The London School of Economics and Political Science

Essays on Labor Markets and Economic Growth

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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I confirm that Chapter 3 is a revised version of the paper I submitted at the end of my MRes in 2017.

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Abstract

This thesis consists of three chapters on labor markets and economic growth. Chapter 1 examines the role of offshoring in the flattening out of the female to male hours ratio in the US since the early 1990s. The leveling off of the gender hours ratio coincides with the rise in service offshoring and the fall in the share of occupations with high offshoring potential in female hours worked. We propose a model with two genders, two sectors, and a continuum of tasks. Due to higher female intensity in the service sector, the gender hours ratio falls when offshoring of service rises. Quantitatively, the increase of service offshoring plays an important role in explaining the plateau of the gender hours ratio after the 1990s.

Chapter 2 studies firm dynamics in Korea before and after the 1997-98 Asian crisis and pro-competitive reforms that reduced the dominance of chaebols. We find that in industries that were dominated by chaebols before the crisis, labor productivity and TFP of non-chaebol firms increased markedly after the reforms (relative to other industries). Furthermore, entry of non-chaebol firms increased significantly in all industries after the reform. Finally, after the crisis, the non-chaebol firms also significantly increased their patenting activity (relative to chaebol firms). These results are in line with a neo-Schumpeterian view of transition from a growth model based on investment in existing technologies to an innovation-based model.

Chapter 3 investigates the factors behind long hours worked in Korea. Koreans work longer hours than Americans although they face higher labor tax rates and lower family care related subsidies. We propose a two-period OLG model incorporating education costs and pension benefits to explain this observation. In Korea, education costs are high due to prevalence of private after-school lessons and limited student loans for college education, restricting households' budgets and driving the prime-aged to work longer. The old receive lower pension benefits, staying longer in the labor market. The calibrated model is successful in generating longer hours worked of the prime-aged and the old in Korea.

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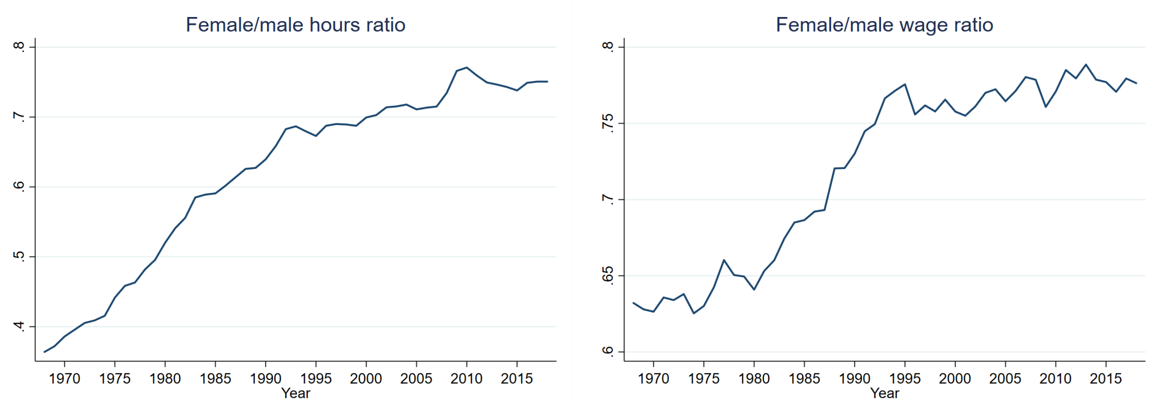
Chapter 1

The Effects of Offshoring on the Gender Hours Gap in the US

1.1 Introduction

Over the past 50 years, there has been a dramatic increase in women's hours of work in the US, while the hours worked by men have fluctuated around business cycles. The ratio of female to male hours increased from below 40% in 1968 to around 75% in 2018. However, the speed of the rise has not been uniform. As Figure 1.1 shows, the gender hours ratio began to flatten out from the early 1990s. The gender wage gap also stopped closing at the same time.

Figure 1.1: Female to male hours and wage ratios in the US



Notes: The hours ratio is the ratio of annual average hours of work for people aged 21 to 65. The wage ratio is calculated as the exponential of the coefficient on a female dummy, after the log of hourly wages is regressed on a female dummy, age, age squared, education levels (4 categories), and ethnicity (non-white dummy) for each year.
Sources: CPS March Supplement

If we consider these trends in a simple labor supply and demand framework, the break for gender hours and wage ratios suggests that the relative demand for female labor has grown more sluggishly since the early 1990s. Before the 1990s, gender hours and wage ratios rose sharply because the relative demand for female labor went up faster than the relative supply. Since then, both ratios have stalled, which indicates the pace of the increase in the relative demand for female labor has markedly slowed down compared to the previous period. Consequently, we suspect that the flattening out of the gender hours ratio is primarily due to factors that affect the relative demand for female labor.

This chapter seeks to explain the change in the gender hours ratio trend with differential impacts of offshoring on female and male labor. We postulate a mechanism whereby the increase in service offshoring has negatively affected women's hours of work from the 1990s, slowing down the rise in the gender hours ratio since then. We provide two pieces of evidence in terms of sectors and occupations. First, both the offshoring of material and service inputs have risen, and the importance of service offshoring has become more marked since the 1990s. Before 1990, material offshoring had more adverse effects on male hours because the share of the manufacturing sector to men's hours worked was higher than the share to women's hours. After 1990, more women were impacted by the emergence of service offshoring relative to men, given that a vast majority of women were employed in the service sector. These two forces can account for the dynamics of the gender hours ratio, which rose before 1990 and flattened out thereafter. Second, the share of 'sales and administrative support occupations' in women's hours worked has been falling saliently since 1990. These occupations have employed the greatest number of women and shown the highest offshoring potential. Thus, their decreasing share is consistent with the rising influence of offshoring. We particularly relate it to the rise in service offshoring because the share of these occupations to men's hours worked has been relatively stable. We also find that the occupation groups with higher offshoring potential show a higher female to male hours ratio and that this observation potentially comes from the negative correlation between the potential for offshoring and the brawn skill requirements of each occupation. Regression results using an IV for service offshoring also corroborate our theory.

We propose a model with two genders, two sectors, and a continuum of tasks motivated by the empirical facts. The assumptions that more women are hired in highly offshorable tasks and that the material offshoring has been more prevalent than the service offshoring both play key roles in the model. Under these assumptions, the model implies a higher female to male hours ratio in the service sector. This result, along with the observation that productivity growth is faster in goods than in the service sector, suggests an increasing female to male hours ratio. However, the decline of offshoring costs in the service sector facilitated by the developments in ICT (Information and Communications Technology) in the 1990s induces the gender hours ratio to fall. This is because the rise in service offshoring replaces highly offshorable and female-oriented domestic tasks with offshored labor.

Quantitative analysis allows for three sources of slowdown in the gender hours ratio since the early 1990s. The first source is the increase in service offshoring. Secondly, the forces that drive structural transformation into the service sector have diminished. Lastly, the pace of decrease in gender discrimination or social norms has been more moderate. The results show that the third source is the most powerful in explaining the plateau of the hours ratio. The rise in service offshoring shows a higher contribution than the weaker structural transformation towards the service sector, but it exhibits a lower contribution than the slowdown of the decline in gender discrimination. Still, the size of its contribution is over 80% of the third source, suggesting that the growth in service offshoring is also instrumental in accounting for the dynamics of the gender hours ratio.

This chapter contributes to the existing literature on women's labor market performance in three aspects. First, we consider both the extensive and intensive margins in the labor market by focusing on hours worked of women and men. Most of the previous research has only looked at the trends in the extensive margin, such as female labor force participation or women's employment to population ratio. However, considering both margins is important because there is more room for women's hours worked to increase due to lower hours worked of employed women, even though the labor force participation of women is rapidly approaching that of men. Second, this chapter sheds light on the demand side of female labor driven by offshoring. The literature has mainly paid attention to the supply related factors of female labor, which are at odds with the gender wage ratio trend. The paper by Ngai and Petrongolo (2017) is a notable exception to both points since it focuses on hours worked and presents a factor that contributes to an increase in the relative demand for female labor. They obtain women's comparative advantage in services by assuming directly that the weight on female labor is higher in the service sector. On the other hand, this chapter provides a novel mechanism that can yield higher female intensity in the service sector. Our model shows that this can endogenously arise due to the unequal impacts of offshoring by gender and the different extents of offshoring across sectors.

Also, this chapter investigates the differential effects of offshoring by gender in an advanced economy for the first time. Previous literature on offshoring has failed to address this issue. It is well known that growth in offshoring gives rise to the reallocation effect from domestic to offshored labor and the scale effect due to an increase in productivity. Studies that explore the size of the reallocation effect report that the aggregate impact of offshoring on domestic employment has been modest at most. However, these studies cannot answer the question of this chapter, since small aggregate employment effects could mask large asymmetric effects on women and men. A few works touch on the issues relevant to this chapter. For instance, Acemoglu and Autor (2011) noted that the average offshorability index is higher for women than men using the 1980 Census data, but they have not pursued it further. Peri and Poole (2013) attempted to uncover the divergent impacts of the increase in offshoring on women and men. However, they use data from Brazil, which is mainly a recipient of offshoring unlike the US. Unlike the aforementioned examples, we address the unequal effects of offshoring by gender in the US, building on the offshorability index of each occupation by Autor and Dorn (2013). By doing this, we establish that growth in offshoring can bear an additional implication on the labor market through the gender dimension.

Regarding methodology, this chapter develops an advanced way of estimating cutoffs for offshoring based on the framework of Grossman and Rossi-Hansberg (2008), who assume perfect substitutability between domestic and offshored tasks. Therefore, tasks with offshorability higher (lower) than the cutoff are provided by offshored (domestic) labor, suggesting the tasks with high offshorability disappear as offshoring increases. However, in the data, the occupation with the highest offshorability still hires workers in the US even after there has been a substantial rise in offshoring.[1] This means that using aggregate data that contains occupations with high offshorability is not consistent with the model's assumption. In order to circumvent the issue, we devise a concept of hypothetical distributions of female hours worked on the offshorability of each occupation in each year. The hypothetical distributions of female hours worked in each year have the same shapes as the base year's hypothetical distributions and replicate the data in women's average offshoring potential of each year. We calibrate the offshoring cutoffs in each year using these hypothetical distributions and the estimated female employment effects of offshoring on the manufacturing and service sectors. This new method can satisfy one of the key assumptions of the model.

Related Literature. A great deal of previous research has presented several candidates that have improved women's labor market outcomes since World War II. These include progress in women's education and human capital (Goldin 2006; Eckstein and Lifshitz 2011), home technology (Greenwood, Seshadri and Yorukoglu 2005), and medical technology (Albanesi and Olivetti 2016), the closing of the gender wage gap (Jones, Manuelli, and McGrattan 2015), and the expansion of the service sector (Ngai and Petrongolo 2017). Less attention has been paid to the stagnation of women's labor market performance, which is a more recent phenomenon. These works document that age-LFP (Labor Force Participation) profiles that differ by cohort (Aaronson et al. 2006; Juhn and Potter 2006; Krueger 2017), single women's

[1] In the quantitative analysis section, we consider occupations, instead of tasks, as basic units of production. Please see Section 5 for further details.

labor supply (Macunovich 2010; Moffitt 2012), family policies (Blau and Kahn 2013), and married women's labor supply response to their husbands' earnings (Albanesi and Prados 2017) are accountable for the stagnation.

This chapter is also closely related to the literature that studies the effects of offshoring on employment, among which the theoretical work of Grossman and Rossi-Hansberg (2008) has been the most influential in recent years. They incorporate trade in tasks in the model, offering a tractable framework for analyzing the impact of offshoring. Empirically, most researchers agree that the influence of service offshoring on aggregate employment was either not statistically significant or modestly negative (Amiti et al. 2005; Liu and Trefler 2008; Amiti and Wei 2009; Berlingieri 2014). A small number of studies including Crinò (2010) probe the employment effects by different demographic groups, but none of them considers the differential impact on men and women except for Peri and Poole (2013). Some works attempt to estimate the share of offshorable jobs by creating a new index (Blinder 2009; Jensen and Kletzer 2010) and implementing a new survey (Blinder and Krueger 2013). Another strand of literature considers the effects of routine-biased technological change along with those of offshoring (Autor and Dorn 2013; Goos, Manning, and Salomons 2014; Autor, Dorn, and Hanson 2015).

A few studies (Ranjan 2013; Zhang 2018) perform calibration exercises with the frameworks based on the model of Grossman and Rossi-Hansberg (2008), although their purpose is to examine the impact of offshoring on unemployment. But they use the aggregate proxy for offshoring in calibrating the offshoring cutoffs, which is inconsistent with their model assumption.

Roadmap. The chapter is organized as follows. Section 2 documents key empirical facts and methods to construct the relevant statistics. Section 3 provides regression results to support these facts. Section 4 develops a model to understand the empirical findings and Section 5 presents the results of the quantitative analysis based on the model. Section 6 concludes.

1.2 Data and Empirical Facts

In this section, we document empirical facts that support our hypothesis in two different ways. First, we look at the trends in offshoring from the perspective of two broad sectors, i.e. service and manufacturing. Then we associate the share of each sector in the hours worked for each gender with these trends. The second approach is to take advantage of the statistics for each occupation level in what is termed an offshorability index. We construct the average offshoring potential of each occupation group and examine the changes in the share of hours worked across different occupation groups for men and women.

1.2.1 Service and Material Offshoring

Offshoring refers to the movement of jobs but not the people performing them across national borders. Conventionally it took the form of material offshoring, which happens in the process of outsourcing material inputs to other countries in manufacturing.[2] Since the 1990s, a new form of offshoring called service offshoring emerged and gained prominence. The advances in ICT made it possible for some types of service to become tradable by lowering technical barriers in transmitting a large volume of information. The most well-known examples of service offshoring are call centers, preparing for tax forms, reading X-rays, and developing software.

It is hard to find a reliable data source that shows the relocation of labor due to offshoring. In the US, the BLS (Bureau of Labor Statistics) collected the number of separations caused by out-of-country relocation through the Mass Layoff Statistics program until 2013. However, these data were incomplete due to a limited coverage of samples and a low response rate of employers.[3] This is why the literature resorts to proxies for offshoring, IV regressions, or the estimation of structural models to identify the employment effects of offshoring. Following the literature, we exploit widely used proxies for service and material offshoring.

Constructing a proxy for service offshoring starts from the idea that a firm that offshores its service component must import the component back to use it as an input for production. Amiti and Wei (2009) suggest the following way to calculate the share of service offshoring in each year and industry, which is analogous to the material offshoring measure by Feenstra and Hanson (1999):

$$SO_{it} = \sum_j \frac{IP_{ijt}}{TIP_{it}} \frac{Imports_{jt}}{Consumption_{jt}}, \tag{1.1}$$

[2] In the context of this chapter, it would be better to phrase material offshoring as manufacturing offshoring. However, we will keep the term material offshoring to refer to the offshoring that affects manufacturing industries because the use of the term 'material offshoring' is established in the literature.

[3] The number of separations due to out-of-country relocation rose from 1996 and reached a peak in 2002. BLS revised the series in 2004 and the number of separations due to out-of-country relocation fell since then (See Brown and Siegel (2005) for details of the revision). The program covered private sector nonfarm establishments with at least 50 unemployment insurance claims during a 5-week period. Therefore, neither relatively small-scale layoffs with less than 50 separations nor gradual layoffs which took longer than 5 weeks to dismiss 50 workers were in the scope of the program. Furthermore, the destination of relocation, whether within or out of country, was known in only 45% of the separations caused by movement of work in 2012, compared to 75% in 2004. These shares were less than 100% because employers failed to provide specific details of the separations. The falling share implies that the capability of the program to identify the number of offshoring-related separations has deteriorated over time. In 2013, the program was eliminated as a measure to meet spending cuts of the Obama administration.

where i and t denote industry and year, respectively. j indicates each of the four types of service inputs, which are ① Insurance, ② Finance, ③ Telecommunication, computer, and information, and ④ Other business services.[4] IP_{ijt} is the input purchases of service j by i in t and TIP_{it} is the total non-utility input purchases by i in t. Consumption is defined as production plus imports minus exports. The measure indicates the share of service input imports and can be considered as a proxy for the forgone demand in domestic service inputs due to offshoring in each year.

The input purchases and production are obtained from the annual input-output data by BLS. The data for import and export are available from the IMF Balance of Payments statistics. Since the IMF does not provide industry-level imports of each service input, we assume that the import share is the same for all industries, as in Amiti and Wei (2009).[5]

We also compute a proxy for material offshoring in a similar manner as (1.1). For material offshoring, j denotes each good instead of service inputs. We utilize the same input-output data as before and acquire industry-level US import and export data from Peter Schott.

Both for service and material offshoring measures, the trends before and after 1997 are not directly comparable. This is due to differences in industry classification and available data sets. From 1986 to 1996, they are computed using the input-output data of 1992 and the trade data of each year based on SIC (Standard Industrial Classification). From 1997 onwards, they are calculated using the input-output and trade data of each year based on NAICS (North American Industry Classification System). The material offshoring figures are only seen from 1989 onwards due to a lack of data.

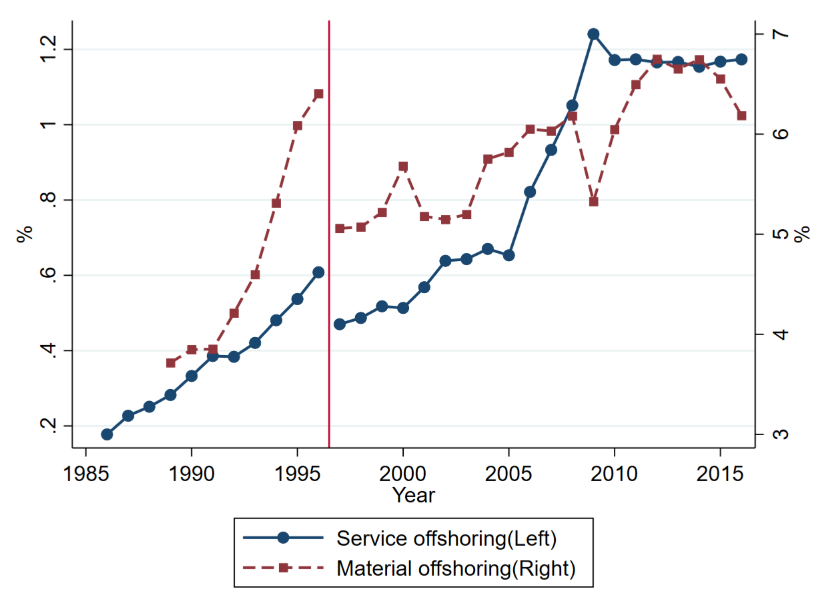
Figure 1.2 shows the trajectories of service and material offshoring for all private sectors. Service offshoring increased steadily from 1986 to 1996 and the trend was similar after 1997. From 1997 to 2016, the share of service offshoring to total non-energy input purchases more than doubled from 0.5% to 1.2%. During the same period, material offshoring witnessed a rising trend as well. It took up 5.1% of non-energy input purchases in 1997 and its share went up to 6.2% in 2016. Previous literature finds similar trends for both service and material offshoring, and Feenstra and Jensen (2012) report the increase in material offshoring since 1980.[6]

[4] Amiti and Wei (2009) originally present five service industries (telecommunications, insurance, finance, business services, and computing and information), but we reduce this category to four, due to data availability in the IMF Balance of Payments statistics.

[5] Another caveat of this measure is that it is likely to underestimate the actual value of service offshoring, because it would be usually more expensive to purchase the services domestically than to import them. Using quantity data would resolve this problem, but they are not available in detailed industry levels.

[6] Amiti and Wei (2009) report an increase in the share of service offshoring from 0.18% to 0.29% between 1992 and 2000. Feenstra and Jensen (2012) document that the share of material offshoring rose from 6.6% in 1980 to 27.0% in 2006. The magnitudes differ between this chapter and the literature mainly because we calculate these shares for all private industries, while both these papers calculate the shares for manufacturing

Figure 1.2: Service and material offshoring



Notes: The numbers shown are average shares of service and material offshoring to total non-energy input purchases in each private industry, weighted by each industry's output. Figures for before and after 1997 are not directly comparable due to differences in industry classifications and available data sets. From 1986 to 1996, they are computed using the input-output data of 1992 and the trade data of each year based on SIC (Standard Industrial Classification). From 1997 onwards, they are calculated using the input-output and trade data of each year based on NAICS (North American Industry Classification System). The trade data for material offshoring is obtained from the US import and export data found on Peter Schott's website. The material offshoring figures are only seen from 1989 onwards due to a lack of data.
Sources: BEA, BLS, IMF Balance of Payments, Peter Schott's website

Fact 1. *Both service and material offshoring have risen since the 1990s.*

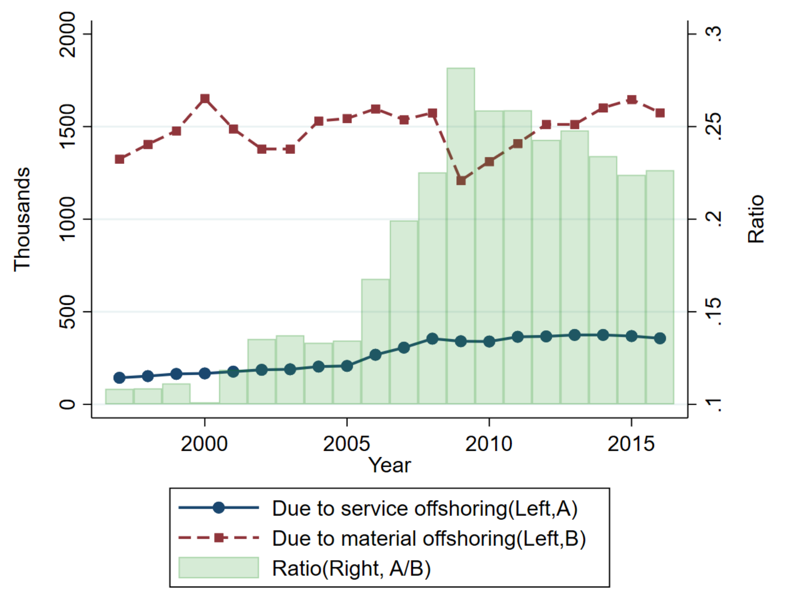
We perform a simple back-of-the-envelope calculation to assess the effects of both types of offshoring on employment. First, we convert the proxies for service and material offshoring to dollar values. Then we obtain the compensation per employee of relevant industries using the data from the BEA (Bureau of Economic Analysis).[7] Finally, we get the estimated losses in employment by multiplying the values of service and material offshoring with the rates of compensation to output and dividing them by the compensation per employee in relevant industries.

Figure 1.3 plots the results of the calculation. The estimated employment loss due to service offshoring increased from around 140,000 in 1997 to 350,000 in 2008 and it has stayed

industries.

[7]The relevant industries for service offshoring are insurance, finance, telecommunication, computer, and information, and other business services. The relevant industries for material offshoring are manufacturing industries. We divide the total compensation of employees by the number of full-time equivalent employees to get the compensation per employee.

