table 4.3 shows the results for this new approach.

First, results show that this new exogenous variable has an important impact on the total cost of production of firms. In absolute value, it is now the regressor with the highest coefficient and suggests that those firms without foreign investment face lower total cost of production, e.g. in model specification (5) the coefficient analyzing foreign investment is 1.526 (in absolute values) that is higher than all of the other coefficients. Second, note that if a firm in the High-Tech Industry sector does not have foreign investment faces higher costs than those with with foreign investment. This result might imply that it is plausible that firms in this sector devote a share of their production to exports. Also, the coefficient of the interaction term between the existence of a R&D unit in the firm and having foreign investment suggests that foreign investment might induce the absence of R&D units in firms in India. Theory suggests that OLS might not account for differences in the tails of the distribution of variables, I then perform a quantile regression as a robustness check of these findings.

4.4.3 Quantile Regression

Koenker and Bassett (1978) and Koenker and Hallock (2001) point out the gains on performing a quantile regression focusing specifically on the efficiency of estimators. Coad and Rao (2008) also show that considering a quantile regression allows to identify the role of innovation in "superstar" fast-growth firms in high-tech sectors. The general form of a quantile regression is:

$$y_i = \boldsymbol{x}_i' \boldsymbol{\beta}_\theta + u_{\theta i}, \tag{4.5}$$

with $Q_\theta(y_i|\boldsymbol{x}_i) = \boldsymbol{x}_i'\beta_\theta$ and $Q_\theta(y_i|\boldsymbol{x}_i)$ denotes the θ^{th} conditional quantile of y_i given $\boldsymbol{x}_i$; see Koenker and Bassett (1978). I consider the same model specifications as before and perform a quantile regression to estimate total cost of production in Indian firms.

Table 4.4 shows the results for the quantile regression of model specifications in Table 4.2. In general, I find similar qualitative results regarding the impact of the considered dependent variables on total cost of production in Indian firms. However, I can identify some new insights. Contrary to the findings of model specification (2) in Table 4.2, results of the quantile regression suggest that those firms in the highest quantile (90%) actually face lower total cost of production if they do not have a R&D unit and are firms in the High-Tech Industry. Also, contrary to the findings of model specification (4) in Table 4.2, results suggest that as the number of workers increases those firms in the highest quantile (90%) face higher total cost of production if they are firms in the High-Tech Industry. Then, I argue that large firms in India might decide not to invest in R&D units and, as a consequence, they might not hire skilled workers either if they are in the High-Tech Industry sector.

Finally, Table 4.5 shows the results for the quantile regression of model specifications in Table 4.3. In general, I find similar qualitative results regarding the impact of the considered dependent variables on total cost of production in Indian firms. The new insights described in the previous paragraph also hold in this quantile regression.

Table 4.2: Linear regression of equation (4.4).

	(1)	(2)	(3)	(4)	(5)
No. Workers	0.674***	0.674***	0.450***	0.460***	0.447***
	(0.002)	(0.002)	(0.011)	(0.011)	(0.011)
R&D Unit					
No	-0.898***	-0.914***	-1.876***	-1.914***	-1.970***
	(0.016)	(0.017)	(0.048)	(0.048)	(0.049)
Sector					
High-Tech Industry	-0.518***	-0.682***	-0.982***	-0.575***	-1.132***
	(0.007)	(0.054)	(0.055)	(0.057)	(0.134)
R&D Unit × Sector					
No × High-Tech Industry		0.167**	0.475***	0.394***	0.958***
		(0.054)	(0.056)	(0.056)	(0.135)
R&D Unit × No. Workers					
No × No. Workers			0.231***	0.246***	
			(0.011)	(0.011)	
Sector × No. Workers					
High-Tech Industry × No. Workers				-0.138***	
				(0.005)	
R&D Unit × Sector × No. Workers					
Yes × High-Tech Industry × No. Workers					0.051
					(0.042)
No × Low-Tech Industry × No. Workers					0.259***
					(0.011)
No × High-Tech Industry × No. Workers					0.118***
					(0.012)
Constant	-3.595***	-3.579***	-2.642***	-2.679***	-2.624***
	(0.018)	(0.019)	(0.047)	(0.047)	(0.049)
Geographic Controls	YES	YES	YES	YES	YES
R^2	0.381	0.381	0.382	0.383	0.383
N	286,093	286,093	286,093	286,093	286,093

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3: Linear regression of equation (4.4) - foreign share.