Figure 1.3: Estimated losses in employment due to offshoring



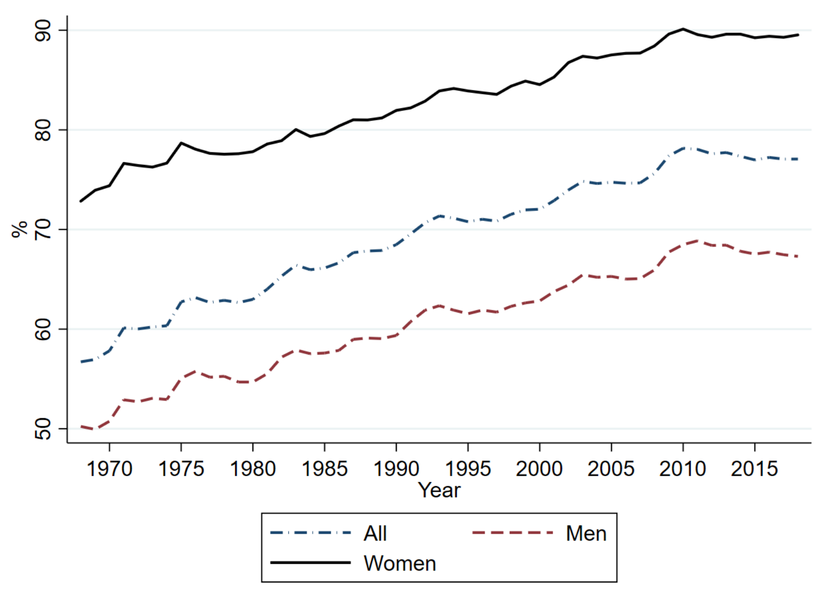
Notes: The numbers shown are calculated by multiplying the values of service and material offshoring with the shares of compensation to output and dividing them by the compensation per employee in relevant industries. The ratios are defined by the employment losses due to service offshoring divided by the employment losses due to material offshoring.
Sources: BEA, BLS, IMF Balance of Payments, Peter Schott's website

around 350,000 to 400,000 after 2009. The employment loss due to material offshoring fluctuated around 1.5 million from 1997 to 2016. The ratio between the two losses has evolved from 11% to 23%, which indicates a growing importance of service offshoring since 1997. Material offshoring is still more prevalent than service offshoring in the labor market, but the significance of service offshoring has increased substantially since the 1990s.

Fact 2. *Material offshoring is more prevalent compared to service offshoring, but the relative importance of service offshoring has grown larger since the 1990s.*

Magnitudes of these changes seem small considering the aggregate employment in the US. However, these estimated employment changes in each year represent flows. The cumulative employment losses between 1997 and 2016 due to service and material offshoring were about 5.4 million and 29.7 million, respectively. For service offshoring, the losses amounted to 4.8% of the average total employment in service-producing industries in the US between 1997 and 2016, which is a non-negligible fraction. For material offshoring, it was 22.2% of the average total employment in goods-producing industries during the same period. Moreover, the size of the aggregate employment effects of offshoring is not necessarily equivalent to the size of the asymmetric effects on women and men, implying that a seemingly small aggregate impact of offshoring on employment is not a big concern for our purpose.

Figure 1.4: Share of hours worked in the service sector for each gender



Note: The numbers shown are the rates of total hours worked in the service sector for each gender divided by total hours worked of each gender.
Sources: CPS March Supplement

In order to understand the differential impacts of the offshoring trends by genders, we depict the share of hours worked in the service sector for each gender in Figure 1.4. Given that women's service share is higher than men's, the expansion of service offshoring is likely to have hit women more badly than men in the labor market. Figure 1.4 also suggests that men's manufacturing share in hours worked has been higher than women's, implying that the increase in material offshoring has affected male labor more negatively.

Once we take these forces into account, the dynamics of the gender hours ratio before and after the 1990s can be explained by the trends in service and material offshoring. Before the 1990s, the rising material offshoring weakened the growth of men's hours, raising the gender hours ratio. While this mechanism persisted, service offshoring emerged in the 1990s, eroding women's hours and slowing down the increase of the gender hours ratio. As the service share for women kept growing and the importance of service offshoring became larger, the adverse impact of service offshoring on the female to male hours ratio grew in dominance since the 1990s.

1.2.2 Average Offshoring Potential

In this part, we investigate the unequal effects of offshoring between genders in terms of occupation using an offshorability index. An offshorability index is calculated from the task measures which can represent the potential of being offshored for each occupation. It indicates the intrinsic nature of an occupation and is treated as pre-determined for labor market participants. Hence, the offshorability index is assumed to be fixed over time.[8] We note that a high offshorability index of an occupation simply implies that it has high potential for offshoring, not that many jobs in this occupation were actually offshored.

We use the offshorability index by Autor and Dorn (2013) who focus on the elements of each job that represent *Face-to-Face contact* and *On-Site Job*, as originally suggested by Firpo, Fortin, and Lemieux (2011).[9] These job contents are available from O*NET (Occupational Information Network), which has been developed and maintained by the US Department of Labor. According to this index, occupations that require more *Face-to-Face contact* and involve more *On-Site Job* have lower offshorability. We choose their index for two reasons. First, most of the previous research that deals with an offshorability index agrees in using the elements of *Face-to-Face contact* and *On-Site Job*. Second, the index uses a consistent occupational classification structure over time, which can be easily imported to the CPS data.

One caveat of various offshorability indices is that they cannot be separated into components for service and material offshoring. The offshorability of the same occupation could be different in service and manufacturing sectors.[10] However, O*NET or other data sources do not provide enough information to construct separate offshorability indices for different industries within an occupation. As a result, the potential for service and material offshoring is conflated in the offshorability indices.

Based on the offshorability index by Autor and Dorn (2013), we first calculate the average offshoring potential of each broad occupation group. This is the average offshorability of each occupation group, weighted by total hours worked of occupations within each occupation group from the CPS (Current Population Survey) March Supplement. It is a combination of the ex-ante offshorability index of each occupation and the realized hours worked of each

[8] The nature of a job changes over time along with the developments in technologies. When we build a time-varying offshorability index based on the method of Ross (2017) and the data of Atalay et al. (2019), the empirical facts in this subsection also hold, justifying the use of a time-invariant offshorability index.

[9] The elements that consist of *Face-to-Face contact* are: Face-to-face discussions (4.C.1.a.2.l), Establishing and maintaining interpersonal relationships (4.A.4.a.4), Assisting and caring for others (4.A.4.a.5), Performing for or working directly with the public (4.A.4.a.8), and Coaching and developing others (4.A.4.b.5). The elements for *On-Site Job* are; Inspecting equipment, structures, or material (4.A.1.b.2), Handling and moving objects (4.A.3.a.2), Controlling machines and processes (4.A.3.a.3), Operating vehicles, mechanized devices, or equipment (4.A.3.a.4), Repairing and maintaining mechanical equipment ($\times 0.5$, 4.A.3.b.4), and Repairing and maintaining electronic equipment ($\times 0.5$, 4.A.3.b.5).

[10] As an example, we can think of food preparation workers in a factory canteen or a restaurant. Although the offshorability of food preparation workers would be low in general, the probability that a factory is relocated abroad and workers in the canteen lose their jobs would be higher than the probability that a restaurant moves its location to a foreign country.

occupation. We classify occupations into five occupation groups based on the classification by Dorn (2009).[11] Sales and administrative support occupations exhibit the highest offshoring potential (0.58), followed by service (-0.12), managers and professionals (-0.14), operators and laborers (-0.16) and craft and repair (-0.82) occupations.

Figure 1.5 plots each occupation group's share of hours worked for each gender. For women, the most important trend is the fall in the share of sales and administrative support occupations from 1990. These occupations have been the largest employer of female labor and have shown the highest potential for offshoring. During the same period, managers and professionals and service occupations, which are relatively less prone to offshoring, have expanded their shares. Given the definition of offshorability, these observations are in line with the increase of offshoring.

In particular, we can relate the weak performance of the sales and administrative support group to the growth of service offshoring from the 1990s. As shown in Figure 1.5, the share of this group to male hours has been stable. Since service offshoring exerts more adverse impacts on female hours worked in our framework, the dynamics of this occupation group's shares in women's and men's hours of work are consistent with the trend in service offshoring. This evidence supports our theory that the rise of service offshoring is behind the slowdown in the gender hours ratio since the 1990s.

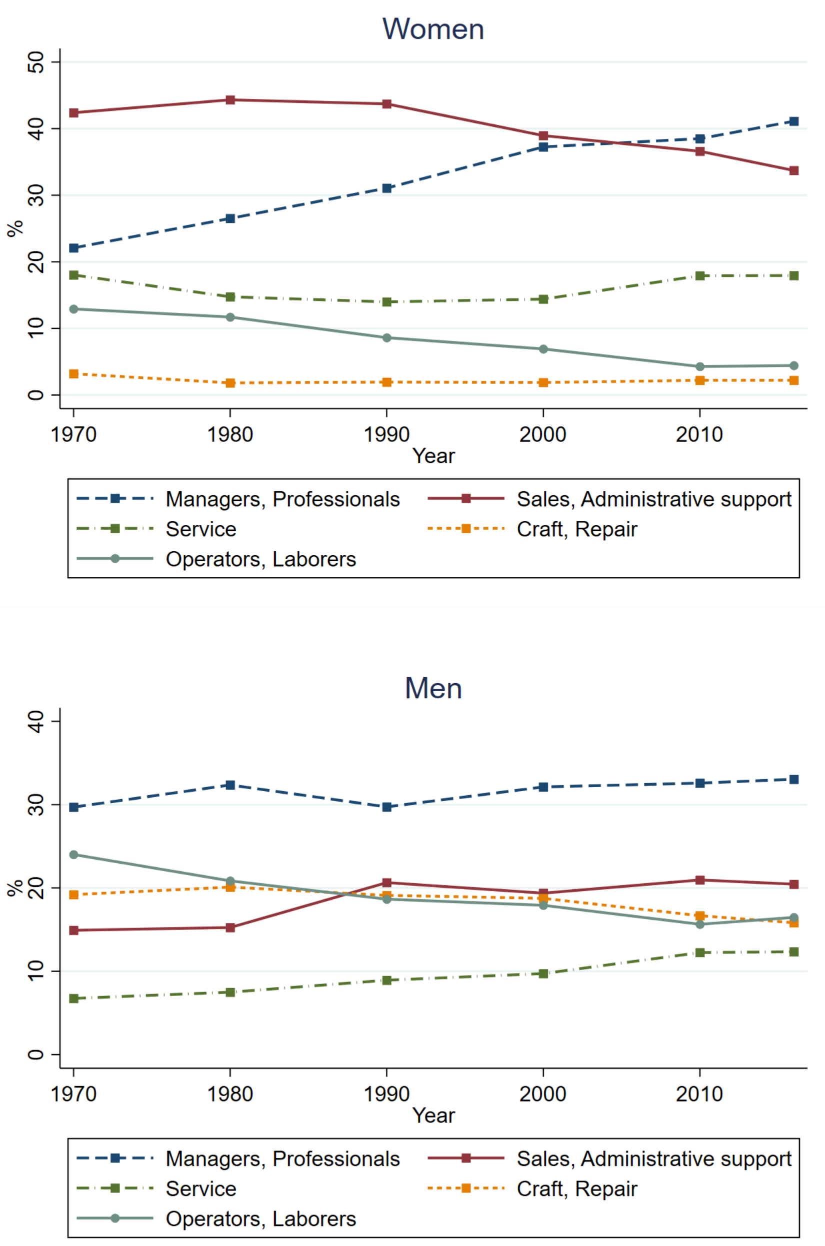
Fact 3. *The sales and administrative support occupations, which have the highest offshoring potential, have witnessed a fall in the share of female hours worked since 1990. At the same time, they have shown a relatively stable share of male hours worked.*

The reallocation of female hours worked from occupations with high offshorability to those with low offshorability from 1990 can be also confirmed by Figure 1.6 and Table 1.1. Figure 1.6 shows the average offshoring potential of each year and gender. We compute this measure using the offshorability of each occupation and hours worked of each occupation, gender, and year. Women's average offshoring potential has continuously fallen, while men's potential has declined slightly by 2000 and gone up since then. The falling female average offshoring potential implies that the share of hours worked in occupations with high offshorability has dropped while the share of hours worked in occupations with low offshorability has gone up for women.

However, the decline of female average offshoring potential started in 1970. In order to show that the periods before and after 1990 are qualitatively different in reallocation patterns, we calculate the contribution of each occupation group in the fall in women's

[11] Dorn (2009) categorizes occupations into six groups, but we leave out 'farming, forestry, and fishing occupations' in our analysis because of the small share of hours worked of this group.

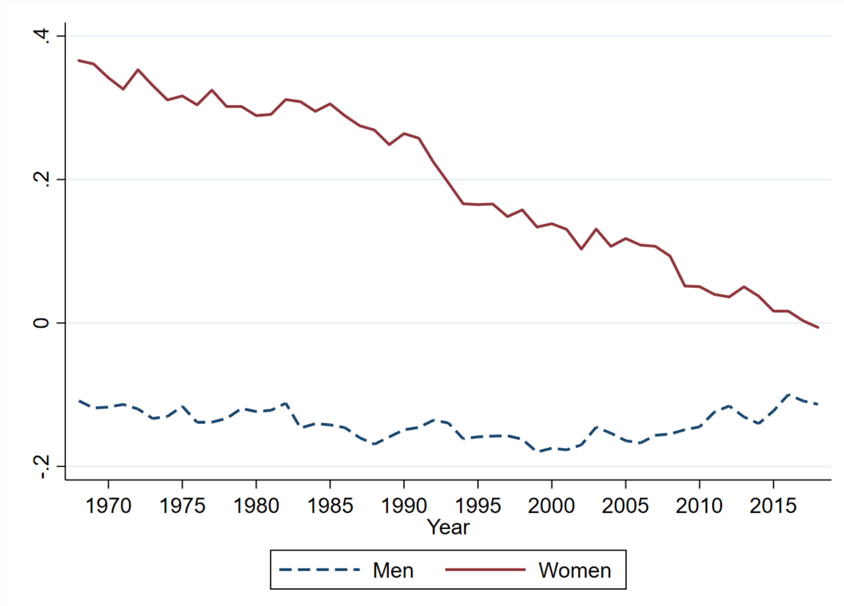
Figure 1.5: Each occupation group's share of hours worked for each gender



Notes: The average offshoring potential of each occupation group is; -0.14 (Managers, Professionals), 0.58 (Sales, Administrative support), -0.12 (Service), -0.82 (Craft, Repair), and -0.16 (Operators, Laborers). These average offshoring potentials are calculated by averaging the offshorability index of occupations in each occupation group, using hours worked from 1968 to 2018 as weights. The figures are 5-year moving averages, except for 2016.
Sources: CPS March Supplement, David Dorn's website

average offshoring potential by period in Table 1.1. From 1970 to 1990, the contributions of craft and repair, service, and sales and administrative support occupations were relatively large, but these groups exhibited mixed trends in their shares of female hours worked. For

Figure 1.6: Average offshoring potential of each gender



Notes: The numbers shown are the average offshorability indices of each year and gender, weighted by total hours worked of each occupation (the sum of individual census weight multiplied by individual annual hours worked for each occupation). The offshorability index of Autor and Dorn (2013) is standardized so that their mean is 0 and standard deviation is 1. The values in the vertical axis represent weighted averages of the standardized index.
Sources: CPS March Supplement, David Dorn's website

this period, the decrease of women's average offshoring potential seems to be a working of composition effects between occupation groups. On the other hand, the fall in the share of women's sales and administrative support occupations has been a main driver of declining women's average offshoring potential since the 1990s. The crucial difference of this period from pre-1990 is that the occupations that are most prone to offshoring experienced a falling share, lowering women's average offshoring potential.

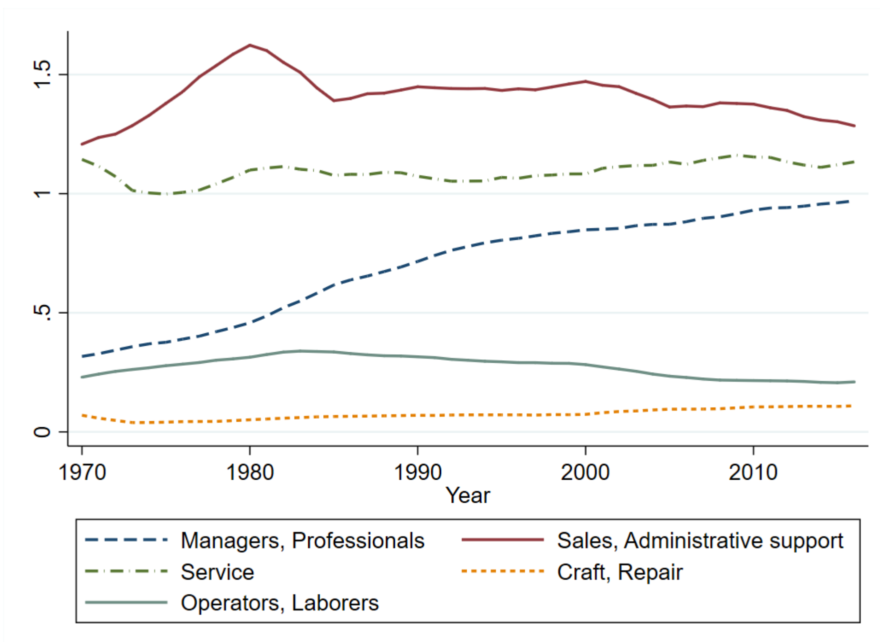
The divergent impacts of offshoring by gender discussed above lead us to suspect that the occupations that are mainly taken up by men and women are different in their offshoring potential. In Figure 1.7, we present the female to male hours ratio of each occupation group to check this hypothesis. Sales and administrative support occupations, which have the highest average offshoring potential, have consistently shown the highest female intensity. They are followed by service occupations, managers and professionals, operators and laborers, and craft and repair occupations. This ranking has been constant from 1970 onwards, and more importantly, exactly coincides with the ranking of the average offshoring potential among the occupation groups. It means that the occupations with higher offshoring potential hire more women relative to men.

Table 1.1: Contribution of each occupation group in the fall in women's average offshoring potential by period

	1970-1990 (%)	1990-2016 (%)
Sales, administrative support (0.58)	54.0	51.3
Service (-0.12)	60.0	11.1
Managers, professionals (-0.14)	-61.0	26.0
Operators, laborers (-0.16)	-51.2	11.4
Craft, repair occupations (-0.82)	88.6	0.7

Notes: The numbers in the parentheses are average offshoring potentials of each occupation group. The contributions do not sum up to 100% because we omit 'farming, forestry, and fishing occupations' in the table.
Sources: CPS March Supplement, David Dorn's website

Figure 1.7: Female to male hours ratio of each occupation group



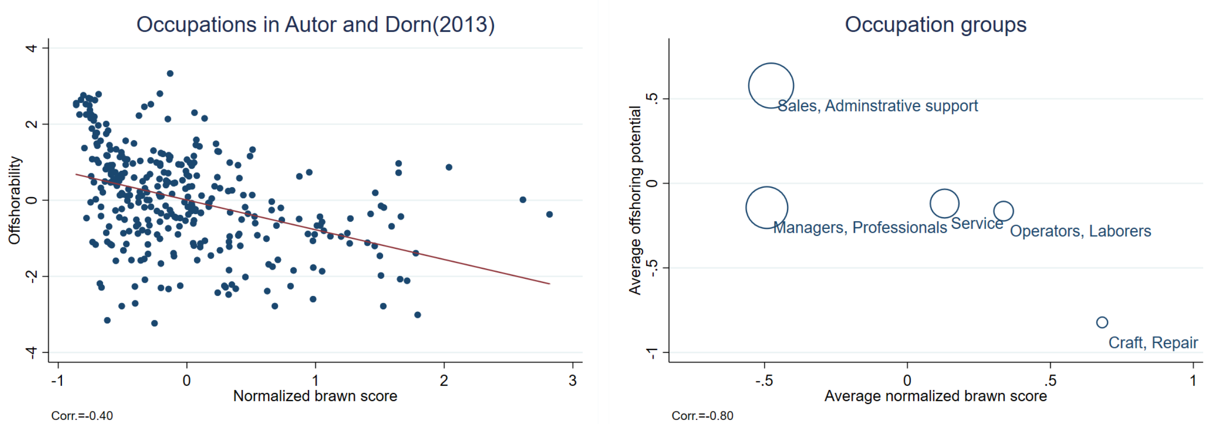
Notes: The figures shown are women's total hours worked divided by men's total hours worked in each occupation group. The average offshoring potential of each occupation group is; 0.58 (Sales, Administrative support), -0.12 (Service), -0.14 (Managers, Professionals), -0.16 (Operators, Laborers), and -0.82 (Craft, Repair).
Sources: CPS March Supplement, David Dorn's website

Fact 4. *The occupation groups with higher offshoring potential show higher female to male hours ratio.*

Where does this tendency come from? The degree of physical abilities required to perform each occupation provides a potential explanation. Generally, women are perceived to have a comparative advantage in brain skills relative to brawn skills and the occupations with higher brawn skill requirements hire more men. In many cases, works in these occupations need to be done on-site, which is a factor that lowers the offshorability index of these occupations. Therefore, it is likely that the offshorability of each occupation is negatively correlated with the brawn skill requirements of the occupation.

In order to verify this hypothesis, we calculate the normalized brawn score of each occupation using the Revised Fourth Edition of the Dictionary of Occupational Titles (DOT). The DOT is the predecessor of the O*NET and contains about 40 job contents for more than 12,000 occupations. We follow Rendall (2018) in choosing the job requirements for computing the normalized brawn score.[12] We first calculate the normalized brawn score by DOT occupations and take the averages of these scores within each occupation by Autor and Dorn (2013). We also calculate the average normalized brawn score by each broad occupation group, using total hours worked of occupations within each group as weights.

Figure 1.8: Average offshoring potential and normalized brawn score



Notes: Points in the left panel represent occupations classified by Autor and Dorn (2013). These points do not include occupations in 'farming, forestry, and fishing occupations' and occupations whose normalized brawn scores are not available. The normalized brawn score of each occupation is the average of the normalized brawn scores of DOT occupations within each occupation by Autor and Dorn (2013). Circles in the right panel denote broad occupation groups and their sizes are weighted by women's total hours worked of each group (the sum of individual census weight multiplied by individual annual hours worked for women in each group). The average normalized brawn score of each occupation group is calculated by weighting the normalized brawn score by total hours worked of each occupation group from 1968 to 2018.
Sources: CPS March Supplement, David Dorn's website, DOT (the Revised Fourth Edition)

The left panel of Figure 1.8 shows that the offshorability index and the normalized brawn score of each occupation are negatively correlated. The correlation coefficient between the two is -0.4. The right panel by occupation groups exhibits a stronger relationship. Sales and

[12]She picks climbing/balancing, stooping/kneeling/crouching/crawling, strength requirement, environmental conditions combined, and exposure to weather to calculate brawn factors. She also shows that the evolution of the brawn score with these elements is robust to using principal component analysis.

administrative occupations which are most prone to offshoring require lower brawn skills, while operators/laborers and craft/repair occupations with lower average offshoring potential need a higher level of physical skills. As expected, more women are employed in occupations with lower brawn scores. In short, the brawn skill requirements of each occupation are important elements behind the high correlation between the average offshoring potential and female intensity.

1.3 Evidence from Regressions

In this section, we attempt to verify the effects of service offshoring on the gender hours gap by performing regressions. First, we run fixed effects regressions to check correlation between the variables. Then we perform IV regressions by instrumenting the endogenous service offshoring variable. We find evidence that service offshoring has negatively affected the female share of hours worked from 1998 to 2017. However, between 1990 and 1997, the effect was not statistically significant.

The full specification for the regressions is the following:

$$Female_{jt} = \alpha_j + \gamma_t + \beta_0 Female_{j,t-1} + \beta_1 SO_{j,t-1} + \beta_2 MO_{j,t-1} + \beta_3 ICT_{j,t-1} + \beta_4 Manu_{jt} + \varepsilon_{jt}. \tag{1.2}$$

All variables differ by occupations (j) and years (t), where 17 occupation groups are classified by Dorn (2009).[13] We could have used the industry by year level variables instead, but then we cannot address the effects of service and material offshoring at the same time because each type of offshoring only affects either the service or manufacturing industries. The dependent variable is the female share of hours worked.[14] The regressors are the lagged female share of hours worked, proxies for service and material offshoring, ICT intensity, and hours worked share in manufacturing. We include fixed effects for each occupation and year as well. The lagged dependent variable is included as a regressor because the female share is highly persistent across time. But the results are qualitatively the same when it is omitted.