	(1)	(2)	(3)	(4)	(5)
No. Workers	0.662*** (0.002)	0.662*** (0.002)	0.661*** (0.002)	0.448*** (0.011)	0.253*** (0.013)
R&D Unit					
No	-0.734*** (0.016)	-0.739*** (0.017)	-0.106*** (0.037)	-1.167*** (0.060)	-1.058*** (0.060)
Sector					
High-Tech Industry	-0.498*** (0.007)	-0.959*** (0.069)	-1.047*** (0.069)	-0.928*** (0.072)	-1.212*** (0.073)
Foreign Share					
No	-0.994*** (0.015)	-1.032*** (0.016)	-0.373*** (0.038)	-0.437*** (0.038)	-1.526*** (0.058)
R&D Unit × Sector					
No × High-Tech Industry		0.064 (0.054)	0.116* (0.054)	0.349*** (0.056)	0.296*** (0.056)
Foreign Share × Sector					
No × High-Tech Industry		0.406*** (0.051)	0.446*** (0.051)	0.398*** (0.051)	0.757*** (0.053)
Foreign Share × R&D Unit					
No × No			-0.790*** (0.041)	-0.703*** (0.041)	-0.623*** (0.041)
Sector × No. Workers					
High-Tech Industry × No. Workers				-0.126*** (0.005)	-0.132*** (0.005)
R&D Unit × No. Workers					
No × No. Workers				0.243*** (0.011)	0.199*** (0.011)
Foreign Share × No. Workers					
No × No. Workers					0.249*** (0.010)
Constant	-2.759*** (0.022)	-2.717*** (0.023)	-3.220*** (0.035)	-2.274*** (0.058)	-1.403*** (0.067)
Geographic Controls	YES	YES	YES	YES	YES
R^2	0.390	0.390	0.391	0.393	0.395
N	286,093	286093	286,093	286,093	286,093

Table 4.4: Quantile regression of equation (4.5).