For each industry, the proxies for service and material offshoring are calculated from the methodology described in the earlier section. The ICT intensity for each industry is constructed using the EU KLEMS data, based on the method of Michaels, Natraj, and Van

[13] We do not use 330 individual occupations as when doing so the data set becomes a highly unbalanced panel. Frequently, no individuals were allocated to a subset of occupations for some years because those occupation codes only became available in later occupational classification systems.

[14] We pick the female share of hours worked instead of the female to male hours ratio because we can restrict the impact of potentially huge ratios in regressions. Still, the female share is a monotonic increasing function of the female to male hours ratio, so we can directly determine the direction of the impact of service offshoring on the female to male hours ratio from the signs of the regression coefficients.

Reenen (2014). Since these variables are defined in industry by year cells, we reconstruct them to each occupation and year level, using each industry's share of hours worked within each occupation group and year from the CPS data. The ICT intensity was introduced because the development in ICT could have affected the female share and we expect the increase in service offshoring was driven by higher ICT intensity. Weinberg (2000) proposes a hypothesis that can rationalize the former channel. He claims that more intensive use of computers reduces the importance of brawn skills, raising the comparative advantage of women who specialize in brain skills. The offshoring variables and ICT intensity are lagged one period, since the female share is as of March in every year. Occupations with high manufacturing shares tend to offshore material inputs more actively and show lower female hours shares. To control for this potential confounding effect, we include the manufacturing share of each occupation as a regressor. Due to the inconsistencies of offshoring measures before and after 1997, we run separate regressions for each period. The period for the first set of regressions is from 1998 to 2017 and the second set of regressions exploits data from 1990 to 1997.[15]

The fixed effects regression results are shown in Appendix A.1. For both periods, none of the estimates for service and material offshoring are significantly different from zero.

Due to the potential endogeneity, we should not interpret these estimates as indicating no causal relationships from service and material offshoring to female hours share. To tackle this issue, we use the offshorability index by Autor and Dorn (2013) interacted with time as an instrument for service offshoring. As discussed in Section 2, the offshorability index is assumed to represent the pre-determined nature of an occupation. Hence, it is free from the factors that contemporaneously determine female shares and the instrument is likely to satisfy the exclusion restriction as long as the female shares in each occupation do not exhibit linear time trends.[16] It is hard to think of a channel whereby the instrument directly affects the share of female hours worked without going through the offshoring measure. The idea of interacting the offshorability index with time comes from Goos, Manning, and Salomons (2014). They assume that offshoring takes place in the form of affecting the costs of offshored employment and that the speed of change in these costs is proportional to each occupation's offshorability. The material offshoring variable is not relevant to this instrument, so we simply instrument service offshoring and additionally control for material offshoring in some specifications.[17]

[15] Since the (lagged) ICT intensity is available until 2015, the sample period for the regressions that include ICT intensity as a regressor is from 1997 to 2015. The second set of regressions starts from 1990 due to the availability of material offshoring measure.

[16] Most of the occupation groups show fluctuations in their female shares, without exhibiting a rising or falling linear time trend.

[17] Existing literature provides some candidates for material offshoring, but most of them are weak. For

Table 1.2: Regression results (FE-IV)

Dependent variable: Female hours share of each occupation in current year						
	1998-2017			1990-1997		
	(1)	(2)	(3)	(4)	(5)	(6)
Service offshoring (lagged)	-2.964*	-4.478**	-4.669**	5.397	5.538	8.438
	(1.549)	(2.017)	(2.206)	(10.987)	(10.507)	(17.686)
Material offshoring (lagged)		-0.761**	-0.796		-0.054	0.024
		(0.370)	(0.504)		(0.291)	(0.406)
ICT intensity (lagged)			0.811			0.787
			(0.571)			(2.364)
Manufacturing share			-0.020			0.038
			(0.099)			(0.137)
Female hours share (lagged)	0.638***	0.620***	0.581***	0.496***	0.492***	0.498***
	(0.082)	(0.094)	(0.112)	(0.091)	(0.080)	(0.096)
Number of observations	340	340	306	136	136	136
R^2	0.439	0.434	0.390	0.352	0.352	0.350
F statistic	8.47	6.82	7.73	7.72	6.99	2.06
Weak-instrument robust test statistics						
Anderson-Rubin Wald test	3.40*	4.10**	5.98**	0.22	0.25	0.19
Stock-Wright LM S	4.30**	4.69**	4.38**	0.21	0.24	0.19

Notes: All regressions contain occupation and year fixed effects. The instrument used for service offshoring is 'Offshorability×Time.' The offshorability index is standardized. Time is defined as year-beginning year of the sample (1998 or 1990). F statistics are those for the excluded instrument in the first stage, which are represented by Kleibergen-Paap Wald rk F statistics. Anderson-Rubin Wald test statistics (chi-squared) and Stock-Wright LM S statistics are provided for weak-instrument-robust inferences. The null hypothesis for these test statistics are that the coefficient of the endogenous regressor (service offshoring) is equal to zero in the structural equation and the orthogonality condition is satisfied. Standard errors are clustered by each occupation. ***, **, * indicate that the coefficients are statistically significant at 1%, 5%, and 10% level, respectively.

Table 1.2 shows the IV regressions results. The IV estimates for service offshoring are negative and statistically significant from 1998 to 2017 (columns (1) to (3)). These estimates suggest that the increase in service offshoring has contributed to the flattening out of the gender hours ratio during this period. The magnitudes of the estimated influence are such that an occupation that offshores its service inputs by 1 standard deviation (0.4 percentage points) higher experiences a lower female share of hours worked by 1.2 to 1.8 percentage points. The F statistics for the excluded instrument are low in these regressions, hinting at a potential issue of weak instrument. However, the coefficients for service offshoring are statistically different from zero at 5% significance level in weak-instrument robust inferences

example, Amiti and Wei (2006) picked freight and insurance cost of inputs as an instrument for material offshoring but the instrument failed to show high relevance.

presented in the last two rows of the table. This means that the negative impacts of service offshoring on female hours share hold even if our instrument is weakly correlated to service offshoring.

From 1990 to 1997 (columns (4) to (6)), the IV regression results become very noisy. The coefficients for service offshoring change signs and lose their statistical significance. In the early 1990s, service offshoring was at a nascent stage, only affecting a few occupations. This immaturity seems responsible for the large noises in the regressions, rendering the estimates for service offshoring insignificant.

In the previous section, we also stipulated a mechanism of material offshoring affecting male labor more negatively before 1990. We cannot confirm this hypothesis from the regression results because we do not have data before 1990 and it is hard to find a good instrument for material offshoring. We find the correlation of material offshoring with female hours share is negative from 1998 to 2017 in column (2), but it becomes insignificant once we control for ICT intensity and hours share in manufacturing in column (3). Although we can observe the negative influence of service offshoring on female hours share, the association between material offshoring and female hours share is inconclusive from the regression results.

1.4 The Model

We present a model to account for the empirical facts discussed above. The model has two market sectors and two gender specific labor inputs. A continuum of tasks defined by their offshorability is introduced to incorporate the elements of offshoring in the model.

1.4.1 Setup

Firms. There are two sectors in the economy: goods and service. Firms in each sector produce their final goods by combining tasks in the following way:

$$Y_j = A_j \underbrace{[\int_0^1 L_j(k)^{\frac{\eta-1}{\eta}} dk]^{\frac{\eta}{\eta-1}}}_{\equiv L_j}, \tag{1.3}$$

where $j = g, s$ denotes either the goods or service sector; A_j is the sector specific productivity, which grows at the rate of $\gamma_j = \dot{A}_j / A_j$; $L_j(k)$ is the labor input in task k, sector j; and L_j is the labor aggregate in sector j. We assume that each task is solely defined and ordered by a continuous index k, which indicates the offshorability of each task and lies on $[0, 1]$. η

is the elasticity of substitution between tasks in the production process.[18]

Tasks can be supplied either by domestic or offshored labor. Offshored labor can perfectly substitute for domestic labor once firms decide to use it:

$$L_j(k) = L_j^D(k) + L_j^*(k), \tag{1.4}$$

where $L_j^D(k)$ and $L_j^*(k)$ are labor inputs provided by domestic and offshored labor in task k, sector j, respectively.[19]

Domestic labor is the CES aggregate of male and female hours of work:

$$L_j^D(k) = [\alpha(k)L_{fj}(k)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha(k))L_{mj}(k)^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1.5}$$

where $L_{fj}(k)$ and $L_{mj}(k)$ are hours of work by women and men in task k, sector j, respectively. ε is the elasticity of substitution between male and female hours. $\alpha(k)$ represents the weight of women in task k within each domestic labor aggregate and lies on $[0, 1]$. In order to reflect Fact 4 that more women are hired in occupations with high offshorability, we impose $\alpha'(k) > 0$. $\alpha(k)$ is identical across sectors, but as will be shown later, the model implies a higher female to male hours ratio in the service sector.[20]

Free labor mobility is assumed, so the wage is equal across all tasks and sectors for each gender. For domestic labor, there is a gender wage gap between men (w_m) and women (w_f).

There is no gender difference for offshored labor and each foreign worker receives w^* as wage. w^* is given exogenously. The actual hiring cost of firms that exploit offshored labor is $\beta_j\tau(k)w^*$. β_j and $\tau(k)$ indicate common and task-specific components in the offshoring cost, respectively. β_j is specific to each sector j. If β_j is lower, the offshoring cost of the sector would be cheaper for all tasks, inducing firms to use more offshored labor. Given that

[18] The elasticity of substitution between tasks is a distinct concept from the offshorability of each task. The former represents the substitutability between different tasks in the production of final goods, while the latter means the potential substitutability from domestic to foreign labor in providing a certain task.

[19] The perfect substitutability assumption between domestic and offshored labor is widely adopted in the literature. It implies that firms' offshoring decisions are entirely determined by the cost conditions. Therefore, by imposing the assumption, we effectively focus on offshoring by the US to developing countries with cheaper labor costs but largely abstract away from offshoring to the US by other countries (called 'onshoring') because the wage level in the US is generally higher than in developing countries. Since onshoring is mainly motivated by the high quality of material and service inputs provided by the US, domestic and offshored labor cannot be perfect substitutes in this case. Even if we additionally consider the differential impacts of onshoring by genders, the possibility that women in the US would benefit more from onshoring is limited. Onshoring could be particularly problematic for business services where the US has been running a large surplus. But the share of female workers in professional and business services (44.3%) is lower than female shares in the service sector (51.8%) and all non-farm workers (46.5%). Hence, the positive impact of service onshoring on female labor is not likely to be large.

[20] This is in contrast to Ngai and Petrongolo (2017) where the female weight is assumed to be higher in the service sector.

material offshoring has been more prominent than service offshoring (Fact 2), we assume $\beta_g < \beta_s$. Rapid developments of ICT from the 1990s can be considered as a factor that reduces β_j by lowering the technical barriers of offshoring. We also impose $\tau'(k) < 0$ to ensure that a task with higher offshorability incurs a lower offshoring cost to firms, thereby is more likely to be actually offshored.

Households. The household's utility is determined by a joint consumption of goods and services and the leisure of a husband and a wife:

$$u(c_g, c_s, L_l) = \ln C + \delta \ln L_l, \tag{1.6}$$

$$C = [\omega c_g^{\frac{\rho-1}{\rho}} + (1-\omega) c_s^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}}, \tag{1.7}$$

$$L_l = [\alpha_l L_{fl}^{\frac{\varepsilon_l-1}{\varepsilon_l}} + (1-\alpha_l) L_{ml}^{\frac{\varepsilon_l-1}{\varepsilon_l}}]^{\frac{\varepsilon_l}{\varepsilon_l-1}}, \tag{1.8}$$

where C is the aggregate of goods and services consumption; δ is the relative weight of leisure compared to consumption in the utility function; L_l is the CES combination of male and female leisure within each household; ω is the weight on consumption of goods; ρ is the elasticity of substitution between goods and services consumption; α_l is the weight of women's leisure within the leisure aggregate; and ε_l is the elasticity of substitution between male and female leisure. We assume $\rho < 1$, suggesting that goods and services are gross complements.

The household's income depends on gender specific wages and hours worked of a husband and a wife, which are equal to the time endowment minus the time for leisure. Households consume goods and services out of their income:

$$p_g c_g + p_s c_s = w_m(T_m - L_{ml}) + w_f(T_f - L_{fl}). \tag{1.9}$$

Equilibrium. The competitive equilibrium consists of wages (w_m, w_f), prices (p_g, p_s), hours worked by domestic workers $\{L_{fg}(k), L_{fs}(k), L_{mg}(k), L_{ms}(k)\}_{k\in[0,1]}$, hours worked by offshored labor $\{L_g^*(k), L_s^*(k)\}_{k\in[0,1]}$, leisure (L_{fl}, L_{ml}), consumption (c_g, c_s), and outputs (Y_g, Y_s) such that:

1. Given wages and prices, firms maximize profits subject to (1.3)-(1.5) and households maximize utility (1.6) subject to (1.7)-(1.9);

2. Wages and prices clear the goods and labor markets;

$$c_j = Y_j, \tag{1.10}$$

$$T_m - L_{ml} = \int_0^1 L_{mg}(k)dk + \int_0^1 L_{ms}(k)dk, \tag{1.11}$$

$$T_f - L_{fl} = \int_0^1 L_{fg}(k)dk + \int_0^1 L_{fs}(k)dk. \tag{1.12}$$

1.4.2 Firm's Profit Maximization

Since domestic and offshored labor aggregates are perfect substitutes, firms will employ either domestic or offshored labor, taking the costs associated with hiring them into account.

Suppose firms only hire domestic labor. In this domain, firms solve the following maximization problem for each task k given w_f and w_m:

$$\max_{L_{fj}(k),L_{mj}(k)} w^D(k)L_j^D(k) - w_f L_{fj}(k) - w_m L_{mj}(k),$$

subject to (1.5). Then $w^D(k)$, the wage of hiring a unit of $L_j^D(k)$, can be expressed as:

$$w^D(k) = [\alpha(k)^\varepsilon w_f^{1-\varepsilon} + (1-\alpha(k))^\varepsilon w_m^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}}. \tag{1.13}$$

Since the cost of hiring a unit of offshored labor for task k is $\beta_j\tau(k)w^*$, firms compare $w^D(k)$ and $\beta_j\tau(k)w^*$ to decide whether to employ domestic or offshored labor.

The cutoff offshorability K_j for each sector j is defined such that $w^D(K_j) = \beta_j\tau(K_j)w^*$. Lemma 1 states that we can guarantee the existence of a unique cutoff for each sector under a set of assumptions. These assumptions are the existence of offshoring in both sectors and the faster rate of decrease in offshoring costs than in domestic hiring costs when offshorability rises.[21] Then tasks with offshorability higher than K_j are offshored and those with offshorability lower than K_j are supplied by domestic workers.

Lemma 1. *If $w^D(0) < \beta_j\tau(0)w^*$, $w^D(1) > \beta_j\tau(1)w^*$, and $\partial w^D(k)/\partial k > \partial(\beta_j\tau(k)w^*)/\partial k$ for all k, then there exists a unique cutoff K_j that satisfies the following conditions:*

1. $w^D(K_j) = \beta_j\tau(K_j)w^*$,
2. $L_j^D(k) > 0$ *and* $L_j^*(k) = 0$ *for* $0 \le k \le K_j$,
3. $L_j^D(k) = 0$ *and* $L_j^*(k) > 0$ *for* $K_j < k \le 1$.

[21] Under our assumptions of $\alpha'(k) > 0$ and $\tau'(k) < 0$, the second part of the assumption is satisfied when $0 \le k \le \alpha^{-1}((w_f/w_m)/(1 + w_f/w_m))$ because $w^D(k)$ is increasing in k and $\beta_j\tau(k)w^*$ is decreasing in k in this range. It is needed for $\alpha^{-1}((w_f/w_m)/(1 + w_f/w_m)) < k \le 1$ where both $w^D(k)$ and $\beta_j\tau(k)w^*$ are decreasing in k.

Proof. See Appendix A.2. $\square$

One feature to note is that K_j is increasing in β_j. The intuition is straightforward; a lower β_j means that offshoring costs in sector j are reduced, therefore the sector hires more offshored labor, which is realized by a lower K_j in the model. Since we are assuming $\beta_g < \beta_s$, $K_g < K_s$.

Lemma 2. *When Lemma 1 holds,*

$$\frac{\partial K_j}{\partial \beta_j} > 0.$$

Proof. See Appendix A.2. $\square$

Given $\{w_f, w_m, p_g, p_s\}$ and the cutoff K_j, the firm's profit maximization problem is:

$$\underset{\{L_{fj}(k), L_{mj}(k), L_j^*(k)\}_{k\in[0,1]}}{max} p_j Y_j - \int_0^{K_j} w^D(k) L_j^D(k) dk - \int_{K_j}^1 \beta_j \tau(k) w^* L_j^*(k) dk,$$

subject to (1.3)-(1.5). Combining the first order conditions gives:

$$\frac{L_{fj}(k)}{L_{mj}(k)} = \varphi(k)^{\varepsilon} x^{-\varepsilon}, \tag{1.14}$$

where $\varphi(k) \equiv \alpha(k)/(1-\alpha(k))$, $x \equiv w_f/w_m$, $0 \le k \le K_j$, and $j = g, s$. x represents the gender wage ratio. The ratio of female to male hours worked in each task is common for both sectors. It is increasing in k, indicating the fact that tasks with higher offshorability hire more women.

Solving for the relationship between prices and wages, we can derive the following condition:

$$p_j A_j = \underbrace{[w_f^{1-\eta} \int_0^{K_j} (\alpha(k)^{-\frac{\varepsilon}{\varepsilon-1}} I(k,x)^{\frac{1}{\varepsilon-1}})^{1-\eta} dk + (\beta_j w^*)^{1-\eta} \int_{K_j}^1 \tau(k)^{1-\eta} dk]^{\frac{1}{1-\eta}}}_{\equiv H(\beta_j, x)}, \tag{1.15}$$

where $I(k,x) \equiv w_f L_{fj}(k)/(w_f L_{fj}(k) + w_m L_{mj}(k)) = 1/(1+\varphi(k)^{-\varepsilon} x^{\varepsilon-1})$. $I(k,x)$ denotes the wage bill share of female labor in task k. $p_j A_j$ is the value of marginal productivity of a task aggregate, L_j. $H(\beta_j, x)$, the right hand side of (1.15), is the cost of hiring a unit of L_j. Therefore, (1.15) is the profit maximizing condition of L_j. It should be noted that the hiring cost $H(\beta_j, x)$ is increasing in β_j because a lower β_j drives firms towards using more offshored labor that is cheaper, thereby reducing total hiring costs.

1.4.3 Household's Utility Maximization

Household's utility maximization generates the following conditions for consumption and leisure:

$$\frac{c_s}{c_g} = (\frac{p_s}{p_g}\frac{\omega}{1-\omega})^{-\rho}, \tag{1.16}$$

$$\frac{L_{fl}}{L_{ml}} = \varphi_l^{\varepsilon_l} x^{-\varepsilon_l}, \tag{1.17}$$

where $\varphi_l \equiv \alpha_l/(1-\alpha_l)$.

Since the utility function is in logs, households spend a fixed share of their full income in consumption and leisure, where the shares are governed by the weight parameter δ.[22] Using this property and (1.17), we can solve for the leisure of a woman and a man:

$$L_{fl} = \frac{\delta}{1+\delta}\frac{w_m T_m + w_f T_f}{w_f} I_l(x), \tag{1.18}$$

$$L_{ml} = \varphi_l^{-\varepsilon_l} x^{\varepsilon_l} \frac{\delta}{1+\delta}\frac{w_m T_m + w_f T_f}{w_f} I_l(x), \tag{1.19}$$

where $I_l(x) \equiv w_f L_{fl}/(w_f L_{fl} + w_m L_{ml}) = 1/(1+\varphi_l^{-\varepsilon_l} x^{\varepsilon_l - 1})$. $I_l(x)$ is the implicit wage bill share of women in leisure.

1.4.4 Hours Worked in the Equilibrium

By the goods market clearing condition (1.10), the profit maximizing condition (1.15), and the utility maximizing condition (1.16), we obtain the ratio between labor aggregates in the goods and service sectors in equilibrium:

$$\frac{L_g}{L_s} = \frac{A_s}{A_g}\frac{c_g}{c_s} = [\underbrace{\frac{H(\beta_s, x)}{H(\beta_g, x)}}_{\equiv H_{sg}(\beta_s, \beta_g, x)} \frac{\omega}{1-\omega}]^{\rho}(\frac{A_g}{A_s})^{\rho-1}. \tag{1.20}$$

$H_{sg}(\beta_s, \beta_g, x)$ is the ratio of hiring costs in service to goods. Since $\partial H(\beta_j, x)/\partial \beta_j > 0$, $\partial H_{sg}(\beta_s, \beta_g, x)/\partial \beta_s > 0$ and $\partial H_{sg}(\beta_s, \beta_g, x)/\partial \beta_g < 0$. Utilizing the connections between labor aggregates and labor inputs in each sector, we can acquire the ratio of hours worked

[22] The full income is defined by the income that households can receive if they devote their entire time endowments to working. In this model, it is $w_m T_m + w_f T_f$.

in goods to service:

$$\frac{L_{fg}(k)}{L_{fs}(k)} = \frac{L_{mg}(k)}{L_{ms}(k)} = H_{sg}(\beta_s, \beta_g, x)^{\rho-\eta} \underbrace{(\frac{A_g}{A_s})^{\rho-1}(\frac{\omega}{1-\omega})^{\rho}}_{\equiv R_{sg}(A_g, A_s)}, \tag{1.21}$$

for $0 \leq k \leq K_g$.

We can show higher female intensity in the service sector based on our assumptions, (1.14) and (1.21). Since we assume $\alpha'(k) > 0$, $\varphi(k)$ is also increasing in k. (1.14) means that female intensity $(L_{fj}(k)/L_{mj}(k))$ in each sector is higher for a task with higher offshorability. We established $K_g < K_s$ using an earlier assumption of $\beta_g < \beta_s$ and the fact that K_j is increasing in β_j (Lemma 2). Because tasks with offshorability below the cutoff K_j only hire domestic labor (Lemma 1), the goods and service sectors hire domestic labor in the ranges of $[0, K_g]$ and $[0, K_s]$, respectively. In other words, firms in the service sector additionally hire domestic tasks in $[K_g, K_s]$ compared to the goods sector. Among the whole range of $[0, K_s]$ where the service sector employs domestic labor, this extra range of $[K_g, K_s]$ exhibits the highest female intensity by (1.14). (1.21) implies that female intensities of the goods and service sectors are the same in $[0, K_g]$.[23] Therefore, the overall female to male hours ratio would be higher in the service sector.

To sum up, this result is derived from the uneven demand for each gender-specific labor input across a continuum of tasks and the difference in the range of offshoring across sectors. Proposition 1 formally proves this relationship.

Proposition 1. *When (1.14) and (1.21) holds, $K_g < K_s$, and $\alpha'(k) > 0$, the female to male hours ratio in the goods sector is lower than the ratio in the service sector:*

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \frac{\int_0^{K_s} L_{fs}(k)dk}{\int_0^{K_s} L_{ms}(k)dk}.$$

Proof. See Appendix A.2. □

Finally, if we plug the derivations for leisure (1.18) and (1.19) in the labor market clearing conditions (1.11) and (1.12), the following equilibrium conditions can be obtained:

$$T_f - \frac{\delta}{1+\delta} \frac{w_m T_m + w_f T_f}{w_f} I_l(x) = \int_0^{K_g} L_{fg}(k)dk + \int_0^{K_s} L_{fs}(k)dk, \tag{1.22}$$

$$T_m - \varphi_l^{-\varepsilon_l} x^{\varepsilon_l} \frac{\delta}{1+\delta} \frac{w_m T_m + w_f T_f}{w_f} I_l(x) = \int_0^{K_g} L_{mg}(k)dk + \int_0^{K_s} L_{ms}(k)dk. \tag{1.23}$$

[23] The first part of (1.21) can be written as $L_{fg}(k)/L_{mg}(k) = L_{fs}(k)/L_{ms}(k)$.

1.4.5 Effects of Productivity Growth on the Gender Hours Ratio

The female to male hours ratio in the aggregate economy is written as follows:

$$FM = \frac{\int_0^{K_g} L_{fg}(k)dk + \int_0^{K_s} L_{fs}(k)dk}{\int_0^{K_g} L_{mg}(k)dk + \int_0^{K_s} L_{ms}(k)dk}. \tag{1.24}$$

If we use (1.14) and (1.21), we can formulate the female to male hours ratio in terms of $L_{fs}(k), H_{sg}(\beta_s, \beta_g, x)$, and $R_{sg}(A_g, A_s)$:

$$FM = \frac{R_{sg}(A_g, A_s)H_{sg}(\beta_s, \beta_g, x)^{\rho-\eta} \int_0^{K_g} L_{fs}(k)dk + \int_0^{K_s} L_{fs}(k)dk}{[R_{sg}(A_g, A_s)H_{sg}(\beta_s, \beta_g, x)^{\rho-\eta} \int_0^{K_g} \varphi(k)^{-\varepsilon} L_{fs}(k)dk + \int_0^{K_s} \varphi(k)^{-\varepsilon} L_{fs}(k)dk]x^{\varepsilon}}. \tag{1.25}$$

In examining the effects of productivity growth and offshoring on the gender hours ratio, the higher female to male hours ratio in the service sector (Proposition 1) plays a crucial role. In particular, the following variant of Proposition 1 holds:

$$\int_0^{K_g} L_{fg}(k)dk \int_0^{K_s} L_{ms}(k)dk - \int_0^{K_s} L_{fs}(k)dk \int_0^{K_g} L_{mg}(k)dk < 0. \tag{1.26}$$

The female to male hours ratio keeps growing when the labor productivity growth is higher in the goods sector than in the service sector. This is formally stated in Proposition 2. When $\gamma_g > \gamma_s$, $R_{sg}(A_g, A_s) = (\omega/(1-\omega))^{\rho}(A_g/A_s)^{\rho-1}$ declines over time as A_g/A_s grows at a rate of $\gamma_g - \gamma_s$ and $\rho < 1$. By (1.21), the fall of $R_{sg}(A_g, A_s)$ decreases the use of labor tasks in the goods sector relative to the service sector. Intuitively, higher productivity growth in the goods sector drives a fall in the relative price of goods. Since goods and services are poor substitutes for households, the relative expenditure share of services goes up and more hours need to be hired by the service sector. Higher female intensity in the service sector suggests that the aggregate female to male hours ratio would rise in this case.

Proposition 2. *If Proposition 1 holds, the aggregate female to male hours ratio rises over time as $\gamma_g > \gamma_s$.*

Proof. See Appendix A.2. □

1.4.6 Effects of Offshoring on the Gender Hours Ratio

Next, we claim that a decline of the offshoring costs in service sector β_s leads to a fall in the gender hours ratio as long as $\beta_g < \beta_s$ after the change in Proposition 3. The impact of a change in β_s on FM can be decomposed into two components: a direct effect and an indirect effect via a change to K_s. The direct effect works through a change in $H_{sg}(\beta_s, \beta_g, x)$. A drop in β_s would result in the fall in the ratio of hiring costs $H_{sg}(\beta_s, \beta_g, x)$. It raises the ratio of hours worked in goods to service by (1.21). This is because firms in the service sector react to a decrease in labor costs by hiring cheaper offshored labor, as foreign labor can easily replace domestic labor due to high substitutability between tasks under the assumption of $\eta > \rho$. This force acts towards reducing the female to male hours ratio due to lower female intensity in the goods sector.

When β_s goes down, K_s also decreases (Lemma 2). When K_s decreases, the service sector employs more offshored labor and sheds domestic labor. But the tasks that are replaced by offshoring as a result of a fall in K_s have the highest offshorability among the range of domestic tasks previously hired, implying that the female intensity in these tasks is also the highest. Therefore, the decline of K_s leads to a decrease in the female to male hours ratio. Putting these two forces together, the female to male hours ratio unambiguously goes down if β_s is reduced.

Proposition 3. *If Proposition 1 holds and $\eta > \rho$, the aggregate female to male hours ratio falls as β_s goes down and $\beta_g < \beta_s$ is still satisfied after the change.*

Proof. See Appendix A.2. □

Lastly, the impact of a change in β_g on the gender hours ratio is ambiguous. The sign of the direct effect is negative but there is uncertainty with the indirect effect. If K_g is relatively far from K_s and women's weight $\alpha(k)$ is highly responsive to the offshorability of each task, then there is a possibility that the indirect effect also becomes negative and the female to male hours ratio could rise when β_g goes down. These conditions imply that the goods sector employs only a few women in the first place because the sector hires domestic labor in low offshorable tasks compared to the service sector. As a result, the impact of a fall in β_g on female labor is limited while it negatively affects male labor, rendering the female to male ratio to go up. But these conditions are highly restrictive and if either of the above conditions is not met, we cannot determine which direction β_g would affect the gender hours ratio.

This section showed that the proposed model can qualitatively account for the evolution of the female to male hours ratio. The gender hours ratio has been in a continuously rising trend since the 1970s due to the higher productivity growth in goods (Proposition 2). But advances in ICT from the 1990s has reduced the cost of service offshoring, slowing down the pace of the rising gender hours ratio (Proposition 3). The key assumptions that shape this mechanism are the high female intensity in highly offshorable tasks and the relative prominence of material offshoring compared to service offshoring. These assumptions reflect empirical facts presented in the earlier section and generate a higher female to male hours ratio in services (Proposition 1).

1.5 Quantitative Analysis

In this section, we calibrate parameters of the model to match the US data in 1970 and compare the model-generated gender hours ratios with those in 1990 and 2016. We examine different counterfactual scenarios and compare them with the baseline to gauge the contribution of our mechanism.

1.5.1 Calibration

In our model, the most basic unit in producing final goods is a task. But it is hard to find data sources that provide consistent information on tasks, as Autor (2013) points out. Thus, we treat an occupation, instead of a task, as a basic unit in implementing quantitative analysis. As in earlier sections, we use the occupational classification and offshorability index by Autor and Dorn (2013). Their offshorability index is re-scaled so that they range from 0 to 1.

The data targets are shown in Table 1.3. M_m and M_f are the average hours worked by men and women, respectively. In the context of our model, $M_m = \int_0^{K_g} L_{mg}(k)dk + \int_0^{K_s} L_{ms}(k)dk$ and $M_f = \int_0^{K_g} L_{fg}(k)dk + \int_0^{K_s} L_{fs}(k)dk$. FM is the gender hours ratio, namely M_f/M_m. M_m and M_f are expressed as shares of the total time endowment of each individual.[24] They are displayed as averages of two years before and after each year to even out the potential influence of outliers.

x is the five-year average of the gender wage ratio in Figure 1.1, which is derived from a regression that controls for the labor market characteristics of each individual. In our calibration, we fix these ratios to the data to keep focus on the model's capability to predict gender hours ratios.

We introduce sector-specific weights on female labor in the quantitative analysis. Our original model assumes a common weight on female labor across sectors and endogenizes the within-sector demand shift away from female labor with the change in offshoring. This assumption implies that the female to male hours ratio should be the same across sectors with no offshoring. But the gender hours ratio was higher in the service sector in 1970 when there was little offshoring. We impose a higher weight on the service sector to reconcile this

[24]The total time endowment including work, school, home production, and leisure is assumed to be 88.5 hours per week, in accordance with Ramey and Francis (2009).

Table 1.3: Data targets

Year	FM	M_m	M_f	x
1968-1972 (1970)	0.384	0.416	0.160	0.631
1988-1992 (1990)	0.646	0.381	0.246	0.733
2014-2018 (2016)	0.746	0.349	0.260	0.776

Notes: FM is the gender hours ratio. M_m and M_f are the five-year averages of the hours worked by men and women. x is the five-year average of the adjusted gender wage ratios in Figure 1.1.
Source: CPS March Supplement

fact. We derive the model equations and discuss lemmas and propositions under this new setting in Appendix A.3.

For the women's weight for each task k in producing domestic labor in sector j and year t, $\alpha_{j,t}(k)$, we pick the simplest specification that matches an assumption of the model; $\alpha_{j,t}(k) = \alpha_{kj,t}k + \alpha_{cj,t}$, where $\alpha_{kj,t} > 0$ for all k, j, and t and t refers to 0, 1, and 2, for 1970, 1990, and 2016, respectively. We assume a common slope and different intercepts in the two sectors; $\alpha_{k,t} = \alpha_{ks,t} = \alpha_{kg,t}$ and $\alpha_{cs,t} \neq \alpha_{cg,t}$. Since $0 < \alpha_{j,t}(k) < 1$ for all k, j, and t, $0 < \alpha_{cj,t} < 1$ and $0 < \alpha_{k,t} + \alpha_{cj,t} < 1$ must hold for all j and t. In practice, $\alpha_{cs,t} > \alpha_{cg,t}$ in the calibration, reflecting the higher female intensity in the service sector. Therefore, we can ensure that $\alpha_{s,t}(k) > \alpha_{g,t}(k)$ is satisfied for all k, which justifies the assumption made in Appendix A.3.

For the functional form of $\tau(k)$, the task-specific portion of offshoring costs, we follow Grossman and Rossi-Hansberg (2008); $\tau(k) = k^{-\tau}$, where $\tau > 0$.[25]

The hours worked distribution of women in the service sector for 1970, $L_{fs,0}(k)$, is far from a continuous function of k, contrary to a model assumption.[26] There are 330 occupations in Autor and Dorn's (2013) classification and not every occupation hires female workers in the service sector. Keeping this discrete distribution in the calibration could be problematic because the implied distributions of $L_{mg,0}(k), L_{ms,0}(k)$, and $L_{fg,0}(k)$ by the model based on the discrete distribution of $L_{fs,0}(k)$ might not fit the actual distributions in 1970. Therefore, we adopt an alternative assumption that $L_{fs,0}(k)$ is a continuous PDF that matches the features of the actual distributions in 1970 and the same parameters govern the distributions of $L_{fs,t}(k)$ in subsequent years. Under this assumption, $L_{fs,t}(k)$ only differs from $L_{fs,0}(k)$ in the offshoring cutoff and the scaling factor of the distribution. We assume that $L_{fs,0}(k)$

[25]Note that their definition of offshorability i is reversed in this chapter, i.e., $i = 1 - k$.

[26]Since $L_{mg,0}(k), L_{ms,0}(k)$, and $L_{fg,0}(k)$ can be expressed with respect to $L_{fs,0}(k)$, we choose $L_{fs,0}(k)$ as the benchmark distribution. This is because the trend for female hours worked in the service sector has been more important in the determination of the gender hours ratio, compared to hours worked of men or in the goods sector.

follows the Beta distribution since its domain is on $[0,1]$.

Parameters. The values of the following parameters are needed to solve the model; (η, ε, $(\gamma_g - \gamma_s)$ for 1970-1990 and 1990-2016, and $\{\alpha_{k,t}, \alpha_{cg,t}, \alpha_{cs,t}\}$ for each t) from the firm's side, (ρ, $T_{m,t}$ for each t, ε_l, α_l, and δ) from the household's side, offshoring-related parameters (τ, $\{K_{g,t}, K_{s,t}, \theta_{g,t} \equiv \beta_{g,t} w_t^*, \theta_{s,t} \equiv \beta_{s,t} w_t^*, R_{sg,t}\}$ for each t) and parameters for the Beta (ψ and ω) distribution.[27] We sketch the methods to obtain important parameters in this part and leave the details for other parameters to Appendix A.4. We basically attempt to get estimates from the model and other data sources. The estimates for η, ε, and ρ cannot be obtained in this way, so we import these values from the existing literature.

We obtain the value for the elasticity of substitution between occupations $\eta = 0.854$ from Goos, Manning, and Salomons (2014). They set up a structural model and estimate the parameter through running regressions using the European data. Ritter (2014) offers another estimate of 0.4 from the 2000-2005 BLS Occupational Employment Statistics. Given that both works classify occupations in broad occupation groups and our calibration is based on detailed occupations, we choose the higher estimate because it is likely to be closer to the elasticity of substitution between finer occupational classifications.[28] We take the figure for the elasticity of substitution between male and female labor $\varepsilon = 2.4$ from Weinberg (2000). The values of the same parameter chosen by Acemoglu, Autor, and Lyle (2004) and Ngai and Petrongolo (2017) are 3 and 2.27, respectively, which are not far from our pick.

The difference in annual growth rates of A_g and A_s can be calculated using the labor productivity data by BLS and the equations of the model. The derivation of the mapping from the labor productivity data by BLS to A_j in our model is given in Appendix A.4.[29] Ngai and Petrongolo (2017) formulate a mechanism that the rise of services induced by the structural transformation is the key in rationalizing the increase in women's hours worked. In fact, their mechanism can also account for a slowdown of the gender hours ratio if $\gamma_g - \gamma_s$ declined after 1990. The calculated estimates are $(\gamma_g - \gamma_s)_{0-1} = 1.6\%$ and $(\gamma_g - \gamma_s)_{1-2} = 0.9\%$

[27] The PDF of Beta distribution in the calibration is defined by $L_{fs,0}(k) = L_{fs} k^{\psi-1}(1-k)^{\omega-1}/B(\psi,\omega)$ where $B(\psi,\omega) = \Gamma(\psi)\Gamma(\omega)/\Gamma(\psi+\omega)$ and L_{fs} is a scaling factor of the distribution.

[28] Occupations that belong to the same occupation group are likely to show higher substitutability, while occupations in different groups would be more complementary. Therefore, if occupations are defined by broad occupation groups, the substitutability is likely to be lower.

[29] One issue with the calculation of A_j using data and our model is that the level of A_j is directly related to K_j in each year, even though we posit that A_j is given exogenously while K_j is endogenously determined from the equalization of hiring costs in the model. This is because the definition of labor productivity by BLS is connected to K_j in the context of our model. The association could be problematic in the next subsection when we consider a counterfactual of no service offshoring in 2016. This is because a change in K_j would also alter the level of A_j, making an isolation of the effect due to a change in K_j impossible. To avoid this issue, we derive A_j by assuming that there has been no offshoring from 1970 to 2016 and apply this common A_j to the baseline and all counterfactuals.

per year for 1970-1990 and 1990-2016, respectively, which are consistent with their view. We embrace this point by assuming that $\gamma_g - \gamma_s$ goes down after 1990.

Instead of calibrating $\alpha_{k,0}$ and $\alpha_{cj,0}$ in 1970 and using these estimates for generating the predictions for 1990 and 2016, we acquire $\alpha_{k,t}$ and $\alpha_{cj,t}$ from the data in each year. This is to incorporate a possibility of rising female demand within each sector. If we use the fixed values from 1970, the model would predict a fall in the gender hours ratio when the gender wage ratio rises, as (A.3) suggests. Since we assume that the slope coefficient in $\alpha_{j,t}(k)$ is identical across sectors, we generalize (1.14) and use the hours worked of women and men in both sectors to obtain the common slope. The slope coefficients for each year $\alpha_{k,0} = 0.233$, $\alpha_{k,1} = 0.284$, and $\alpha_{k,2} = 0.239$ are derived from the simple regressions of $\alpha_t(k)$ on k, where $\varphi_t(k) = (L_{f,t}(k)/L_{m,t}(k))^{\frac{1}{\varepsilon}} x_t$ and $\alpha_t(k) = \varphi_t(k)/(\varphi_t(k) + 1)$.[30] For the intercepts, we utilize the relationship between female and male hours worked (A.3) and match men's total hours of work in each sector and year.[31] More specifically, $\alpha_{cj,t}$ is the value that satisfies the following condition, given the $\alpha_{k,t}$:

$$L_{mj,t} = \sum_{k=0}^{1} L_{mj,t}(k) = \sum_{k=0}^{1} L_{fj,t}(k)\left(\frac{\alpha_{k,t}k + \alpha_{cj,t}}{1 - \alpha_{k,t}k - \alpha_{cj,t}}\right)^{-\varepsilon} x_t^{\varepsilon}. \tag{1.27}$$

The resulting estimates are $\alpha_{cg,0} = 0.118$, $\alpha_{cs,0} = 0.221$, $\alpha_{cg,1} = 0.145$, $\alpha_{cs,1} = 0.281$, $\alpha_{cg,2} = 0.174$, and $\alpha_{cs,2} = 0.331$.

Parameters from the household's side are discussed in Appendix A.4. We note that we fix $T_{m,t} = 0.870$ for all years using the figure in 1970 and estimate T_f/T_m from the model.[32]

For the offshoring-related parameters, we start from estimating offshoring cutoffs in each year. Previous works by Ranjan (2013) and Zhang (2018) use proxies for offshoring, similar to the one that we used in Section 2, to obtain the cutoffs for offshoring. They assume perfect substitutability between domestic and offshored labor as in our model. The assumption implies that occupations with offshorability higher than the cutoff are taken up by foreign labor and should not show up in the domestic data. But in reality, these occupations do not disappear from the data.[33] The aggregate data that Ranjan (2013) and Zhang (2018) exploited contain these occupations, which are inconsistent with their model assumptions.

[30] Occupations with both zero $L_{f,t}(k)$ and $L_{m,t}(k)$ are dropped. All coefficients for $\alpha_{k,t}$ are statistically different from 0 at 1% significance level.

[31] We only take slope coefficients from regressions, since we want to utilize the trends in total hours worked of each sector as well as the trends extracted from regressions in the individual occupation level.

[32] The reason we choose to fix T_m is because men's total time endowments (net of home production) derived to calculate men's leisure in Appendix A.4 have been relatively stable from 1970 to 2016, while women's have risen during the same period.

[33] This is natural because an offshorability index simply measures the potential of being offshored, not the actual degree of offshoring, as emphasized before.

To overcome this issue, we produce hypothetical distributions of female hours worked for each sector and year on the offshorability of each occupation. These distributions are constructed from the distributions of hours worked in the base year. The hypothetical distributions of each year mimic women's average offshoring potential of the actual distributions. They are assumed to have the same shapes as the ones in the base year, but their cutoffs for offshoring are different.[34] We choose 1983 as the base year because it is effectively the earliest year with a consistent occupational classification.[35]

First, we impose the simplifying assumptions of $K_{g,0} = K_{s,0} = 1$ and $K_{s,1} = 1$, which means there was no material and service offshoring in 1970 and service offshoring only emerged after 1990. These simplifications are based on the trends for service and material offshoring in the earlier section. Then we calibrate $K_{g,1}$, $K_{g,2}$, and $K_{s,2}$ using the hypothetical distributions of 1990 and 2016. They are jointly calibrated to match the average offshoring potential for women and the rate of estimated female employment losses in service to goods in each year. These targets are expressed in the following way:

$$\overline{Off_{f,t}} = \frac{\sum_{k=o}^{K_{g,t}} kL^H_{fg,t}(k) + \sum_{k=o}^{K_{s,t}} kL^H_{fs,t}(k)}{\sum_{k=o}^{K_{g,t}} L^H_{fg,t}(k) + \sum_{k=o}^{K_{s,t}} L^H_{fs,t}(k)}, \tag{1.28}$$

$$\chi_{f,t} = \frac{\sum_{k=K_{s,t}}^{1} L^H_{fs,t}(k)}{\sum_{k=K_{g,t}}^{1} L^H_{fg,t}(k)}, \tag{1.29}$$

where $L^H_{fj,t}(k)$ refers to female hours worked in sector j and occupation k from each year's hypothetical distribution; $\overline{Off_{f,t}}$ and $\chi_{f,t}$ represent the average offshoring potential for women and the ratio of estimated female employment loss in service to goods in each year, respectively. $\chi_{f,t}$ can be computed using the losses derived in Figure 1.3 and female shares of employment in both sectors. The calibration generates $K_{g,1} = 0.836$, $K_{g,2} = 0.568$, and $K_{s,2} = 0.836$.

For the parameter of the offshoring costs function, we simply assign $\tau = 1$, but the

[34] We previously employed a similar strategy in specifying $L_{fs,0}(k)$, assuming that $L_{fs,0}(k)$ followed a continuous PDF. Here, the difference is that we generate hypothetical distributions based on the actual, discrete distributions of hours worked in the base year.

[35] Even though Autor and Dorn (2013) provide a comparable occupational classification across years, there were many occupations with no individuals prior to 1983. This is because these occupation codes were unavailable in the surveys during that period. After the reform of the classification in 1983, this issue becomes less problematic. The number of occupations that have non-trivial hours worked has been around 262 to 264 out of 330 from 1971 to 1982. It has increased to 329 in 1983 and continuously remained above 320 by 2016.

results do not change much when we consider other values. Given $K_{g,t}$, $K_{s,t}$, x_t, and the other parameters, we can compute the values for $\theta_{g,t}$ and $\theta_{s,t}$ from the connection between the hiring costs of domestic and offshored labor $w_j^D(K_j) = \theta_j \tau(K_j)$. The resulting values are $\theta_{g,0} = 1.621$, $\theta_{s,0} = 1.595$, $\theta_{g,1} = 1.437$, $\theta_{s,1} = 1.578$, $\theta_{g,2} = 0.936$, and $\theta_{s,2} = 1.424$.

Lastly, we estimate the distributional parameters of $L_{fs,0}(k)$ along with $R_{sg,0}$. We only need to specify the benchmark distribution of $L_{fs,0}(k)$ because $L_{ms,0}(k)$, $L_{fg,0}(k)$, and $L_{mg,0}(k)$ can be expressed with respect to $L_{fs,0}(k)$ and the other parameters using (A.3) and (A.6). Two parameters of the Beta distribution are estimated to match the total hours worked of women and men in 1970. In this way, these parameters would also fit the female to male hours ratio in 1970. The figures we get are $\psi = 1.418$ and $\omega = 0.951$. With these parameters, we can obtain $R_{sg,0} = 0.933$ by matching the women's total hours worked in the goods sector in 1970, while using the relationship between $L_{fg,0}(k)$ and $L_{fs,0}(k)$ in (A.6). $R_{sg,1} = 0.680$ and $R_{sg,2} = 0.541$ are determined by $R_{sg,0}$, $\gamma_g - \gamma_s$, and ρ, in accordance with the definition $R_{sg}(A_g, A_s) \equiv (\omega/(1-\omega))^\rho (A_g/A_s)^{\rho-1}$.

Table 1.4 summarizes the calibrated parameters.

1.5.2 Results

Using the calibrated parameters, we first predict the gender hours ratio for 1990. Then we consider three different counterfactuals along with the baseline in producing the estimates for 2016. These counterfactuals reflect three forces that are potentially responsible for the slowdown in the gender hours ratio since 1990: the emergence of service offshoring, the weakening of structural transformation towards the service sector, and the lower pace of diminishing gender discrimination. The baseline contains all these elements and we change one corresponding mechanism for each counterfactual. Using the forecasts of the baseline and counterfactuals in 2016, we compute changes in the gender hours ratio from the prediction for 1990. We measure the contribution of each counterfactual by how much of the change in the gender hours ratio is reduced in the baseline compared to the change for each counterfactual.

The first counterfactual considers the possibility that the trend for service offshoring between 1970 and 1990 has been the same since 1990. Since we adopt a simplifying assumption that there was no service offshoring in 1970 and 1990, this scenario hypothesizes that service offshoring did not appear until 2016. We impose $K_{s,1} = K_{s,2} = 1$ to enforce this counterfactual because we treat the cutoff for offshoring as a proxy that represents the degree of offshoring. This counterfactual is designed to test Proposition 3 that the gender hours ratio falls when the service offshoring rises due to a drop in offshoring costs in the service sector.