	(1)					(2)					(3)					(4)					(5)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
No. Workers	0.811***	0.812***	0.706***	0.563***	0.442***	0.809***	0.811***	0.706***	0.563***	0.442***	0.702***	0.577***	0.439***	0.320***	0.210***	0.713***	0.586***	0.448***	0.324***	0.208***	0.707***	0.575***	0.436***	0.313***	0.204***
	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.011)	(0.008)	(0.013)	(0.011)	(0.012)	(0.012)	(0.009)	(0.010)	(0.010)	(0.011)	(0.015)	(0.010)	(0.008)	(0.008)	(0.008)
R&D Unit																									
No	-1.293***	-0.937***	-0.783***	-0.600***	-0.479***	-1.356***	-0.966***	-0.792***	-0.599***	-0.460***	-1.861***	-2.094***	-2.074***	-1.724***	-1.514***	-1.970***	-2.157***	-2.135***	-1.755***	-1.501***	-1.998***	-2.207***	-2.193***	-1.808***	-1.521***
	(0.018)	(0.014)	(0.012)	(0.011)	(0.015)	(0.024)	(0.017)	(0.013)	(0.012)	(0.014)	(0.061)	(0.049)	(0.066)	(0.052)	(0.060)	(0.062)	(0.047)	(0.047)	(0.046)	(0.059)	(0.073)	(0.056)	(0.046)	(0.038)	(0.053)
Sector																									
High-Tech Industry	-0.222***	-0.331***	-0.552***	-0.793***	-0.861***	-0.677***	-0.605***	-0.665***	-0.779***	-0.635***	-0.845***	-0.990***	-1.110***	-1.181***	-0.898***	-0.094	-0.289***	-0.680***	-0.958***	-1.047***	-0.547**	-1.096***	-1.251***	-1.612***	-1.609***
	(0.014)	(0.010)	(0.010)	(0.011)	(0.014)	(0.057)	(0.045)	(0.053)	(0.073)	(0.077)	(0.066)	(0.078)	(0.076)	(0.074)	(0.074)	(0.085)	(0.059)	(0.041)	(0.068)	(0.074)	(0.186)	(0.161)	(0.172)	(0.146)	(0.313)
R&D Unit × Sector																									
No × High-Tech Industry						0.468***	0.279***	0.115*	-0.014	-0.233**	0.637***	0.675***	0.577***	0.404***	0.046	0.506***	0.520***	0.508***	0.353***	0.105	0.968***	1.343***	1.089***	1.016***	0.672*
						(0.063)	(0.048)	(0.056)	(0.074)	(0.075)	(0.063)	(0.079)	(0.075)	(0.076)	(0.076)	(0.076)	(0.061)	(0.037)	(0.065)	(0.070)	(0.196)	(0.157)	(0.177)	(0.137)	(0.319)
R&D Unit × No. Workers																									
No × No. Workers											0.114***	0.244***	0.278***	0.255***	0.243***	0.154***	0.266***	0.297***	0.263***	0.240***					
											(0.012)	(0.009)	(0.013)	(0.011)	(0.013)	(0.012)	(0.009)	(0.009)	(0.009)	(0.010)					
Sector × No. Workers																									
High-Tech Industry × No. Workers																-0.253***	-0.225***	-0.142***	-0.067***	0.034***					
																(0.013)	(0.007)	(0.006)	(0.007)	(0.007)					
R&D Unit × Sector × No. Workers																									
Yes × High-Tech Industry × No. Workers																					-0.097	0.038	0.051	0.149***	0.213*
																					(0.056)	(0.043)	(0.052)	(0.040)	(0.092)
No × Low-Tech Industry × No. Workers																					0.160***	0.277***	0.309***	0.276***	0.244***
																					(0.017)	(0.011)	(0.009)	(0.008)	(0.010)
No × High-Tech Industry × No. Workers																					-0.096***	0.045***	0.164***	0.205***	0.276***
																					(0.015)	(0.010)	(0.010)	(0.011)	(0.009)
Constant	-5.934***	-5.091***	-3.767***	-2.275***	-1.034***	-5.869***	-5.063***	-3.758***	-2.275***	-1.049***	-5.383***	-3.967***	-2.517***	-1.191***	-0.040	-5.413***	-4.007***	-2.555***	-1.204***	-0.029	-5.387***	-3.960***	-2.499***	-1.153***	-0.010
	(0.028)	(0.019)	(0.018)	(0.015)	(0.025)	(0.038)	(0.021)	(0.019)	(0.015)	(0.022)	(0.064)	(0.052)	(0.069)	(0.051)	(0.059)	(0.057)	(0.047)	(0.048)	(0.051)	(0.057)	(0.070)	(0.054)	(0.046)	(0.041)	(0.046)
Geographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.201	0.244	0.246	0.211	0.171	0.201	0.244	0.246	0.211	0.171	0.202	0.245	0.248	0.212	0.173	0.204	0.247	0.249	0.212	0.173	0.204	0.247	0.249	0.212	0.173
N	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Quantile regression of equation (4.5) - foreign share.