The second scenario assumes that the intensity of structural transformation into ser-

Table 1.4: Summary of calibrated parameters

Parameters	Values	Sources/Targets
Firm's side		
η	0.854	Goos, Manning, and Salomons (2014)
ε	2.4	Weinberg (2000)
$(\gamma_g - \gamma_s)_{0-1}$	1.6%	BLS data and relation between labor productivity and A_j
$(\gamma_g - \gamma_s)_{1-2}$	0.9%	BLS data and relation between labor productivity and A_j
$\alpha_{k,0}$	0.233	Relation between gender hours ratio and offshorability
$\alpha_{k,1}$	0.284	Relation between gender hours ratio and offshorability
$\alpha_{k,2}$	0.239	Relation between gender hours ratio and offshorability
$\alpha_{cg,0}$, $\alpha_{cs,0}$	0.118, 0.221	Men's total hours of work in goods and service, given $\alpha_{k,0}$
$\alpha_{cg,1}$, $\alpha_{cs,1}$	0.145, 0.281	Men's total hours of work in goods and service, given $\alpha_{k,1}$
$\alpha_{cg,2}$, $\alpha_{cs,2}$	0.174, 0.331	Men's total hours of work in goods and service, given $\alpha_{k,2}$
Household's side		
ρ	0.002	Herrendorf, Rogerson, and Valentinyi (2013)
$T_{m,0}$, $T_{m,1}$, $T_{m,2}$	0.870	Valerie Ramey's data on home production in 1970
ε_l	0.210	Relation between gender leisure and wage ratios from 1970 to 2016
α_l	0.329	Relation between gender leisure and wage ratios in 1970
δ	1.404	Expression for female leisure in 1970
Offshoring related and distributional parameters		
$K_{g,0}$, $K_{s,0}$	1, 1	Simplifying assumption
$K_{g,1}$, $K_{s,1}$	0.836, 1	Women's average offshoring potential & trend for service offshoring
$K_{g,2}$, $K_{s,2}$	0.568, 0.836	Women's average offshoring potential
		& rate of estimated female employment loss in goods to service
τ	1	Arbitrary
$\theta_{g,0}$, $\theta_{s,0}$	1.621, 1.595	Hiring costs of domestic and offshored labor
$\theta_{g,1}$, $\theta_{s,1}$	1.437, 1.578	Hiring costs of domestic and offshored labor
$\theta_{g,2}$, $\theta_{s,2}$	0.936, 1.424	Hiring costs of domestic and offshored labor
ψ, ω	1.418, 0.951	Total hours worked for women and men in 1970, along with $R_{sg,0}$
$R_{sg,0}$	0.933	Women's total hours of work in goods in 1970, along with ψ and ω
$R_{sg,1}$	0.680	Using $R_{sg,0}$, ρ, and $(\gamma_g - \gamma_s)_{0-1}$
$R_{sg,2}$	0.541	Using $R_{sg,1}$, ρ, and $(\gamma_g - \gamma_s)_{1-2}$

Note: $(\gamma_g - \gamma_s)_{0-1}$ and $(\gamma_g - \gamma_s)_{1-2}$ represent the difference in annual growth rates from 1970 to 1990 and from 1990 to 2016, respectively.

vice has remained identical after 1990. Proposition 2 of our model predicts that the faster productivity growth in the goods sector induces a rise in the female to male hours ratio, and it also implies that the ratio declines when the gap in productivity growth between sectors closes.[36] The counterfactual attempts to evaluate the contribution of this mecha-

[36]From the proof of Proposition 2 in Appendix A.2, we know that $\partial FM/\partial R_{sg} < 0$. As R_{sg} rises when $\gamma_g - \gamma_s$ falls from 1.6% to 0.9%, we can expect FM to go down.

nism, and is realized by equating the difference in annual productivity growth between the goods and service sectors from 1990 with the difference from 1970 to 1990. Since $\gamma_g - \gamma_s$ has fallen from 1.6% between 1970 and 1990 to 0.9% between 1990 and 2016, we postulate $(\gamma_g - \gamma_s)_{0-1} = (\gamma_g - \gamma_s)_{1-2} = 1.6\%$.

The third counterfactual posits that the pace of decrease in gender discrimination since 1990 has been the same as the previous period. It is motivated by the fact that the hypothesis based on the changes in gender norms or discrimination is one of the most natural candidates in explaining the stagnation of women's labor market performance. Among the various ways to quantify the degree of gender discrimination, we focus on the women's weight in the domestic labor aggregate $\alpha_{j,t}(k)$ and the gender wage ratio.[37] These are the elements that directly affect the gender hours ratio in each occupation level in the model, as (A.3) shows. The gender wage ratio is also a widely used proxy that represents the degree of gender discrimination. In implementing the counterfactual, we assume that the gender wage ratio has evolved at the same pace since 1990 and derive $\alpha^H_{k,2}$ and $\alpha^H_{cj,2}$ under this hypothetical gender wage ratio.[38] The estimated values are $\alpha^H_{k,2} = 0.249$, $\alpha^H_{cs,2} = 0.354$ and $\alpha^H_{cg,2} = 0.191$, which are higher than the baseline parameter values of 0.239, 0.331, and 0.174. Therefore, women's comparative advantage becomes more responsive to the offshorability of each occupation and is increased for all occupations and sectors in this counterfactual.

Table 1.5 presents the quantitative results. From 1970 to 1990, the baseline forecasts a rise of the gender hours ratio by 63.8%, which almost replicates the increase of 68.2% in the data. After 1990, the change reduces to 10.0%, similar to 15.5% in the data. Overall, the baseline model is successful in replicating a flattening out of the gender hours ratio since 1990.

Under the assumption that service offshoring did not exist in 2016 as in 1990, the gender hours ratio is predicted to go up by 33.9% between 1990 and 2016. Contrasting the change with the baseline, we can see that the emergence of service offshoring has reduced the change in the gender hours ratio by 23.8%p. In this counterfactual, women work more and men work less than the baseline, implying that the emergence of service offshoring in the baseline has indeed negatively affected female hours worked. The result confirms our main hypothesis that the rise of service offshoring is behind the flattening out of the gender hours ratio since the 1990s.

[37] The choice of these two elements is supported by the existing literature. Ngai and Petrongolo (2017) introduce a wedge in women's comparative advantage parameter to reflect the factors that reduce women's perceived productivity compared to men. Rendall (2018) and Buera, Kaboski, and Zhao (2019) see the gender discrimination as a wedge between female and male wages in their counterfactual analysis.

[38] The hypothetical gender wage ratio in 2016 is $x^H_2 = 0.865$. We are using this hypothetical ratio just to obtain hypothetical parameters in women's weight, still fixing the gender wage ratio to the level of 2016.

Table 1.5: Quantitative results

	FM	M_m	M_f	x
Data				
1970	0.384	0.416	0.160	0.631
1990	0.646	0.381	0.246	0.733
(Changes from 1970 data, %)	(68.2)	(-8.6)	(53.8)	(16.1)
2016	0.746	0.349	0.260	0.776
(Changes from 1990 data, %)	(15.5)	(-8.3)	(5.9)	(5.9)
Model predictions in 1990 and 2016				
1990	0.629	0.391	0.246	0.733
(Changes from 1970 data, %)	(63.8)	(-6.0)	(53.9)	(16.1)
2016				
- Baseline	0.692	0.384	0.266	0.776
(Changes from 1990 predictions, %)	(10.0)	(-1.8)	(8.1)	(5.9)
- Counterfactual 1: Increase of service offshoring	0.842	0.369	0.310	0.776
(Changes from 1990 predictions, %)	(33.9)	(-5.8)	(26.1)	(5.9)
- Counterfactual 2: Structural transformation into services	0.726	0.381	0.276	0.776
(Changes from 1990 predictions, %)	(15.3)	(-2.7)	(12.2)	(5.9)
- Counterfactual 3: Decrease in gender discrimination	0.871	0.366	0.319	0.776
(Changes from 1990 predictions, %)	(38.5)	(-6.5)	(29.5)	(5.9)
Contribution of each counterfactual (%p)				
- Counterfactual 1: Increase of service offshoring	23.8	-4.0	18.1	-
- Counterfactual 2: Structural transformation into services	5.3	-0.9	4.2	-
- Counterfactual 3: Decrease in gender discrimination	28.5	-4.7	21.4	-

Notes: Counterfactual 1 assumes that service offshoring did not appear until 2016, i.e., $K_{s,1} = K_{s,2} = 1$. Counterfactual 2 postulates that the difference in annual productivity growth between goods and service sector has remained identical since 1990, i.e., $(\gamma_g - \gamma_s)_{0-1} = (\gamma_g - \gamma_s)_{1-2} = 1.6\%$. Counterfactual 3 posits that the pace of decrease in gender discrimination has been the same since 1990. This is achieved by assuming that the gender wage ratio has evolved at the same pace after 1990 and deriving $\alpha^H_{k,2}$ and $\alpha^H_{cj,2}$ under this hypothetical gender wage ratio. The contribution is computed by subtracting the change in baseline from the change in each counterfactual.

In counterfactual 2 where the same pace of structural transformation towards the service sector is assumed, the predicted rise of the gender hours ratio from 1990 to 2016 is 15.3%. This means that the slowdown of the between-sector forces after 1990 is accountable for a fall by 5.3%p in the change of the gender hours ratio between 1990 and 2016. Proposition 2 is quantitatively verified by this result, although the magnitude of the contribution is modest compared to that of the counterfactual 1.

If the trend for gender discrimination proxied by the gender wage ratio continued in the same pace after 1990, the female to male hours ratio would have risen by 38.5% from 1990. This figure suggests that the plateau in the pace of diminishing gender discrimination works towards decreasing the change in the gender hours ratio by 28.5%p. The higher speed of decrease in gender discrimination in this counterfactual raises the slopes and intercepts of $\alpha_{j,2}(k)$ in both sectors. The overall increase in the comparative advantage of female labor raises women's perceived labor productivity, causing a boost in the demand for female labor. The gender hours ratio goes up as a result of the increased demand.

Among the three potential forces that drove the gender hours ratio to level off, the decrease in gender discrimination exhibits the highest contribution. Service offshoring follows right after the gender discrimination channel and the structural transformation towards the service sector shows the smallest contribution. The increase in service offshoring lowers the change in the gender hours ratio by 23.8%p, which is 84% of the contribution brought by the gender discrimination channel. Although its performance in generating a lower change in the gender hours ratio is a bit weaker, the magnitude of its contribution is still significant. In sum, the rise in service offshoring is quantitatively important in accounting for the flattening out of the gender hours ratio since 1990.

Table 1.6: Comparison of service and material offshoring

	FM	M_m	M_f	x
Model predictions in 2016				
- Baseline	0.692	0.384	0.266	0.776
(Changes from 1990 predictions, %)	(10.0)	(-1.8)	(8.1)	(5.9)
- Service offshoring remained at the level of 1990	0.842	0.369	0.310	0.776
(Changes from 1990 predictions, %)	(33.9)	(-5.8)	(26.1)	(5.9)
- Material offshoring remained at the level of 1990	0.643	0.390	0.250	0.776
(Changes from 1990 predictions, %)	(2.1)	(-0.4)	(1.8)	(5.9)
Contribution of each counterfactual (%p)				
- Service offshoring remained at the level of 1990	23.8	-4.0	18.1	-
- Material offshoring remained at the level of 1990	-7.9	1.4	-6.3	-

Notes: The scenario that service offshoring remained at the level of 1990 assumes $K_{s,1} = K_{s,2} = 1$ and corresponds to the counterfactual 1 (no service offshoring) in Table 1.5. The scenario that material offshoring remained at the level of 1990 assumes $K_{g,1} = K_{g,2} = 0.836$. The changes from 1990 predictions are calculated using the 1990 predictions in Table 1.5. The contribution is computed by subtracting the change in baseline in Table 1.5 from the change in each scenario.

It would be also interesting to compare the contribution of service and material offshoring on the evolution of the gender hours ratios. For this comparison, we consider two scenarios whereby service and material offshoring remained the level of 1990 by imposing either $K_{s,1} = K_{s,2} = 1$ or $K_{g,1} = K_{g,2} = 0.836$. We note that the first case is equivalent to the counterfactual 1 of no service offshoring in Table 1.5.

Our model predicts that the gender hours ratio falls as the costs of service offshoring decline. We verified that this mechanism quantitatively matters in explaining the leveling off of the gender hours ratio in Table 1.5. However, the effect of a change in the material offshoring costs on the hours ratio is theoretically not clear in the model. The results in Table 1.6 reveal that the change of the gender hours ratio from 1990 to 2016 would be lower than the change in the baseline by 7.9%p if material offshoring remained at the level of 1990. In this counterfactual of a lower degree of material offshoring, men's hours worked are higher than in the baseline, while women's hours worked are lower. This means that the increase in material offshoring facilitated by a fall in material offshoring costs has had a negative effect on male hours while raising female hours, resulting in an increase of the gender hours ratio since 1990 quantitatively. These results are consistent with our earlier hypothesis that an increase in material offshoring can induce the rise in the gender hours ratio.

1.6 Conclusion

The main goal of this chapter is to understand the plateau of the rising gender hours ratio since the 1990s. The trends for the gender hours and wage ratios imply a slower growth of relative demand for female labor from the 1990s. We take note of the ICT-enabled emergence of service offshoring as a demand factor. Our claim is that the expansion of service offshoring has hit women worse than men, restraining a further growth of the gender hours ratio.

This chapter complements the existing literature in several ways. Our focus on hours worked and the demand side enables us to consider both the extensive and intensive margins in the labor market and reconcile the dynamics of gender hours and wage ratios together. In addition, our framework can yield the key proposition of a higher female to male hours ratio in the service sector endogenously, in contrast to the literature that explicitly assumes this. The chapter also introduces an additional layer of the labor market effects of offshoring in terms of gender, enriching the literature that has mostly concentrated on aggregate impacts. Lastly, this chapter presents an advanced way of calibrating the cutoffs for offshoring from the data.

We document that the increasing trend of service offshoring and the falling share of women's hours worked in highly offshorable sales and administrative occupations since the 1990s support our hypothesis. The regression results corroborate our findings by showing that the rise in service offshoring is likely to have slowed the gender hours ratio down. The model with two sectors, two genders, and a continuum of tasks predicts an increasing hours ratio when the labor productivity grows faster in the goods sector and a falling hours ratio when the offshoring costs in the service sector decline due to a women's comparative advantage in services. Quantitatively, the contribution of the service offshoring channel is less than the gender discrimination channel. But given that the magnitude of its contribution is large, the rise in service offshoring plays a significant role in the plateau of the gender hours ratio since 1990.

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Chapter 2

Chaebols and Firm Dynamics in Korea

2.1 Introduction

Developing countries need to rely on different growth models depending on their level of development. The Schumpeterian growth framework (Aghion and Howitt 1992; Aghion et al. 2014) implies a major distinction between the performance of "investment-based" and "innovation-based" models conditional on the distance to the global productivity frontier. Economies that are far from the productivity frontier can catch up with advanced economies through investment-based model adopting technologies developed elsewhere. This growth model requires substantial capital investments and often involves centralized coordination of investments – by the state or by large business groups. As the economy gets closer to the frontier, it needs to switch to the "innovation-based" model: growth comes from inventing new technologies rather than from importing those invented elsewhere. Innovation-based growth model requires high-skilled workforce, investment in advanced research and development as well as dynamic competitive environment: competition between decentralized firms, their entry and exit.

Switching from the investment-based model to the innovation-based one may be delayed because of the political economy of institutional change. Investment-based model creates powerful interest groups that are keen to preserve status quo and may resist adopting the innovation-based model. In this case, the investment-based model may overstay its welcome – with adverse implications for the productivity growth and economic development. In this case, the economy may end up in a "middle-income trap" (Gill and Kharas 2007).

In this chapter, we study firm-level data in Korea to develop a granular understanding of the transition from investment-based to innovation-based model after the 1997-98 crisis that substantially reduced the political influence of incumbent business groups (chaebols). Korea is a quintessential testing ground for the Schumpeterian growth theory. The conventional description of Korea's economic transformation in recent decades includes three key elements (Chang 2003). First, before the 1997-98 Asian crisis Korea relied on the chaebol model. Chaebols' member firms and banks supported each other (through access to subsidized finance, providing explicit and implicit bailout guarantees) and effectively restricted entry of independent firms (and of foreign direct investors). Chaebol-based model did manage to deliver in terms of industrialization, investment and export growth – exactly in line with the Schumpeterian growth framework.[1] Second, the Asian crisis undermined the legitimacy of chaebol model and provided a window of opportunity for reform. At this point, the blueprints for pro-competitive reforms have already been discussed in Korea but it was the crisis that provided a critical impetus for reforms due to the pressure of the IMF. Third, the restructuring of under-performing chaebols and removal of entry barriers and implicit financial support for chaebol members opened up Korean economy for competition. This helped to shift to the post-industrial model based on innovation.[2]

While the narrative above seems to fit macroeconomic trends, it has never been tested using disaggregated data. In this chapter, we use the census of Korean manufacturing firms to understand whether the 1998 reforms did indeed result in greater entry of non-chaebol firms and their productivity growth in industries that used to be dominated by chaebols.

We find – consistent with the conjecture above – that after the crisis the industries previously dominated by chaebols have seen relatively faster growth of productivity (both labor productivity and total factor productivity) of non-chaebol firms. Furthermore, entry of non-chaebol firms increased significantly in all industries after the reform.

Finally, we study the firm-level data on patenting activity. We find that before the crisis chaebol firms had slightly faster growth of patents per year relative to their non-chaebol counterparts. However, after the crisis, annual number of patents by chaebol firms stopped growing – while patenting by non-chaebol firms accelerated. The acceleration of patenting by non-chaebol firms was uniform across all industries.

This evolution in patenting activity is consistent with the dynamics of Korean firms' markups. The markups of non-chaebol firms increased after the crisis in all industries.

[1] In 1963-97, Korean GDP per capita has been growing with an average rate of 7 per cent per year, making it one of the most impressive economic growth episodes in history.

[2] For example, according to the US Patents and Trademarks Office (USPTO), in 1992, Korea filed 8 times fewer patents applications to the USPTO than Germany; in 2003, the respective ratio was only 1.8 times. Since 2012, Korea has overtaken Germany in terms of US patents applications; in 2015, it has filed 30% more patent applications to the USPTO than Germany (despite having roughly half the population of Germany and less than half of German GDP, either in nominal or PPP terms).

However, the markups of chaebol firms only increased in industries with lower pre-crisis presence of chaebols. In the industries previously dominated by chaebols, there was no significant change of chaebol firms' markups after the crisis.

The rest of the chapter is structured as follows. In Section 2 we discuss related literature. In Section 3 we provide a background discussion of pre-crisis economic institutions in Korea, the role of chaebols and describe the 1998 reforms. In Section 4 we discuss the data and the methodology. In Section 5 we present the main results. Section 6 concludes.

2.2 Literature Review

The fact that the 1997-98 crisis and the subsequent IMF-backed reform reduced the chaebols' grip on the Korean economy and thus promoted access to finance, entry, exit and productivity growth has already been documented in the literature – albeit using much smaller datasets. Borensztein and Lee (2002) have shown that before the crisis the chaebol firms had preferential access to credit. After the crisis there was no significant difference between chaebol and non-chaebol firms. This has helped to increase efficiency: while before the crisis credit was not directed to more efficient firms, after the crisis it was. Hong, Lee and Lee (2007) studied the level of investment controlling for cash flows and investment profitability and showed that before the crisis chaebol firms invested more than non-chaebol firms. This difference disappeared after the crisis. Both papers' datasets are limited to listed firms.

Borensztein and Lee (2005) have analyzed both listed and non-listed firms but used aggregated industry-level data for 32 sectors. They also showed that before the reform credit was not likely to be directed towards more efficient sectors – nor that sectors receiving more credit demonstrated higher growth.

Minetti and Yun (2015) use data from KISLINE on 242 firms (including 37 chaebol firms) and 1,608 syndicated loans to these firms. They show that before the reforms banks had weaker incentives to monitor their chaebol borrowers (relative to non-chaebol borrowers) than after the reform. They argue that the reform removed the implicit bailout guarantee to chaebols.

The only paper that uses the same Mining and Manufacturing survey that we use is Asturias et al. (2017) – who also utilize similar data for Chile and for the US. They show, both theoretically and empirically, that during the period of fast growth, net entry explains a higher share of growth (thus focusing on the change of aggregate performance change over time). We use the same dataset for Korea but our focus is on the industry-level outcomes, the role of chaebols and the change in competitive environment due to 1998 reforms.

Another relevant paper is Hemous and Olsen (2017) that shows that domination of business groups reduces market size for potential innovators resulting in fewer patents. They use data from the US and Japan where keiretsus are similar to Korean chaebols.

2.3 Chaebols and the 1998 Reforms

Chaebol is a Korean term that refers to a large business group in Korea.[3] Chaebols have played a critical role in the rapid growth of Korean economy, and some of its member firms such as Samsung Electronics and Hyundai Motors have become major global players. Chaebols emerged as Korean businessmen and government developed close ties after the World War II. Chaebol founders benefited from the sales of the assets previously held by Japanese owners and from the allocation of foreign currency due to their connections with high-ranking government officials. During the 1960s, the government carried out a series of five-year plans to accelerate economic growth. The government examined the validity of large investment projects and effectively directed the use of the limited amount of foreign loans to projects that can foster export-oriented industries. Many chaebols grew rapidly since they were selected by the government to take on these projects and therefore benefited from various forms of government support. As real wages increased in 1970s, the government modified the target of its plans to promote the heavy equipment and chemical industries. It continued providing subsidies to chaebol firms in these industries and bailed out failed companies in the aftermath of the oil price shocks. Following the end of 18-year Chung-Hee Park's regime in 1979, the government's support of chaebols became less prominent. But deregulation of financial sector – including privatization of banks and elimination of the limits on ownership of non-bank financial institutions – provided chaebols with opportunities for funding their investments through internal capital markets and cross-subsidization within the groups.

Most of the chaebols diversified their business to unrelated areas, and each of the affiliate firms acted as if it was a subsidiary of the business group, sharing technology, brand, human resources, and capital within the group. Chaebols have formed their internal capital markets and utilized the practices including loans, debt guarantees, and cross-shareholding to facilitate the expansion of their business. At their peak in mid- to late 1990s, the top 30 chaebols accounted for 16 percent of Korean GDP – with top 5 chaebols alone (Hyundai, Samsung, LG, Daewoo and SK) accounting for 10 percent of GDP (Chang, 2003, p. 11).

The mutual debt guarantees and cross-subsidization effectively limited access to finance

[3] Its definition by the Korean Standard Dictionary is 'a group of capitalists and businessmen who manage several firms and own huge wealth.' The word chaebol consists of chae ("wealth or finance") and bol ("lineage or clique, with a strong connotation of exclusivity", Haggard et al. 2003, p. 25).

for non-chaebol members.[4] Chaebols also benefited from restrictions on foreign ownership which before 1997 was limited to 26% of capital of Korean firms.[5]

The implicit bailout protection provided by the government (Minetti and Yun, 2015), mutual debt guarantees, cross-subsidization and non-transparent corporate governance have however resulted in funding of inefficient activities.[6] Within-group moral hazard has resulted in overinvestment: while chaebols' capital intensity has grown, the productivity of capital has declined in 1990s by a factor of two (Chang 2003, p.18).

Eventually, the accumulation of inefficiencies and mutual debt guarantees amplified the chain reaction of insolvencies and bankruptcies of chaebol affiliates during the 1998 crisis. The number of bankruptcies in Korean economies in 1998 was twice as high as in the previous years (Chang, 2003, p.5); a top-5 chaebol Daewoo went bankrupt in 1999 (OECD, 2000).

In late 1997, the Korean government applied for IMF funds and agreed to implement several important pro-competitive reforms and restructuring of chaebols. First, the government forced them to cut their debt-equity ratios to less than 200%, and to eradicate the mutual debt guarantees (Chang, 2003, pp. 190, 195, 213). It also required to improve corporate governance and to consolidate accounts. It has also introduced transparent regulation of financial institutions.

The reform also liberalized entry for foreign investors (lifting the foreign ceiling ownership to 50% by the end of 1997 and to 55% by the end of 1998).

The government also radically strengthened antitrust enforcement, both chaebol regulation and traditional competition policy (Haggard et al. 2003, p. 320). The number of corrective orders issued and amounts of surcharges imposed increased threefold and 25-fold, respectively, in 1998-2000 relative to pre-crisis levels (Shin 2003, p. 277).

All these measures drastically lowered barriers to entry for non-chaebol firms (including foreign-owned) and reduced chaebol firms' preferential access to finance – thus further leveling the playing field for non-chaebol firms.[7]

[4]The Federal Trade Commission effectively started to police chaebols' anti-competitive practices involving debt guarantees and cross-subsidization only in 1998 (Chang, pp. 127, 222, 237, World Bank, 1999, p. 76). See World Bank (1999, pp. 83-84) for a discussion of the role of chaebols in limiting independent firms' access to finance before the reform.

[5]Haggard et al. (2003, p. 319) refer to the FDI regime in pre-crisis Korea as "one of the most restrictive in Asia" providing firms with substantial protection in the domestic market.

[6]Through cross-shareholding among affiliated firms, families of chaebol founders have practically dominated the entire group although they owned a small portion of shares. This has brought about several problems such as lack of accountability by chaebol chairmen, expropriation through inside trading or internal transfer pricing scheme (World Bank, 1999, ch.6).

[7]As shown in Yun (2003), the reforms resulted in dramatic increase in FDI flows – from 0.5% of GDP before the crisis to 2% of GDP already in 1998-2000.

2.4 Empirical Methodology and Data

2.4.1 Methodology

We employ differences-in-differences as our main methodology. The key regressor in our specification is the interaction term between the share of chaebol firms in industry sales and the post-crisis time dummy. The main specification is the following:

$$Y_{it} = \alpha_i + \beta_1 PostCrisis_t + \beta_2 (ChaebolShare_i \times PostCrisis_t) + u_{it}. \tag{2.1}$$

The subscripts i and t denote each industry and year, respectively. We include industry fixed effects α_i and cluster standard errors at the industry level. Y_{it} refers to the dependent variables of which dynamics we want to look at. We define the $PostCrisis_t$ variable as a dummy variable that is 0 for years before 1998, 1 after 1998, and has no value for year 1998. We tried other variations such as including 1998 to either pre or post crisis period; the results did not change. (The results are also robust to replacing the $PostCrisis_t$ dummy with individual year fixed effects).

The $ChaebolShare_i$ is the average pre-crisis chaebol share in industry sales. As the $ChaebolShare_i$ variable is absorbed by the industry fixed effects, we only use $PostCrisis_t$ dummy and the interaction term as regressors. The results were also robust to choosing the lagged chaebol share as the chaebol share variable.

We run main regressions using each dependent variable for all firms, and for chaebol and non-chaebol firms separately.

In all regressions we exclude top and bottom 1% firm-level observations in order to make sure that our results are not influenced by outliers.

2.4.2 Data

Since chaebol is a general term that is used to denote a large business group in Korean, it is crucial to start with a clear definition of chaebol. In this chapter, we consider the 30 largest private business groups of each year based on the total asset values of affiliated firms as 'chaebols.' The most important reason for picking the criterion is that this has been a main standard set by Korean government, meaning that the information on the names and the list of affiliated firms has been consistently collected by the government's Fair Trade Commission throughout our sample period. Naturally, this definition has been extensively used in the literature. Tables 2.1 and 2.2 show the list of 30 largest business groups for each year.

Table 2.1: List of 30 largest business groups (chaebol groups) from 1992 to 1997

Rank	1992	1993	1994	1995	1996	1997
1	Hyundai	Hyundai	Hyundai	Hyundai	Hyundai	Hyundai
2	Daewoo	Samsung	Daewoo	Samsung	Samsung	Samsung
3	Samsung	Daewoo	Samsung	Daewoo	LG	LG
4	LG	LG	LG	LG	Daewoo	Daewoo
5	Ssangyong	SK	SK	SK	SK	SK
6	Hanjin	Hanjin	Hanjin	Ssangyong	Ssangyong	Ssangyong
7	SK	Ssangyong	Ssangyong	Hanjin	Hanjin	Hanjin
8	Hanwha	Kia	Kia	Kia	Kia	Kia
9	Daelim	Hanwha	Hanwha	Hanwha	Hanwha	Hanwha
10	Lotte	Lotte	Lotte	Lotte	Lotte	Lotte
11	Donga	Kumho	Kumho	Kumho	Kumho	Kumho
12	Hanil	Daelim	Daelim	Doosan	Doosan	Halla
13	Kia	Doosan	Doosan	Daelim	Daelim	Donga
14	Doosan	Donga	Donga	Donga	Hanbo	Doosan
15	Pan Ocean	Hanil	Hyosung	Halla	Donga	Daelim
16	Hyosung	Hyosung	Hanil	Dongkuk Steel	Halla	Hansol
17	Dongkuk Steel	Dongkuk Steel	Halla	Hyosung	Hyosung	Hyosung
18	Sammi	Sammi	Dongkuk Steel	Hanbo	Dongkuk Steel	Dongkuk Steel
19	Hanyang	Halla	Sammi	Tongyang	Jinro	Jinro
20	Kukdong Engineering & Construction	Hanyang	Tongyang	Hanil	Kolon	Kolon
21	Kolon	Tongyang	Kolon	Kolon	Tongyang	Kohap
22	Kumho	Kolon	Jinro	Kohap	Hansol	Dongbu
23	Dongbu	Jinro	Kohap	Jinro	Dongbu	Tongyang
24	Kohap	Dongbu	Woosung Construction	Haitai	Kohap	Haitai
25	Hanbo	Kohap	Dongbu	Sammi	Haitai	Newcore
26	Haitai	Kukdong Engineering & Construction	Haitai	Dongbu	Sammi	Anam
27	Daesang	Woosung Construction	Kukdong Engineering & Construction	Woosung Construction	Hanil	Hanil
28	Samwhan Corporation	Haitai	Hanbo	Kukdong Engineering & Construction	Kukdong Engineering & Construction	Keopyung
29	Halla	Byuksan	Daesang	Byuksan	Newcore	Daesang
30	Woosung Construction	Daesang	Byuksan	Daesang	Byuksan	Shinho

Notes: Rankings are based on the total asset values of affiliated firms. The list is based on the current names of chaebols. For example, LG has been known as Lucky Goldstar before 1994, and SK was known as Sunkyung before 1997. From 2002, public enterprises were included in the designation of large business groups by Fair Trade Commission. This list excludes public enterprises. Some chaebols were divided into several groups sharing the common name primarily due to the inheritance to the founder's offspring. For example, Hyundai Motors, Hyundai Oilbank, Hyundai Development Company, and Hyundai Department Store were separated from Hyundai after the death of its founder, Ju-Young Chung in 2001.
Source: Korea Federal Trade Commission

According to this definition, the same firm could be a chaebol member in a year and a non-chaebol firm in a different year depending on the chaebol status of the business group that it belonged to. In other words, the chaebol status is not a firm-specific characteristic,

Table 2.2: List of 30 largest business groups (chaebol groups) from 1998 to 2003

Rank	1998	1999	2000	2001	2002	2003
1	Hyundai	Hyundai	Hyundai	Samsung	Samsung	Samsung
2	Samsung	Daewoo	Samsung	Hyundai	LG	LG
3	Daewoo	Samsung	LG	LG	SK	SK
4	LG	LG	SK	SK	Hyundai Motors	Hyundai Motors
5	SK	SK	Hanjin	Hyundai Motors	Hanjin	KT
6	Hanjin	Hanjin	Lotte	Hanjin	POSCO	Hanjin
7	Ssangyong	Ssangyong	Daewoo	POSCO	Lotte	Lotte
8	Hanwha	Hanwha	Kumho	Lotte	Hyundai	POSCO
9	Kumho	Kumho	Hanwha	Kumho	Kumho	Hanwha
10	Donga	Lotte	Ssangyong	Hanwha	Hyundai Heavy Industries	Hyundai Heavy Industries
11	Lotte	Donga	Hansol	Doosan	Hanwha	Hyundai
12	Halla	Hansol	Doosan	Ssangyong	Doosan	Kumho
13	Daelim	Doosan	Hyundai Oilbank	Hyundai Oilbank	Dongbu	Doosan
14	Doosan	Daelim	Donga	Hansol	Hyundai Oilbank	Dongbu
15	Hansol	Dongkuk Steel	Dongkuk Steel	Dongbu	Hyosung	Hyosung
16	Hyosung	Dongbu	Hyosung	Daelim	Daelim	Shinsegae
17	Kohap	Halla	Daelim	Tongyang	Kolon	Daelim
18	Kolon	Kohap	S-Oil	Hyosung	CJ	CJ
19	Dongkuk Steel	Hyosung	Dongbu	CJ	Dongkuk Steel	Tongyang
20	Dongbu	Kolon	Kolon	Kolon	Hanaro Telecom	Kolon
21	Anam	Tongyang	Tongyang	Dongkuk Steel	Hansol	KT&G
22	Jinro	Jinro	Kohap	Hyundai Development Company	Shinsegae	Hanaro Telecom
23	Tongyang	Anam	CJ	Hanaro Telecom	Tongyang	Dongkuk Steel
24	Haitai	Haitai	Daewoo Electronics	Shinsegae	Hyundai Department Store	Hyundai Department Store
25	Shinho	Saehan	Hyundai Development Company	Youngpoong	Hyundai Development Company	Hansol
26	Daesang	Kangwon Industries	Anam	Hyundai Department Store	Youngpoong	Daewoo Shipbuilding & Marine Engineering
27	Newcore	Daesang	Saehan	Oriental Chemical Industries	Daesang	Daewoo Motors
28	Keopyung	CJ	Jinro	Daewoo Electronics	Dongwon	Hyundai Development Company
29	Kangwon Industries	Shinho	Shinsegae	Taekwang Industry	Taekwang Industry	Youngpoong
30	Saehan	Samyang	Youngpoong	Kohap	KCC	KCC

Notes: Rankings are based on the total asset values of affiliated firms. The list is based on the current names of chaebols. For example, LG has been known as Lucky Goldstar before 1994, and SK was known as Sunkyung before 1997. From 2002, public enterprises were included in the designation of large business groups by Fair Trade Commission. This list excludes public enterprises. Some chaebols were divided into several groups sharing the common name primarily due to the inheritance to the founder's offspring. For example, Hyundai Motors, Hyundai Oilbank, Hyundai Development Company, and Hyundai Department Store were separated from Hyundai after the death of its founder, Ju-Young Chung in 2001.
Source: Korea Federal Trade Commission

but it differs by each year and firm level. The chaebol status of a firm/plant can change over time in three cases. The first case is a firm that was a member of a continuing business group, which appeared in the list of top 30 only for some years due to fluctuations in the total asset value of the group. This case has been mainly prevalent among groups below the rank of 20 on the list. The second case is a firm that was separated from a chaebol group and joined a smaller business group or remained as an independent firm that were not top 30. The third case, which was more relevant for larger business groups after the crisis, is a business group whose key members went bankrupt in the aftermath of the crisis. For example, the affiliates of Daewoo and Kia lost its chaebol status after these groups collapsed. Interestingly, some of the previous members of these business groups which survived through the dissolution formed an independent business group or were acquired by other large business groups, becoming chaebol affiliates again later. For instance, Daewoo Electronics regained its chaebol status in 2001 and 2002 after becoming independent from Daewoo group in 1999 and Hyundai group purchased Kia Motors in 1999 that previously went bankrupt in 1997, making Kia Motors a chaebol member from 1999.

The press releases of the Fair Trade Commission (FTC), announced in every April, contains detailed information from which we can identify each firm's chaebol status in each year accurately. FTC is a ministry within Korean government that regulates chaebols based on the "Monopoly Regulation and Fair Trade Act." It has annually published the list of top 30 chaebol groups based on the total asset values of the member firms, which were under differential regulations of the government, from 1991.[8] The press releases contain either the whole list of firms that are members of top 30 chaebol groups or changes in affiliated firms within each top 30 chaebol group compared to the previous year. By following the lists of chaebol firms based on the information provided by FTC, we can correctly determine whether a firm was a chaebol member or not in each year.

There could be some concerns that the changes in a firm's chaebol membership could affect the variables, especially the regressor *Chaebol share* variable, used in regressions. But we consider the impact of these changes on *Chaebol share* variable as minor. This is because most of the changes in chaebol status before the crisis were either the first or second case, which primarily happened among lower ranking business groups. The dominance of top 5 chaebols among the top 30 was prominent as discussed earlier, which implies that changes in chaebol status of affiliates of smaller chaebols had limited effects.

Our main source of plant-level data is annual Mining and Manufacturing Survey imple-

[8]There have been several changes in the criteria for designating chaebols that are subject to regulations, but the criteria remained mostly consistent throughout our sample period (1992-2003) except for the inclusion of public enterprises from 2002. Taking these changes into account, we focus on 30 largest private business groups (excluding public enterprises in 2002 and 2003) based on the total asset value of affiliated firms.

mented by Statistics Korea.[9] The survey covers all plants located in Korea with at least 5 employees, running a business in mining and manufacturing industry according to the KSIC (Korean Standard Industrial Classification).[10] As 99.9% of the plants in this population have complied with the survey in 1992-2003, we can assume that the observations in the survey are effectively the universe of Korean mining and manufacturing plants. Each observation in the micro data is a plant, which is distinct from a firm in the sense that a firm can have multiple plants. We will keep this distinction until we explain our data collection method and follow the convention of calling the entities in the data 'firms' in later sections. The survey provides a wide range of information on plants' business activities such as number of employees, sales, manufacturing costs, selling and management expenses, and value of tangible assets.

We fix the sample period from 1992 to 2003, as the survey data are available from 1992 and we want to consider periods of the same span before and after the 1997-1998 crisis. To take full advantage of the rich micro data, we choose to use the industry classification up to 5-digit level, which is the finest level in KSIC. The industry classifications are converted to the 8th KSIC for all years following the concordance by Statistics Korea.[11] We focus on manufacturing plants and ignore mining plants.

In the micro data each plant is identified with its unique plant ID, but the plants are anonymous. This is a major challenge as we need to be able to distinguish plants that are owned by chaebol-affiliated firms in the micro data. Most of the previous research that has analyzed chaebol's behavior circumvents this obstacle by using other non-anonymous but less comprehensive data sets such as KIS VALUE.[12] We try to identify plants operated by chaebol members in our micro data by matching the basic information in the micro data with the information from various other sources. To the best of our knowledge, this has never been done; we consider the identification of chaebol plants in the anonymous micro data as one of the most novel aspects of our research.

In order to identify chaebol-affiliated manufacturing plants we use year and month of establishment, 5-digit KSIC industry codes, locations, and sales of firms. Therefore, we need

[9]The micro data were accessed using remote access service from the MDIS (Microdata Integrated Service), which is operated by Statistics Korea.

[10]The population has changed to plants with at least 10 employees from 2008 survey, but it was kept to those with at least 5 employees for our sample period.

[11]The industry classifications from 1998 to 2003 are based on the 8th KSIC code and the 6th KSIC code from 1992 to 1997 in the micro data.

[12]KIS VALUE is the Korean data set provided by NICE, which is a firm that specializes in credit ratings for Korean firms. It offers information on private firms that must be audited by external examiners. By the current Korean law, firms whose assets are above 12 billion wons (around 10 million dollars) need to submit audit reports by external examiners. Thus, the coverage of KIS VALUE is much narrower than 'Mining and Manufacturing Survey'.

to collect these data for every chaebol-affiliated manufacturing plant from external data sources.

As the first step, we construct the list of chaebol manufacturing firms in each year during the sample period. We can retrieve the names of chaebol-affiliated firms in every industry from the data by FTC.[13] From 2001 to 2003, year and month of establishment and 2-digit KSIC codes can be obtained from OPNI.[14] In order to get the 5-digit KSIC industry codes for each chaebol manufacturing firm, we use information provided by DART.[15] Based on OPNI and DART, we can acquire year and month of establishment and 5-digit KSIC code of a firm that was a chaebol member between 2001 and 2003. Moreover, we can extend this information to firm-year pairs that correspond to firms that were affiliated with chaebols from 2001 to 2003, since the date of establishment and industry code of a firm are time-invariant characteristics.[16] Locations and sales of firms can be found in annual business reports of each firm from DART.

For firms which were chaebol affiliates before 2000 but not after 2001, we can only recover the names of firms and the affiliated chaebol groups from FTC. Various sources of data have been utilized to gather the dates of establishment and the industry classifications of these firms. Our search started from DART and history section of the firm's website. If both of these sources had no relevant data, we attempted to collect the information from search engines. The most useful sources include past news articles from newspaper websites and basic firm information from online hiring websites. In this process, we could not find any information for less than 5% of all chaebol members.

Next, we set up firm-plant links for chaebol firms. The survey offers firm IDs for every plant only from 2002. Hence, spotting chaebol plants in 2002 and 2003 is straightforward if we match the plant ID and firm ID of each plant. For links before 2001, we check changes in each chaebol firm's plants using annual business reports from DART, history section of each firm's website and news articles to modify the links in 2002 and 2003.[17] Whenever

[13]The press releases since 2001 can be found from the webpage of FTC (http://www.ftc.go.kr) and the press releases before 2001 can be found in KDI (Korea Development Institute) Economic Information Center (http://eiec.kdi.re.kr).

[14]OPNI (http://groupopni.ftc.go.kr) is the Korean website that provides detailed information on chaebol affiliated firms, including the name of each firm, the date of establishment, and its 2-digit KSIC code. It is run by Korea Fair Trade Commission.

[15]DART (http://dart.fss.or.kr/) is the website operated by the Financial Supervisory Service that offers information on every listed and statutory audited firms in Korea. It shows the date of foundation, detailed industry codes of the goods and services that a firm produces.

[16]In some cases, the same firm changed its KSIC code possibly due to the change of products. But the changes can be accommodated by considering the basic information of the firm for all years during the sample period, as described in the procedure for the identification exercises.

[17]We cannot produce such links for chaebol firms that did not exist in 2002 or 2003 because their firm IDs are unknown. These are mainly firms that went out of business, were acquired or merged by other

available, we compared sales of a firm from financial statements in DART with total sales of the firm in the micro data to ensure that they are the same. Exploiting these links allows accommodating both multiple plants and industry classifications that one firm can have, because the survey treats the plants separately if either locations or industry classifications of products are different.

Along with identifying the firm-plant links, we apply the basic information to the micro data to discern chaebol-affiliated plants at the same time.[18] In practice, the most crucial variables for the identification were the year of establishment, 3-digit KSIC code, and location of the plant. The months of establishment and 5-digit KSIC codes that we obtained from other sources showed a lot of discrepancies with those in the micro data. To deal with these discrepancies and potential measurement errors more generally, we performed the identification exercise based on the basic information of the firm for all years during the sample period, not just for the year when the firm was a chaebol member. In this way, we can prevent the risk of failing to identify a chaebol member due to a measurement error in that specific year. In addition to checking the year of establishment, 3-digit KSIC code, and location of the plant, we matched the sales of a firm that the plant belonged to based on our firm-plant links to the sales of the firm from DART. We confirmed that we identified a chaebol-affiliated plant when its basic information fit these four variables. Having pinpointed the chaebol plants in the micro data, we calculate sales shares of chaebols in each industry for each year, by dividing the total sales of chaebol plants by the total sales of all plants.

The main dependent variables in our regressions are productivity (logarithms of industry-level average labor productivity and TFP), entry, exit, employment, capital stock, and growth of capital stock. They are computed for each industry and year. The average labor productivity is defined by total real value added over total number of workers. Since the value added is in nominal terms, we divide it by the GDP deflator for manufacturing. We follow the method of Asturias et al. (2017) to compute TFP of each firm. The only difference with their method is that we use value added rather than gross output. We proxy entry and exit by the market share of entering and exiting plants. They are calculated by dividing the total sales of entering and exiting plants by total sales of all plants. The capital stock of a plant is the average of capital stock at the beginning and the end of each year. The growth of capital stock is the logarithm of the ratio of the current year's value to the previous year's value.

The other important variable in our regressions is the number of patents. We use the

firms before 2001. We can identify at most one plant per firm based on the basic information although it is possible that they owned multiple plants.

[18] We cannot provide examples of our identification exercises in this part because it is forbidden to reveal any information that could potentially infringe the confidentiality of the survey respondents.

Orbis Historical data set provided by Bureau van Dijk. We classify each Korean firm as chaebol affiliates and non-chaebol firms based on our previous list of chaebol firms and count the number of patents for chaebols and non-chaebols by the publication dates. We aggregate the number of patents for all, chaebol, and non-chaebol firms by each year and industry. Since majority of the patents are owned by Korean firms that represent their industry classification by the US SIC (Standard Industrial Classification), we define industries by the ISIC Rev. 4.[19] We assume that the current owner of each patent was the one that was engaged in research for the patent at the time of publication. Effectively, what we use in our regressions is the logarithm of the number of new patents that were published each year for all, chaebol, and non-chaebol firms.

To calculate plant-level markups used in Section 2.5.3 we rely on the methodology of De Loecker and Warzynski (2012). Their method requires estimates of the production function to obtain markups, and we consider the Cobb-Douglas production function with endogenous productivity process. We use a plant's chaebol membership as a variable affecting optimal input demand. The industry-level markups are the mean of plant-level markups in each industry.

2.4.3 Summary Statistics

Table 2.3 shows the summary statistics of chaebol plants and industries with chaebol plants. Through the identification process, we could eventually pinpoint 2,058 chaebol manufacturing firm-year pairs in the micro data out of 2,620 firm-year pairs in the list that we constructed. The success rate of the identification for the entire sample period was 78.5% and yearly success rates have been constantly above 70%. Chaebol plants have taken up around 0.4% of total number of plants, but their sales shares have amounted to 33.9% in the data, reflecting the strong influence of chaebols in Korean economy. 29% of the KSIC 5-digit industries have had chaebol plants for at least one year during the sample period, and the unweighted mean of chaebol sales share in these industries was 31.2%. Comparison with the chaebol sales share in all industries (33.9%) implies that chaebol plants have primarily operated in industries with larger plants. We should also note that the share of chaebols in industry sales increased before the crisis and declined only slightly after the crisis. Therefore, our results are not driven by major changes in market structure but by the change in conduct.

The summary statistics for the key variables are provided in Table 2.4. The table shows means and standard deviations of industry level variables in industries where the values of

[19] 73.6% of the patents are owned by firms that represent their industry classification by the US SIC during our sample period. The rest are owned by firms whose main industry classification is the 9th KSIC.