	(1)					(2)					(3)					(4)					(5)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
No. Workers	0.794***	0.796***	0.694***	0.550***	0.436***	0.791***	0.796***	0.694***	0.550***	0.436***	0.786***	0.794***	0.694***	0.550***	0.436***	0.700***	0.575***	0.437***	0.310***	0.217***	0.577***	0.349***	0.207***	0.098***	0.025*
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.014)	(0.012)	(0.013)	(0.011)	(0.014)	(0.021)	(0.012)	(0.011)	(0.010)	(0.011)
R&D Unit																									
No	-1.022***	-0.762***	-0.641***	-0.500***	-0.376***	-1.053***	-0.773***	-0.646***	-0.494***	-0.348***	-0.051	-0.070	-0.078*	-0.131***	-0.084*	-0.744***	-1.383***	-1.467***	-1.285***	-1.006***	-0.762***	-1.237**	-1.253***	-1.083***	-0.909***
	(0.022)	(0.020)	(0.014)	(0.019)	(0.013)	(0.025)	(0.016)	(0.015)	(0.015)	(0.017)	(0.042)	(0.039)	(0.034)	(0.033)	(0.035)	(0.096)	(0.073)	(0.072)	(0.064)	(0.072)	(0.099)	(0.071)	(0.061)	(0.063)	(0.055)
Sector																									
High-Tech Industry	-0.222***	-0.321***	-0.531***	-0.760***	-0.836***	-1.008***	-0.969***	-0.943***	-0.729***	-0.510***	-1.429***	-1.143***	-0.960***	-0.822***	-0.603***	-0.717***	-0.754***	-0.988***	-0.988***	-1.013***	-0.907***	-1.189***	-1.331***	-1.308***	-1.282***
	(0.010)	(0.010)	(0.008)	(0.010)	(0.013)	(0.090)	(0.044)	(0.049)	(0.103)	(0.115)	(0.103)	(0.099)	(0.060)	(0.089)	(0.086)	(0.122)	(0.086)	(0.067)	(0.119)	(0.087)	(0.115)	(0.139)	(0.077)	(0.091)	(0.098)
Foreign Share																									
No	-1.180***	-1.029***	-0.950***	-0.781***	-0.598***	-1.250***	-1.072***	-0.979***	-0.784***	-0.606***	-0.218***	-0.346***	-0.370***	-0.396***	-0.331***	-0.282***	-0.470***	-0.449***	-0.440***	-0.283***	-0.953***	-1.704***	-1.878***	-1.791***	-1.567***
	(0.023)	(0.020)	(0.012)	(0.014)	(0.021)	(0.024)	(0.015)	(0.013)	(0.014)	(0.017)	(0.049)	(0.035)	(0.040)	(0.027)	(0.030)	(0.053)	(0.042)	(0.031)	(0.034)	(0.033)	(0.079)	(0.075)	(0.037)	(0.044)	(0.054)
R&D Unit × Sector																									
No × High-Tech Industry						0.210*	0.101*	0.059	-0.065	-0.342***	0.451***	0.229***	0.084	-0.009	-0.297***	0.479***	0.501***	0.492***	0.323***	0.016	0.462***	0.462***	0.390***	0.232**	-0.022
						(0.083)	(0.040)	(0.038)	(0.064)	(0.099)	(0.052)	(0.064)	(0.051)	(0.066)	(0.076)	(0.078)	(0.064)	(0.069)	(0.098)	(0.051)	(0.099)	(0.060)	(0.061)	(0.072)	(0.083)
Foreign Share × Sector																									
No × High-Tech Industry						0.601***	0.560***	0.361***	0.034	0.009	0.793***	0.615***	0.357***	0.074	0.060	0.606***	0.458***	0.308***	0.058	0.076	0.827***	0.960***	0.788***	0.507***	0.426***
						(0.069)	(0.055)	(0.033)	(0.065)	(0.057)	(0.093)	(0.064)	(0.073)	(0.084)	(0.050)	(0.083)	(0.075)	(0.057)	(0.090)	(0.078)	(0.073)	(0.111)	(0.072)	(0.067)	(0.033)
Foreign Share × R&D Unit																									
No × No											-1.333***	-0.910***	-0.705***	-0.460***	-0.330***	-1.181***	-0.733***	-0.604***	-0.408***	-0.379***	-1.129***	-0.736***	-0.537***	-0.310***	-0.173***
											(0.049)	(0.040)	(0.041)	(0.034)	(0.040)	(0.058)	(0.041)	(0.028)	(0.039)	(0.038)	(0.065)	(0.056)	(0.047)	(0.043)	(0.041)
Sector × No. Workers																									
High-Tech Industry × No. Workers																-0.228***	-0.208***	-0.124***	-0.053***	0.038***	-0.232***	-0.215***	-0.132***	-0.063***	0.028***
																(0.009)	(0.007)	(0.005)	(0.005)	(0.005)	(0.011)	(0.008)	(0.005)	(0.007)	(0.008)
R&D Unit × No. Workers																									
No × No. Workers																0.137***	0.257***	0.290***	0.260***	0.223***	0.133***	0.228***	0.230***	0.195***	0.161***
																(0.014)	(0.012)	(0.013)	(0.010)	(0.014)	(0.015)	(0.011)	(0.010)	(0.011)	(0.008)
Foreign Share × No. Workers																									
No × No. Workers																					0.136***	0.267***	0.302***	0.292***	0.268***
																					(0.018)	(0.013)	(0.008)	(0.007)	(0.008)
Constant	-4.999***	-4.214***	-2.947***	-1.589***	-0.551***	-4.899***	-4.162***	-2.918***	-1.592***	-0.568***	-5.595***	-4.682***	-3.390***	-1.885***	-0.780***	-5.135***	-3.544***	-2.144***	-0.811***	0.127*	-4.520***	-2.494***	-1.037***	0.193***	1.062***
	(0.035)	(0.028)	(0.016)	(0.022)	(0.021)	(0.045)	(0.030)	(0.021)	(0.023)	(0.026)	(0.052)	(0.037)	(0.038)	(0.030)	(0.034)	(0.091)	(0.070)	(0.077)	(0.065)	(0.064)	(0.106)	(0.074)	(0.055)	(0.048)	(0.061)
Geographic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.207	0.250	0.253	0.217	0.176	0.208	0.250	0.253	0.217	0.176	0.210	0.251	0.253	0.217	0.177	0.212	0.254	0.256	0.218	0.178	0.212	0.255	0.257	0.220	0.180
N	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093	286,093

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5 Conclusions

Within a theoretical framework, I show that the elasticity of substitution between skilled workers and intangible capital is a key parameter that characterizes the competitive equilibrium. I argue that those firms in high TFP sectors might show a elasticity of substitution lower than 1 and, then, skilled workers might be allocated in these sectors as investment in intangible capital increases.