Table 2.3: Summary statistics of chaebol plants and industries with chaebol plants

	1992-2003	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Chaebol firms and plants													
- Number of chaebol firms	2,620	229	238	233	232	236	279	269	239	163	178	162	162
- Number of chaebol firms identified in the micro data (% of total number of chaebol firms)	2,058 (78.5)	179 (78.2)	189 (79.4)	185 (79.4)	185 (79.7)	184 (78.0)	212 (76.0)	200 (74.3)	186 (77.8)	136 (83.4)	142 (79.8)	131 (80.9)	129 (79.6)
- Number of chaebol plants identified in the micro data (% of total number of plants in the micro data)	4,455 (0.39)	269 (0.35)	309 (0.34)	315 (0.34)	342 (0.35)	375 (0.38)	427 (0.46)	424 (0.53)	459 (0.50)	346 (0.35)	391 (0.37)	408 (0.37)	390 (0.34)
- Sales share of chaebol plants in all industries (%)	33.9	27.5	28.8	29.7	31.8	32.3	35.4	35.9	37.6	34.8	35.5	34.2	34.6
Industries with chaebol plants													
- Share of industries with chaebol plants (%)	29.0	22.9	24.8	26.5	26.7	29.4	30.7	29.6	31.4	28.2	30.9	34.2	32.6
- Mean of chaebol sales share in industries with chaebol plants (%)	31.2	32.1	32.2	33.8	34.4	31.5	32.7	31.6	30.9	29.8	29.7	28.5	28.9

Note: Industries are defined by the 8th KSIC, up to 5-digit.
Source: Authors' own calculation based on the data from OPNI, Fair Trade Commission, Mining and Manufacturing Survey, and various other data sources

Table 2.4: Summary statistics for selected variables in each industry level

	Mean						Standard deviation					
	All plants		Chaebol plants		Non-chaebol plants		All plants		Chaebol plants		Non-chaebol plants	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
log (Labor productivity)	3.849	4.220	4.626	5.206	3.801	4.154	0.515	0.569	0.710	0.781	0.480	0.501
log (TFP)	5.797	5.999	8.445	8.604	5.711	5.918	0.972	0.978	1.483	1.546	0.868	0.883
Share of entering plants	0.119	0.184	0.003	0.008	0.119	0.180	0.114	0.154	0.021	0.036	0.111	0.147
Share of exiting plants	0.099	0.191	0.001	0.007	0.105	0.185	0.105	0.160	0.012	0.033	0.105	0.155
log (Employment)	7.891	7.831	6.567	6.046	7.787	7.736	1.308	1.311	1.575	1.701	1.301	1.321
log (Capital stock)	11.566	11.911	11.393	11.496	11.396	11.727	1.505	1.533	1.859	1.932	1.418	1.464
Growth of capital stock	0.085	0.033	0.083	-0.018	0.084	0.038	0.104	0.087	0.175	0.143	0.106	0.089
log (Number of new patents)	2.001	3.631	0.793	1.159	1.624	3.308	1.827	1.995	1.738	2.262	1.506	1.765
Markups (Model 2)	2.485	2.704	4.025	4.594	2.454	2.640	1.052	1.191	2.653	3.025	1.024	1.129

Notes: Mean and standard deviation were calculated after excluding top and bottom 1% of each variable for the whole sample period, except for the log of total number of new patents. Industries are defined by the 8th KSIC, up to 5-digit, except for the log of total number of new patents where industries are defined by the ISIC Rev 4., up to 4-digit. Log of total number of new patents is calculated by log (1+Total number of new patents) to accommodate the 0's.
Source: Authors' own calculation based on the data from Mining and Manufacturing Survey and the Orbis Historical.

these variables are non-missing. Most of the variables have increased after the crisis except for the employment and the growth of capital stock.

2.5 Main Results

2.5.1 Entry, Exit, and Productivity Growth

Tables 2.5-10 present our main results. In each table we consider the results for the whole sample (column 1), then for the subsample of chaebol firms (column 2), then for the subsample of non-chaebol firms in industries with non-trivial presence of chaebols (column 3), and the subsample for the non-chaebol firms in the industries with zero chaebol presence (column 4). Industries with non-trivial presence of chaebols denote the industries that showed a positive sales share of chaebols for at least one year during the sample period (1992-2003). Industries with zero chaebol presence are the industries that had zero chaebol shares throughout the period.

Table 2.5: Firm dynamics: Labor productivity

Dependent variable: log (Average labor productivity)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	0.373*** (0.011)	0.539*** (0.067)	0.355*** (0.017)	0.347*** (0.014)
Post crisis × Average Chaebol share in the industry before the crisis	0.292*** (0.080)	0.301* (0.153)	0.300*** (0.093)	–
# of Observations	5,080	1,463	2,438	2,639
# of Industries	471	226	227	245

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

In Table 2.5 we consider the change in labor productivity. Labor productivity growth is faster in all industries after the crisis, and for both chaebol and non-chaebol firms. As can be seen from the coefficients on the interaction terms, there is a stronger acceleration of labor productivity growth after the crisis in industries with higher pre-crisis chaebol shares, compared to those not dominated by chaebols before the crisis. This holds both for chaebol and non-chaebol firms.

Table 2.6: Firm dynamics: TFP

Dependent variable: log (Total Factor Productivity)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	0.214*** (0.017)	0.366*** (0.096)	0.153*** (0.027)	0.200*** (0.021)
Post crisis × Average Chaebol share in the industry before the crisis	0.176 (0.167)	-0.162 (0.246)	0.465*** (0.171)	–
# of Observations	5,081	1,464	2,458	2,622
# of Industries	469	224	227	243

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

In Table 2.6, we consider the change in TFP. The increase in TFP after the crisis is larger for non-chaebol firms in (previously) chaebol-dominated industries: the reforms of these industries did open up additional opportunities for non-chaebol firms. This is not the case for the chaebol firms whose total factor productivity increased after the crisis, but mostly in the industries with lower pre-crisis share of chaebols.

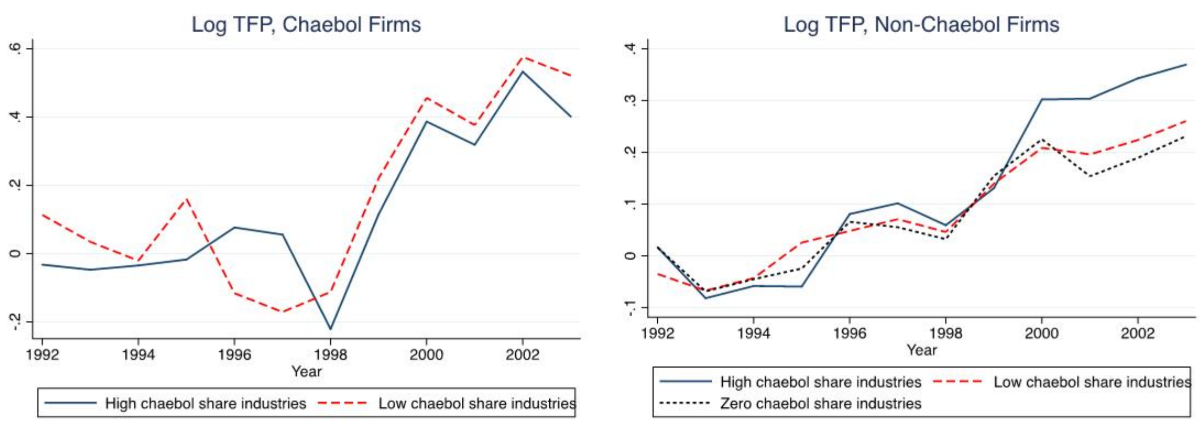
The magnitudes of the effects are important. As the average *Chaebol share* before the crisis was 0.32, the post-crisis increase in TFP of non-chaebol firms would be 15 percentage points higher in industries that originally had chaebol presence ($0.465 \times 0.32 = 0.15$).[20] This

[20]The comparison is similar if we compare the industries with a one standard deviation difference in

implies that the non-chaebol firms in industries affected by the 1998 competitive reforms had TFP growth twice as fast as those in the industries which initially had no chaebol presence (and therefore were not directly affected).

In Figure 2.1, we show that the results are not driven by pre-trends. Before the crisis, total factor productivity of non-chaebol firms in industries with zero, low or high chaebol share were growing in sync. After the crisis, the industries with high pre-crisis chaebol share experienced much faster growth in TFP than the other industries.

Figure 2.1: Logarithm of total factor productivity (TFP) in chaebol and non-chaebol firms in industries with high, low and zero chaebol share



Notes: Industries are classified by the average 1992-97 chaebol share: high (above median), low (below median), and zero. Industry-level log TFPs are normalized by 1992-97 average = 0. The median average chaebol share in 1992-97 is 0.20.

In Table 2.7 we consider entry before versus after the crisis. We see a substantial increase in entry after the crisis, mainly driven by non-chaebol firms – and weaker in chaebol-dominated industries. The magnitudes are substantial. Given that the average *Chaebol share* is around 0.32, the industries with chaebol presence have 2 percentage point less entry after the crisis (which amounts to about a quarter of all entry). In this sense, the reforms did not completely remove barriers to entry in chaebol-dominated industries. However, we do find that after the crisis the increase in entry was much higher for non-chaebol firms than for chaebol firms (whether in chaebol-dominated industries or in other industries).

In Table 2.8 we see that exit also increased after the crisis. Increase in both entry and exit after the crisis points to lower barriers to entry and exit; this was the main objective of the reforms. The change in exit was different in industries with and without domination of chaebols. The post-crisis increase in exit rates of non-chaebol firms from chaebol-dominated

Chaebol share. The within-year standard deviation of *Chaebol share* in our dataset is very stable across the years ranging from 0.24 to 0.28; the average within-year standard deviation is 0.26 both before and after the crisis. The magnitude of the effect is therefore $0.465 \times 0.26 = 0.12$.

Table 2.7: Firm dynamics: Entry

Dependent variable: Share of entering firms				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	0.071*** (0.005)	0.006*** (0.001)	0.054*** (0.006)	0.071*** (0.006)
Post crisis × Average Chaebol share in the industry before the crisis	-0.060*** (0.020)	-0.008 (0.006)	-0.023 (0.019)	–
# of Observations	4,662	2,244	2,257	2,314
# of Industries	473	227	227	245

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

industries was significantly smaller than in other industries.

In Tables 2.9 and 2.10 we compare the evolution of employment and capital stock (as well as annual capital investment proxied by the change in capital stock) between before and after the crisis. We find substantial decline of both capital and labor after the crisis in chaebol firms and substantial increase in both capital and labor in non-chaebol firms in industries previously dominated by chaebols. These results are consistent with the view that the reforms resulted in reallocation of capital and labor from chaebols to independent firms and complement our findings on TFP: the reforms resulted both in moving factors of production from chaebol to non-chaebol firms and in making the use of these factors more efficient.

2.5.2 Patents

In addition to the analysis of productivity, we also study patenting by firms. The sample is much smaller due to a different industry classification and to the fact that only 128 industries

Table 2.8: Firm dynamics: Exit

Dependent variable: Share of exiting firms				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	0.099*** (0.006)	0.006*** (0.002)	0.074*** (0.008)	0.094*** (0.007)
Post crisis × Average Chaebol share in the industry before the crisis	-0.071*** (0.022)	0.003 (0.005)	-0.061*** (0.019)	–
# of Observations	4,678	2,250	2,264	2,227
# of Industries	473	227	227	245

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

have non-trivial patenting activity (including only 97 industries with non-trivial pre-crisis chaebol presence). In these industries, patenting activity has been growing steadily both before and after the crisis (Figure 2.2). This implies the need to control for a linear time trend.

Table 2.11 presents the results controlling for the linear time trend, the post crisis dummy and the interaction of the dummy with the trend. This specification allows identifying both the jump in patenting activity after the crisis and the change in differences in time trends of patenting activity before and after the crisis. We find that for the whole sample of firms, the linear trend is positive and significant. However, we find a positive shift: after the crisis, the firms on average patent twice as much after the crisis (exp(0.77)=2.2).

As the second, third and fourth columns show, the results for the whole sample mask an important heterogeneity between chaebol and non-chaebol firms. Before the crisis, chaebol firms had a slightly faster growth of patenting activity over time than their non-chaebol counterparts (9 percent vs. 8 percent per year, respectively). However, after the crisis the situation has changed. Chaebol firms' patenting growth after the crisis slowed down to zero.

Table 2.9: Firm dynamics: Employment

Dependent variable: log (Employment)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	-0.088*** (0.024)	-0.081 (0.126)	-0.129*** (0.037)	-0.128*** (0.034)
Post crisis × Average Chaebol share in the industry before the crisis	-0.096 (0.147)	-0.692** (0.312)	0.458** (0.215)	–
# of Observations	5,078	1,477	2,449	2,626
# of Industries	471	222	226	245

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

Also, for the chaebol firms there is no upward shift after the crisis (the coefficient at the Post Crisis dummy is very small and is not significantly different from zero).

On the contrary, the results for the non-chaebol firms show both upward shift and a positive change in the slope of the time trend. The slope of the time trend increases from 8 percent per year before the crisis to 19 percent per year after the crisis; the difference is statistically significant. There is also a 2.5-fold jump in the level of patenting activity of non-chaebol firms after the crisis (the coefficient at the Post Crisis dummy ranges from 0.85 to 0.95; exp(0.9)=2.5).

In Table 2.12, we examine the heterogeneity of these results with regard to the share of chaebol firms in the industry before the crisis. We add an interaction of the Chaebol share with the linear time trend, with the post crisis dummy, and the triple interaction of the Chaebol share with the dummy and the trend. For the non-chaebol firms, the coefficients at the interactions of Chaebol share with the post crisis dummy and the triple interaction are positive (thus in line with the conjecture that the results are stronger in industries previously dominated by chaebols); they are however not significant, likely due to a small sample size.

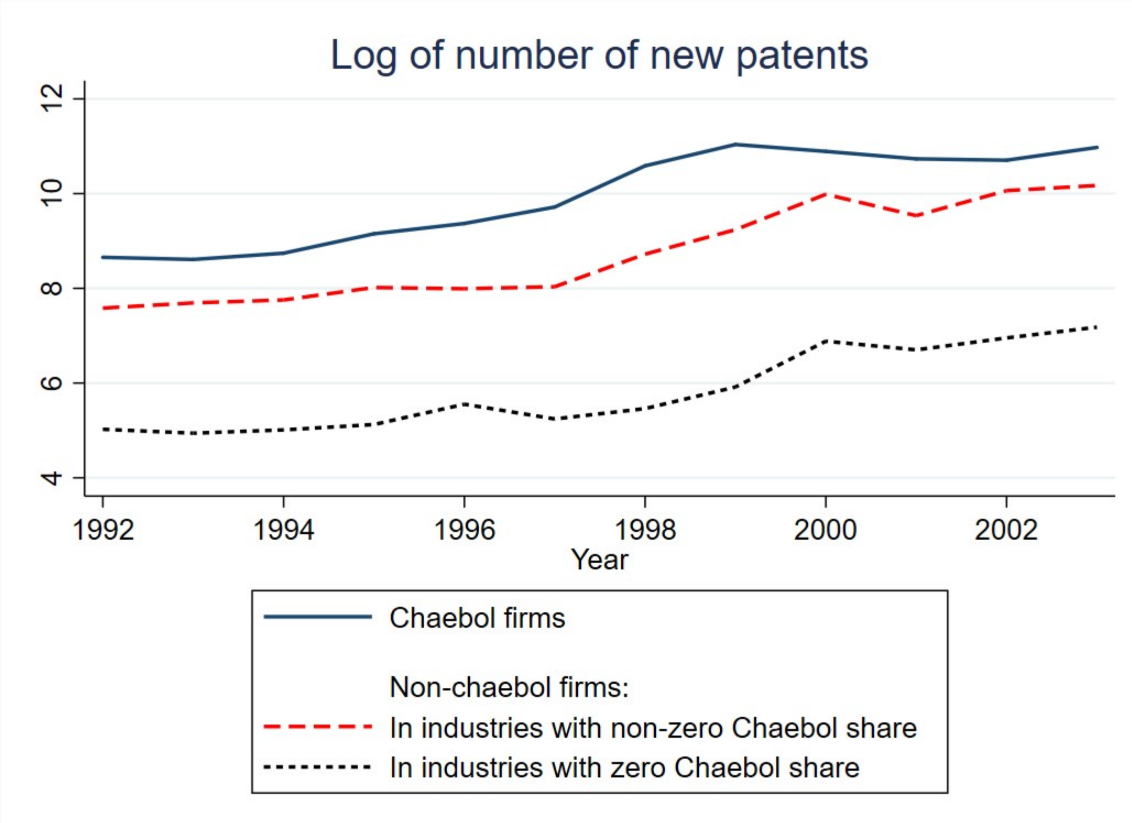
Table 2.10: Firm dynamics: Capital

Dependent variable: log (Capital stock)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms in industries with zero chaebol share
Post Crisis	0.339*** (0.028)	0.550*** (0.143)	0.333*** (0.041)	0.233*** (0.035)
Post crisis × Average Chaebol share in the industry before the crisis	0.139 (0.208)	-0.556 (0.368)	0.567** (0.220)	–
# of Observations	5,081	1,472	2,428	2,648
# of Industries	472	224	226	246
Dependent variable: Growth of capital stock				
Post Crisis	-0.043*** (0.003)	-0.088*** (0.016)	-0.061*** (0.005)	-0.033*** (0.004)
Post crisis × Average Chaebol share in the industry before the crisis	-0.015*** (0.016)	-0.072** (0.032)	-0.007 (0.020)	–
# of Observations	5,085	1,453	2,446	2,635
# of Industries	473	222	227	246

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for the second and third columns use industries that showed non-trivial Chaebol shares during the sample period (1992-2003), and the regression for the fourth column use industries that showed zero Chaebol shares during the sample period.

There are however interesting findings for the chaebol firms (and therefore for the whole sample). Before the crisis was a faster growth of patenting activity by chaebol firms in industries dominated by chaebols (the coefficient at the interaction of Chaebol share with time trend is positive and statistically significant). However, after the crisis this effect was actually fully reversed: the coefficient at the triple interaction is negative, significant and

Figure 2.2: Patenting activity in chaebol and non-chaebol firms



larger in magnitude than the coefficient before the crisis. Therefore after the crisis, chaebol firms in industries previously dominated by chaebols had slower growth in patenting activity than before the crisis.

2.5.3 Markups

We have followed De Loecker & Warzynski (2012) methodology to calculate firm-level markups. We use three models: Cobb-Douglas production function, Cobb-Douglas production function with endogenous productivity process, and translog production function with endogenous productivity process. Our preferred specification is the one using Cobb-Douglas production function with endogenous productivity process – as we assume Cobb-Douglas production function elsewhere. The results from the other two specifications are similar.

In Figure 2.3 we show the time trends for markups for chaebol and non-chaebol firms in industries with pre-crisis chaebol share above and below its median. These graphs show that all Korean manufacturing industries had very high markups (ranging from 2 to 6).[21]

[21] Markups are generally higher in industries with lower chaebol share. The cross-industry comparison of markup levels is not very informative as it is driven by the differences in the industry-specific ratios in fixed

Table 2.11: Firm dynamics: Patents

Dependent variable: log (Number of new patents)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms including industries with zero chaebol share
Post Crisis	0.772***	0.096	0.954***	0.852***
	(0.081)	(0.117)	(0.093)	(0.082)
Trend	0.114***	0.094***	0.078***	0.077***
	(0.017)	(0.022)	(0.019)	(0.016)
Trend × Post crisis	0.037	-0.087**	0.115***	0.108***
	(0.029)	(0.043)	(0.032)	(0.028)
# of Observations	1,406	1,067	1,067	1,406
# of Industries	128	97	97	128

Notes: Industries are defined by the ISIC Rev. 4, up to 4-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. Trend = Year − 1998.

Second, the chaebol firms had much higher markups (both before and after the crisis) than their non-chaebol counterparts. Finally – consistent with our story – the markups were increasing before the crisis but started to decrease after the crisis.

Table 2.13 presents the regression results, separately for chaebol and non-chaebol firms. We find that both chaebol and non-chaebol firms increased their markups after the crisis. However, the increase in markups of chaebol firms was different in industries with higher pre-crisis chaebol share and other industries. The increase in markups of chaebol firms was fully explained by industries less dominated by chaebol firms before the crisis (which were less affected by reforms). In the industries previously dominated by chaebols, the increase in markups for chaebol firms was not statistically different from zero, whereas the increase in markups of non-chaebol firms was positive and significant in all industries; there is no difference between the increase in markups between industries with high and low chaebol presence.

Why did markups increase after the crisis in the non-chaebol firms? The first potential explanation could be a survivor bias – the firms with high markups may be more likely to

vs. variable costs. In all regressions we control for industry dummies.

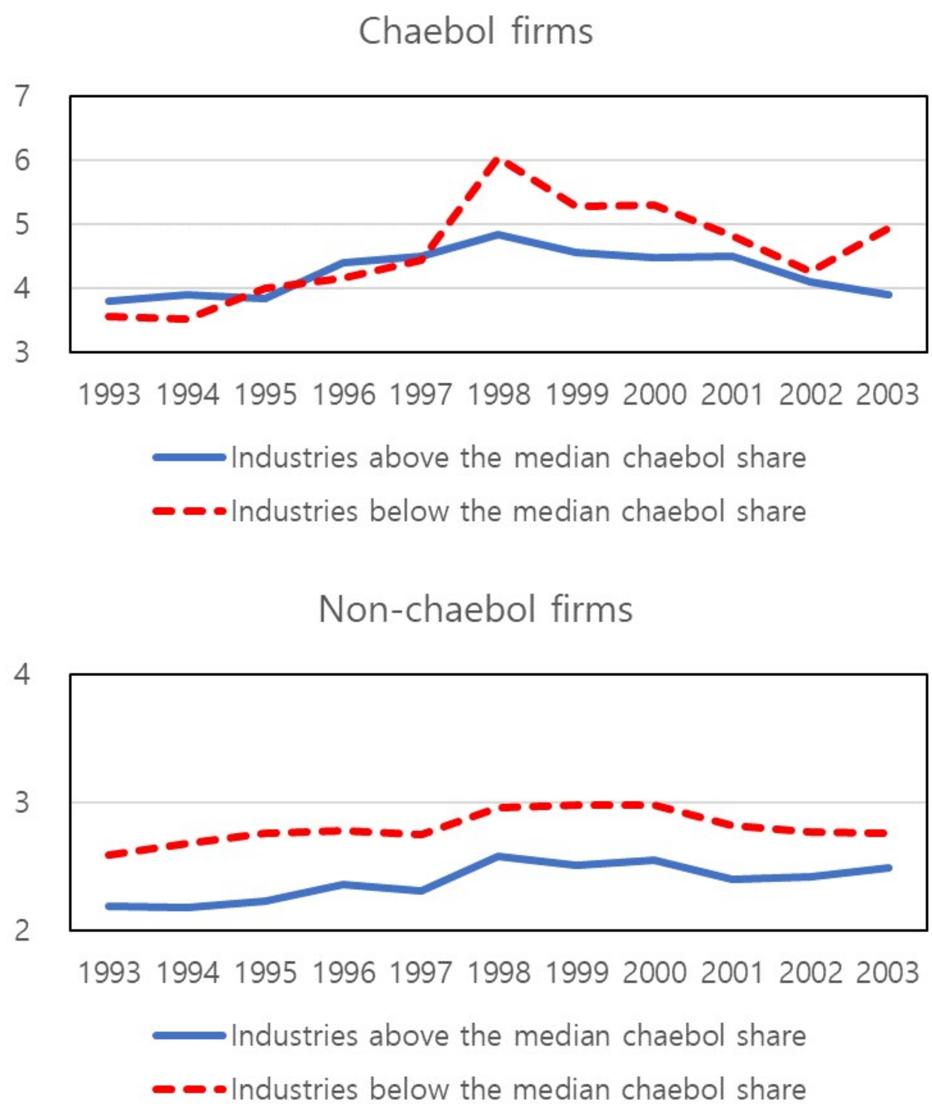
Table 2.12: Firm dynamics: Patents controlling for pre-crisis chaebol share

Dependent variable: log (Number of new patents)				
	All firms	Chaebol firms	Non-chaebol firms in industries with non-trivial chaebol share	Non-chaebol firms including industries with zero chaebol share
Post Crisis	0.775*** (0.098)	-0.032 (0.108)	0.930*** (0.125)	0.789*** (0.101)
Trend	0.082*** (0.018)	0.016 (0.017)	0.085*** (0.024)	0.081*** (0.018)
Trend × Post crisis	0.088*** (0.032)	0.039 (0.037)	0.076* (0.040)	0.079** (0.032)
Post crisis × Average Chaebol share in the industry before the crisis	-0.020 (0.442)	0.675 (0.505)	0.127 (0.538)	0.440 (0.489)
Trend × Average Chaebol share in the industry before the crisis	0.222*** (0.081)	0.410*** (0.080)	-0.033 (0.087)	-0.024 (0.079)
Trend × Post crisis × Average Chaebol share in the industry before the crisis	-0.351*** (0.131)	-0.662*** (0.140)	0.204 (0.147)	0.197 (0.138)
# of Observations	1,406	1,067	1,067	1,406
# of Industries	128	97	97	128

Notes: Industries are defined by the ISIC Rev. 4, up to 4-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. Trend = Year − 1998.

survive the crisis. In Table 2.14 we present results separately for the panel of surviving firms. If the increase in markup were fully due to the survivor bias, we should have observed zero increase of markups for surviving firms. This is not what we find in Table 2.14. While coefficients are smaller (so there is certainly survivor bias), they are still qualitatively similar to those in Table 2.13. Therefore, the crisis has indeed resulted in higher markups for surviving firms (except for chaebol firms in industries previously dominated by chaebols;

Figure 2.3: Mean markups of chaebol and non-chaebol firms by industry categories



Note: The figures are mean of each industry level average markup for chaebol and non-chaebol firms, excluding top and bottom 1% for the whole sample period in each industry categories.

these industries were more affected by the 1998 anti-chaebol reforms).