Through a microdata approach on firms' total cost of production I find that this phenomenon might be different in India. Specifically, I perform a linear and a quantile regression to analyze the impact of R&D units on firm' total cost of production. Results suggest that those firms in the highest quantile (90%) actually face lower total cost of production if they do not have a R&D unit and are firms in the High-Tech Industry. Moreover, I find that as the number of workers increases those firms in the highest quantile (90%) also face higher total cost of production if they are firms in the High-Tech Industry. Then, I argue that large firms in India might decide not to invest in R&D units and, as a consequence, they might neither hire skilled workers if they are in the High-Tech Industry sector. This finding might explain why the domestic services value added share of gross exports in the High-Tech Industry sector is higher than in the Low-Tech Industry sector in India, different from other countries.

Chapter 5

Conclusions

In the last century, many developed and developing countries have experienced a structural transformation of their economies. In their process of growth, economies have moved from agriculture to industry and, then, to services. This phenomenon has been accompanied by the increase in the relative share of skilled workers. Even though studies on structural transformation suggest that these skilled workers are mainly allocated to services, a wider multisector analysis has gained attention in macroeconomic discussions. In this context, this thesis focuses on the allocation of skilled workers among a broader classification of economic sectors according to their skill intensity. Moreover, this thesis builds on directed technical change theory to provide relevant insights for structural transformation theory.

First, the second chapter of the thesis studies the existence of directed technical change during structural transformation, given an increase in the relative share of skilled labor force. The main finding is that it is a necessary condition for skilled workers to be allocated to high TFP sectors and, then, for economies to reach high income levels. Two paths of structural change suggested in previous literature —skill-biased structural transformation and stagnant structural transformation —are described and find that if there is no directed technical change, skilled workers end up in low TFP sectors, as the path of stagnant structural transformation suggests. An analysis of relative TFP between skilled and unskilled sectors —macrodata evidence—and an estimation of wages —microdata evidence—are the proposed mechanisms to identify the existence of directed technical change. Evidence for U.S., South Korea, France, Canada, Italy, and Spain is used. With the macrodata evidence, an increasing relative TFP of skilled versus unskilled sectors is identified in the U.S., France and South Korea and, therefore, directed technical change has existed in those countries. This finding is supported at micro level through a GLS estimation of wages, in which the coefficients of the interaction term between tertiary education and high TFP sectors reveals the existence of directed technical change. Namely, if these coefficients are the highest and significant, then, directed technical change has existed. This behavior is also found in the cases of the U.S., France and South Korea. Given the existence of directed technical change, skilled workers have been allocated to high TFP sectors in these countries, following the path of skill-biased structural transformation. However, results are different for the other analyzed countries. Specifically, Canada has not experienced directed technical change yet and Italy and Spain do not show clear evidence that allows to identify the existence of directed technical.

Second, the third chapter of the thesis focuses on the allocation of skilled women during structural transformation. Given the increase in skilled female participation in labor markets, relevant characteristics across sectors define workers' preferences to end up working in them. Namely, a small gender wage gap, low number of hours to work with a relatively high compensation, and better demographic indicators make Skilled Non-Market Services sector more favorable for skilled women. A theoretical model that focuses on the preferences of an empowered woman is built. The first relevant characteristic of this sector matches the fact that as gender wage gap increases the fraction of her wage mass devoted to satisfy family consumption decreases in the theoretical model. The largest weight of "own" leisure and family consumption on utility matches the second relevant characteristic. The third characteristic matches the fact that in order for the fraction of her wage mass devoted to satisfy family consumption to increase, she has to work more hours and, then, she faces a high cost: a lower number of children. Then, the trade-off between marriage, having children and participating in the labor market is more favorable for those women in the Skilled Non-Market Services sector since it offers them lower hours to work and a relatively high compensation per hour worked. These findings are supported through a logit model of the probability to end up working in the Skilled Non-Market Services sector —microdata approach—. Data from U.S. ASEC supplement to the CPS is used.

The results of the microdata approach suggest that when we consider age those individuals in the older ages have higher probability to end up working in this sector than those in the youngest ages. It is specially true for a woman in the older ages—e.g. an increase of 0.196 is expected in the log odds of our dummy with respect to a male in all groups of age and females in the 25-34 group—. These results depict a work stability in the older ages for individuals in this sector, specially for women. Moreover, regarding work characteristics such as hours worked, the probability for the individual to end up working in the Skilled Non-Market Services sector decreases if hours worked increases. It is true for both, males and females—a higher decrease is expected in the log odds of our dummy for a male (0.021 compared to 0.010)—. Regarding the income of the individual, its increase has a positive impact on the analyzed probability for females while it is negative for males. Also, when considering the individual's type of contract, the probability of working in the Skilled Non-Market Services sector increases if it is a full time contract and the individual is a female—an increase of 0.126 is expected in the log odds of our dummy with respect to individuals with part time contract—. With this result, an "unobserved" stability is pointed out in this sector to females. Second, when emphasizing the role of tertiary education, results suggest that those with tertiary education actually have higher probability to end up working in the Skilled Non-Market Services sector regardless the type of contract—an increase of 2.311(2.495) is expected in the log odds of our dummy with respect to individuals without tertiary education working with a part(full)-time contract—. This result suggests that job flexibility might be an important characteristic offered to skilled women in this sector. Finally, the probability for a skilled woman to end up working in the Skilled Non-Market Services increases if she decides to have babies—an increase of 1.253 is expected in the log odds of our dummy with respect to individuals without tertiary education that have babies—. These findings support the claim about a balanced trade-off between family and working life for skilled women in this sector.

The fourth chapter explores the role of intangible capital in Structural Transformation. Within a theoretical framework, I show that the elasticity of substitution between skilled workers and intangible capital is a key parameter that characterizes the competitive equilibrium. I argue that those firms in high TFP sectors might show a elasticity of substitution lower than 1 and, then, skilled workers might be allocated in these sectors as investment in intangible capital increases.

Through a microdata approach on firms' total cost of production I find that this phenomenon might be different in India. Specifically, I perform a linear and a quantile regression to analyze the impact of R&D units on firm' total cost of production. Results suggest that those firms in the highest quantile (90%) actually face lower total cost of production if they do not have a R&D unit and are firms in the High-Tech Industry. Moreover, I find that as the number of workers increases those firms in the highest quantile (90%) also face higher total cost of production if they are firms in the High-Tech Industry. Then, I argue that large firms in India might decide not to invest in R&D units and, as a consequence, they might neither hire skilled workers if they are in the High-Tech Industry sector. This finding might explain why the domestic services value added share of gross exports in the High-Tech Industry sector is higher than in the Low-Tech Industry sector in India, different from other countries.

To this extent, the results obtained in the chapters of this thesis have important policy implications. Specifically, in terms of the impact of the allocation of skilled labor force, the second chapter indicates that it is important that profit maximizing firms invest in innovation in high TFP sectors. It makes productivity (and then wages) increase, implying at the same time an increase in the incentives for skilled workers to work in these sectors. Also, the third chapter indicates that government is essential for skilled female participation in the labor market since it regulates that sector that offers a favorable trade-off between family and working life —Skilled Non-Market Services—. Finally, the fourth chapter indicates that skilled workers and intangible capital are complements in high TFP sectors and, then, firms decide to invest in units to develop intangible capital. As a consequence, productivity of these firms increases and, then, skilled workers are allocated to these sectors.

To conclude, it is important to acknowledge some drawbacks that characterize the empirical research of this thesis. Specifically, due to data limitations at the macro or at the microdata level, the analysis of the second chapter focuses on a limited group of developed countries. With a wider group of countries, i.e. developed and developing, more interesting insights on the existence of directed technical change would be provided. As for the third chapter, U.S. is the only country considered for the analysis due to data limitation. It could be interesting to compare results with those of other countries (e.g. where government is not the biggest employer of women). Finally, the microdata used in the fourth chapter does not provide information on workers' education and, then, the analogy between skilled workers and intangible capital can not be addressed. Even if available, it would be also important to have microdata for other countries to make robustness checks on the arguments of this chapter. Also, this information should include data related to international trade. In any case, I will try to overcome these shortcomings in future research.

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