The other explanation for the evolution of markups in non-chaebol firms, is the innovation activity of these firms. As shown in the previous section, the non-chaebol firms increased patenting after the crisis in all industries – which is consistent with post-crisis increase in their markup. At the same time, patenting activity of chaebol firms was strikingly different in industries previously dominated by chaebols and other industries – also in line with the evolution of their markups.

Table 2.13: Firm dynamics: Markups

All industries				
	Chaebol	Non-Chaebol	Chaebol	Non-Chaebol
Post Crisis	0.335** (0.130)	0.201*** (0.020)	0.643*** (0.218)	0.203*** (0.025)
Post crisis × Average Chaebol share in the industry before the crisis	–	–	-0.927* (0.553)	-0.016 (0.091)
# of Observations	1,292	2,226	1,292	2,226
# of Industries	216	227	216	227
	Industries above the median Chaebol share		**Industries below the median Chaebol share**	
Post Crisis	0.278 (0.187)	0.246*** (0.043)	0.490*** (0.179)	0.207*** (0.028)
# of Observations	665	759	490	757
# of Industries	78	78	77	77

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. The regressions for all industries use industries that showed non-trivial Chaebol shares during the sample period (1992-2003). The industries above and below the median Chaebol share are based on the median of each industry's Chaebol sales share before the crisis (1992-1997). Markups are calculated assuming Cobb-Douglas production function and the endogenous productivity process.

2.6 Conclusion

In this chapter we analyzed firm dynamics in Korea before and after the 1997-98 Asian crisis and pro-competitive reforms that reduced the dominance of chaebols. We found that in industries that were dominated by chaebols before the crisis, labor productivity and TFP of non-chaebol firms increased markedly after the reforms (relative to other industries). However while labor productivity increased for both, chaebol and non-chaebol firms and to similar extent, the increase in TFP after the crisis was larger for non-chaebol firms in (previously) chaebol-dominated industries.

Furthermore, we found that entry of non-chaebol firms increased significantly in all in-

Table 2.14: Firm dynamics: Markups (Surviving firms)

	All industries			
	Chaebol	Non-Chaebol	Chaebol	Non-Chaebol
Post Crisis	0.260** (0.112)	0.180*** (0.021)	0.488*** (0.184)	0.188*** (0.025)
Post crisis × Average Chaebol share in the industry before the crisis	–	–	-0.710* (0.420)	-0.047 (0.096)
# of Observations	1,134	2,215	1,134	2,215
# of Industries	174	226	174	226
	Industries above the median Chaebol share		**Industries below the median Chaebol share**	
Post Crisis	0.242 (0.177)	0.213*** (0.044)	0.395** (0.178)	0.194*** (0.028)
# of Observations	604	748	472	756
# of Industries	71	78	74	77

Notes: The regressions were run after excluding top and bottom 1% of each dependent variable for the whole sample period. Industries are defined by the 8th KSIC, up to 5-digit. Industry fixed effects and the constant term are included in the regressions. ***, **, and * represent that coefficients are statistically significant at 1%, 5%, and 10% level, respectively. Standard errors are clustered in each industry level and given in parentheses. Surviving firms denote firms that first appeared in the sample during 1992-1997, last appeared during 1999-2003, and appeared for at least 3 years. The regressions for all industries use industries that showed non-trivial Chaebol shares during the sample period (1992-2003). The industries above and below the median Chaebol share are based on the median of each industry's Chaebol sales share before the crisis (1992-1997). Markups are calculated assuming Cobb-Douglas production function and the endogenous productivity process.

dustries after the reform. Finally, after the crisis, the non-chaebol firms also significantly increased their patenting activity. These results are in line with a neo-Schumpeterian view of a transition from investment-based growth to more innovation-based growth as the crisis weakened chaebols' power.

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Chapter 3

Why Are Hours Worked in Korea Long?

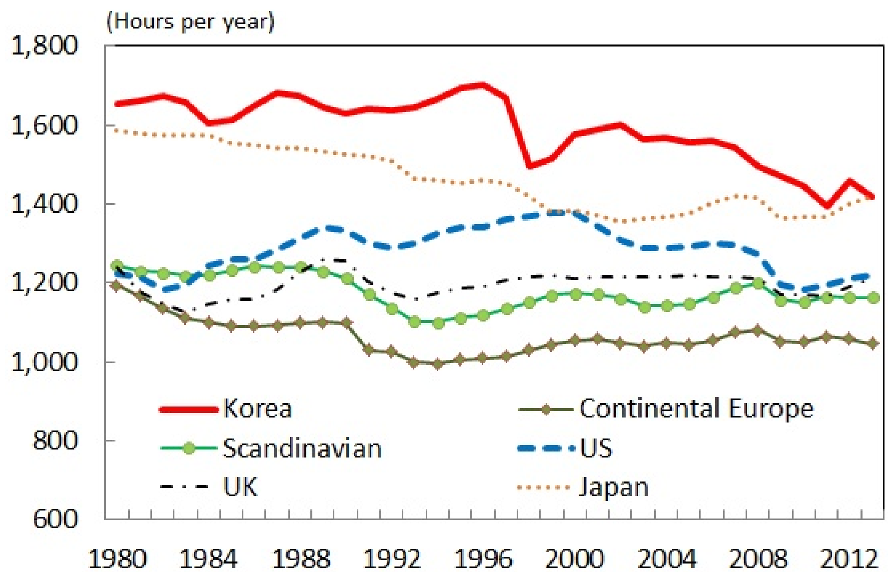
3.1 Introduction

One of the most consistent trends in the labor market since 1950 is the fall in the average hours worked per capita across the world. This is in stark contrast with the GDP per capita of the world, which has steadily grown during the same period. The negative correlation between hours worked and income level over time is widely accepted as a norm because leisure is usually considered as a normal good.

However, when it comes to the comparison across countries, differences in income level cannot fully account for the cross-country differences in hours of work. When we look at the average annual hours of work per working age population in OECD countries, the caveat of applying the norm to a cross-section of countries becomes evident. In 2012, people aged between 15 and 64 years old worked less than 1,000 hours on average in Turkey, Belgium, Spain, and France, while the average hours worked per working age population in Luxembourg, Iceland, Korea, Israel, and Japan were higher than 1,400. There are substantial gaps in hours of work within the OECD, which is a group of advanced economies in the world.

Previous literature has mainly focused on hours worked of the United States, European countries, and other advanced economies to find out potential drivers of cross-country differences in hours worked. Prescott (2004) and many other researchers have documented that the differences in the tax rate on labor income can explain a sizable portion of gaps in hours worked between the US and continental European countries. They find that people in a country with higher marginal labor tax rate tend to work less. However, this reasoning does not hold for Scandinavian countries, where both hours worked and labor tax rates are higher than the continental Europe. In order to reconcile this fact, some researchers including Rogerson (2007) and Ragan (2013) have presented a complementary explanation that the higher subsidies to home work have contributed to longer market hours of work in Scandinavian countries.

Figure 3.1: Average annual hours of work per working age population



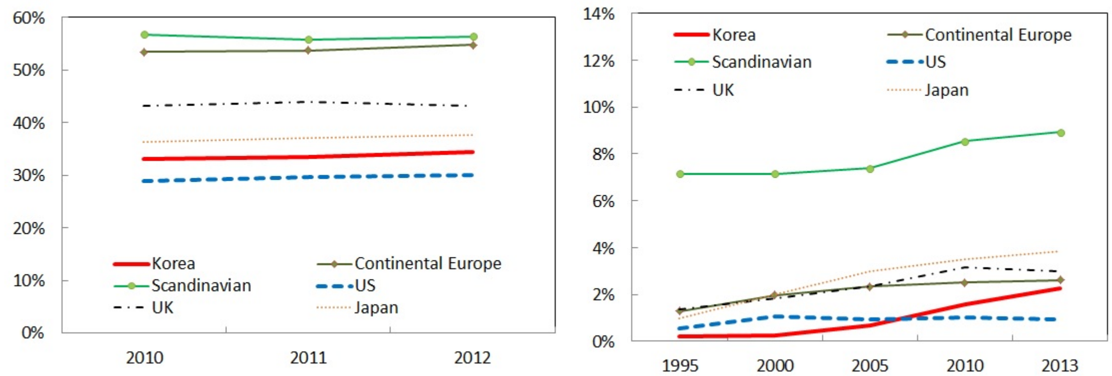
Notes: The average annual hours of work per working age population are calculated by dividing total hours of market work by working age (age 15 to 64) population. Continental Europe refers to the average of Belgium, France, Germany, Italy, and Netherlands, and Scandinavian denotes the average of Denmark, Finland, Norway, and Sweden.
Sources: The Conference Board (Total Economy Database), OECD (Labor Force Statistics)

Even though the above mechanisms can rationalize the differences in hours worked between the US and the European countries, they are not valid in the comparison of hours worked in Korea and the US. Figure 3.1 shows that the average hours worked in Korea have been consistently longer than those in the US. Although the gap in income level between Korea and the US has narrowed over time, the gap in hours worked still remains substantial.[1] However, the effective tax rate on labor income is higher in Korea than in the US, and the share of public expenditures on family care to household consumption is not higher on average in Korea, as seen from Figure 3.2. The existing literature should predict that Koreans work less than Americans based on these figures, but it is actually the opposite.

This chapter seeks to identify potential candidates that have driven Koreans to work long. The literature has been mostly silent in the determinants of hours worked in Korea. Even

[1]In 1990, the PPP adjusted GDP per capita in constant 2011 international dollars by the World Bank in Korea was 31.6% of the US. The ratio has risen to 66.0% in 2018.

Figure 3.2: Effective tax rates on labor income and shares of public expenditures on old-age and family benefits in kind to household consumption



Notes: The effective tax rate on labor income is formulated by McDaniel (2011) as $(\tau_{ss} + \phi\tau_{inc} + \tau_c)/(1 + \tau_c)$, where τ_{ss} represents average payroll tax rate, τ_{inc} average tax rate on household income, and τ_c average tax rate on consumption expenditure. ϕ is assumed to be 1.6 following Prescott (2004). Data for each tax rate is obtained from Cara McDaniel. Public expenditures on old-age and family benefits in kind include old-age benefits in kind, early childhood education care, home help and accommodation, and other benefits in kind for family services. Continental Europe refers to the average of figures for Belgium, France, Germany, Italy, and Netherlands, and Scandinavian denotes the average of figures for Denmark, Finland, Norway, and Sweden.
Sources: Cara McDaniel's website, OECD (Social Expenditure Database, National Accounts Statistics)

in a few cases where Korea is included in the data set, either the focus is narrow compared to the question addressed in this chapter or Korea is considered as an outlier of the model. For example, Alonso-Ortiz (2014) has used data for OECD countries including Korea, but his main focus was the impact of social security program on employment to population ratio of the old (50+ years old). Ngai and Pissarides (2011) has indicated that the allocation of market and home hours worked in Korea cannot be accounted for by their model. We attempt to fill this gap and complement the literature by suggesting new factors behind the long hours of work in Korea. These factors would be detected through contrasting hours worked in Korea and the US.

We first document hours worked in Korea and the US by demographic groups and decompose each demographic group's contribution to differences in hours worked between the two countries. After pinpointing the key demographic group to married male workers, we present suggestive evidence that is particularly relevant to this group. The education costs in Korea are high, mainly due to the active participation in private after-school education and the low beneficiary rate of student loans. These forces induce the prime-aged with children to work longer. Moreover, the pension benefits are lower, making Koreans effectively retire the last among the OECD countries.

Then we set up a simple two-period OLG model incorporating education costs and pension benefits and qualitatively show that higher education costs and lower pension benefits lead to longer hours worked of the prime-aged and the old. Quantitative analysis demonstrates that the model can replicate longer hours worked of the prime-aged and the old in Korea. Lower pension benefits exhibit higher contribution in raising hours worked of the old, compared to the contribution of higher education costs in accounting for the hours worked of the prime-aged.

Related Literature. Since the seminal work by Prescott (2004), the labor tax rates has been emphasized as a dominant factor in accounting for differences in hours worked across countries. Prescott (2004) has focused on G7 countries in his work, and Ohanian, Raffo, and Rogerson (2008) has corroborated his theory based on a wider set of data in cross-section and time-series.

Many studies have reached a similar conclusion, mainly with a model with market and home work. They agree that the labor tax rate is the most influential factor in the determination of hours worked, but they present other potential candidates as well. These factors include productivity (Rogerson 2008; McDaniel 2011; Durenecker and Herrendorf 2018), broader government policies (Olovsson 2009), and subsidies on family care (Ragan 2013; Duval-Hernández, Fang, and Ngai 2019). Ngai and Pissarides (2011) has also stressed the role of taxation and subsidies on the allocation of market and home hours across countries, although they have not discussed determinants of total hours of work. Chakraborty, Holter, and Stepanchuk (2015), and Bick and Fuchs-Schündeln (2017) have focused on the decision of hours worked for married couples, arguing that divorce rates and ways of treating couples in labor tax schemes are essential drivers of female labor supply, respectively. Rogerson (2006, 2007) has compared the different impacts of labor tax rate on hours worked by various types of government spending programs in a setting without the market-home substitution.

In recent years, there has been an increasing amount of literature that has emphasized the role of social security programs on labor supply in older ages using life-cycle settings. Erosa, Fuster, and Kamborouv (2012), Wallenius (2013), and Alonso-Ortiz (2014) are examples that take this approach. But their works are different from this chapter in the sense that they are more oriented towards showing the effects on older workers and an extensive margin of labor participation.

Some authors have highlighted factors other than taxes and social security programs. Alesina, Glaeser, and Sacerdote (2005) has argued that unionization and labor market regulation are primary factors causing the difference in hours worked between the US and Europe. Fang and Rogerson (2011) has claimed that product market regulations are another important source of the difference in market hours of work.

Roadmap. This chapter is organized as follows. Section 2 describes hours worked in Korea and the US and provides evidence on high education costs and low pension benefits in Korea. Section 3 presents the two period OLG model encompassing education costs and pension benefits. Section 4 provides the quantitative results based on the model. Section 5 concludes.

3.2 Data

3.2.1 Hours Worked in Korea and the US

Hours worked data by Total Economy Database of the Conference Board offers the headline figures for hours of work in each country. But the data set does not provide information by detailed demographic groups.

Therefore, we construct time series of weekly hours worked for each demographic group in Korea and the US from the micro data. For the US, we use the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG) data from the National Bureau of Economic Research. This data set is available from 1979 and contains weekly hours of work and demographic characteristics of over 300,000 individuals every year. For Korea, we use the micro data of the 'Economically Active Population Survey'.[2] The data is available from 1986 and includes data for weekly hours worked of about 700,000 to 1,000,000 observations.[3]

The key question to identify hours of work from the data is 'How many hours did you work in the last week?'[4] An individual is deemed employed if she is working or she is with a job, but not at work. For all years from 1986 to 2015, we calculate employment rates, weekly hours worked per employed and per adult for each demographic group of the two countries following the method of Bick, Fuchs-Schündeln, and Lagakos (2018).[5] We categorize subgroups by gender and age. Each age group consists of individuals from 16 to

[2] This data set is available from the Microdata Integrated Service (https://mdis.kostat.go.kr/index.do) run by Statistics Korea.

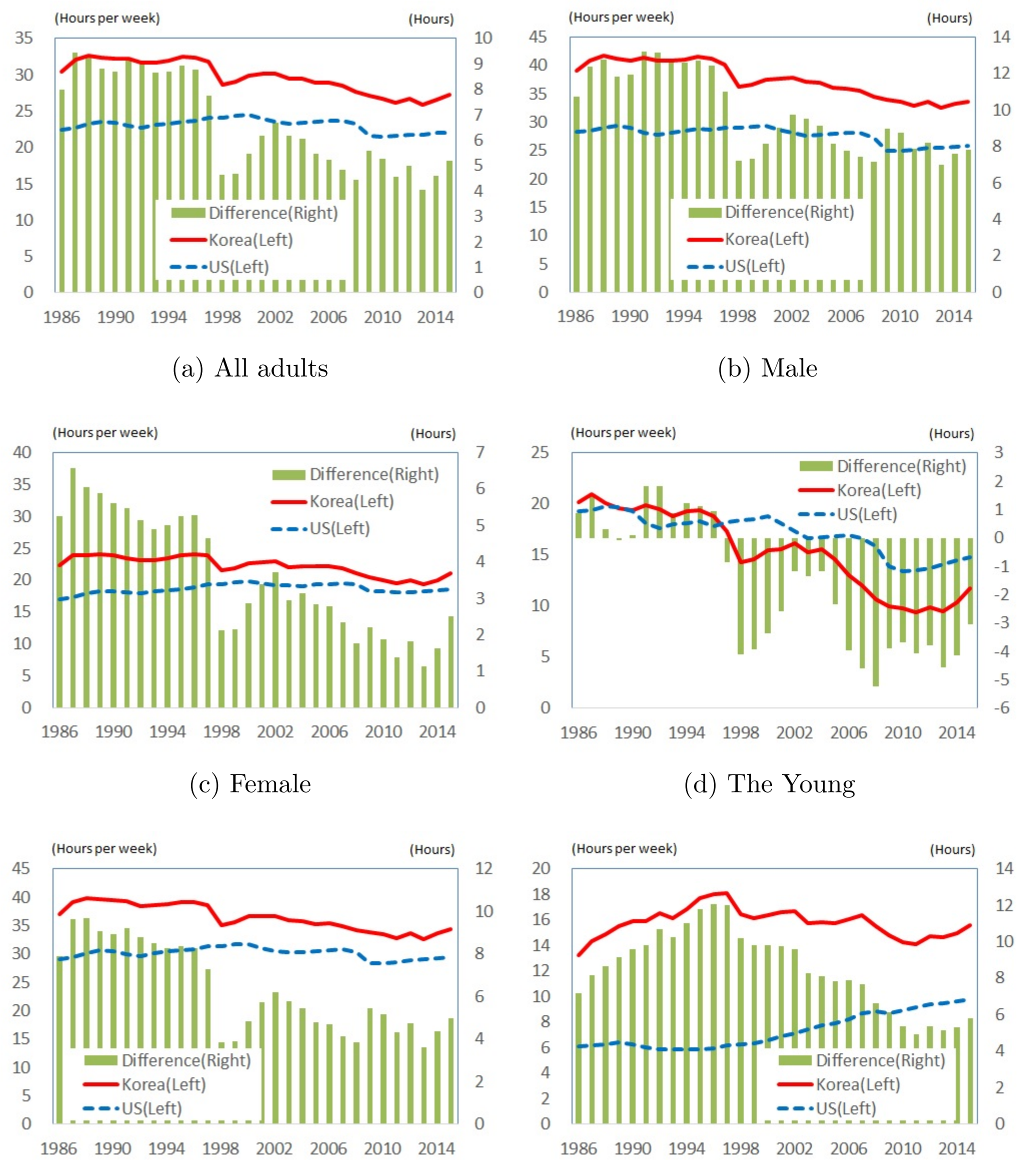
[3] The sample sizes of the two data sets are not directly comparable. Every new household to the CPS is interviewed each month for 4 months, takes a break for 8 months, then gets surveyed again for 4 months. The CPS MORG extracts only include data from outgoing rotation groups, which consist of households in their 4th and 8th interview. Thus each observation in this yearly data set strictly corresponds to each different individual. On the other hand, the Economically Active Population Survey interviews every individual from about 33,000 households, replacing around 900 households every month. Since the data set contains all of the monthly data, a substantial portion of the observations are the data from the same individual, interviewed in different months.

[4] Bick, Brüggemann, and Fuchs-Schündeln (2019) suggests adjustments for the potential bias in hours worked arising from sampling of reference weeks or under-reporting of vacation weeks. But it is not feasible here because the usual hours of work are not available in Korean data.

[5] Adult is defined as a person over 16 in this chapter. This is because the CPS MORG only contains data for individuals over 16. Also we do not place an upper limit on the age as before (64 for working age population), for the reason that is discussed in the later part of this section.

24, from 25 to 59, and over 60 for the young, the prime-aged, and the old, respectively.[6] We focus on hours worked per adult since they reflect both the intensive and extensive margins of labor supply.

Figure 3.3: Average weekly hours worked per adult of each gender and age group in Korea and the US



(a) All adults

(b) Male

(c) Female

(d) The Young

(e) The Prime-aged

(f) The Old

Note: The young denote individuals of age 16-24, the prime-aged 25-59, and the old over 60.
Sources: Economically Active Population Survey (Korea), CPS MORG (US)

Figures 3.3 show hours worked of each gender and age group in the two countries. Hours

[6] The reasons for choosing these ranges are discussed in the quantitative analysis section.

worked of male, female, and the prime-aged follow a similar pattern with those of all adults in the two countries. After the Asian crisis, there was a large dip of hours worked in Korea, which reduced the gap between the two countries. In the early 2000's, Korean hours of work picked up a bit, but the gap started to decrease again as the workweek reduction in Korea began to be phased in from 2004.[7] The Great Recession from 2008 led to a temporary surge in the gap, reducing hours of work in the US more than in Korea. For the young, working hours in the US have been longer than in Korea since 1997. Presumably, this reflects the higher age of labor market entry in Korea due to mandatory military service combined with higher enrollment in tertiary education.[8] For the older generation, the difference in hours worked has been falling steadily after the Asian crisis, but it has been stabilized recently as hours of work in both countries have risen in a similar pace.

3.2.2 Decomposition of Differences in Hours Worked by Demographic Groups

In this part, we compute contribution of each demographic group to the differences of hours worked between Korea and the US. This is to analyze which demographic groups have played important roles in generating the differences. For the years 1986, 1990, 1995, 2000, 2005, 2010, and 2015, we perform a standard shift-share analysis as follows:

$$\bar{h}_{us} - \bar{h}_k = \sum_{i=1}^{N} \omega_{i,us} h_{i,us} - \sum_{i=1}^{N} \omega_{i,k} h_{i,k} \tag{3.1}$$

$$= \sum_{i=1}^{N} (h_{i,us} - h_{i,k}) \omega_{i,us} + \sum_{i=1}^{N} (\omega_{i,us} - \omega_{i,k}) h_{i,k}, \tag{3.2}$$

where i refers to each demographic group; $\bar{h}_j$ is the hours worked per adult in country j; $\omega_{i,j}$ indicates the share of subgroup i in country j; and $h_{i,j}$ is the hours worked per adult of subgroup i in country j. The first component represents the behavioral effect. It is the fraction that can be attributed to the difference in hours worked of each subgroup as the demographic structure is assumed to be fixed to that of the US. The second component

[7] Workplaces that hired over 1,000 employees, workplaces in the finance and insurance sector, and public enterprises had to reduce their workweeks from 44 to 40 hours by July 1, 2004. From then on, the size of employment subject to the application of the revised law decreased sequentially every year, eventually enforcing every workplace that employed over 5 workers to adopt 40 hour workweek by July 1, 2011.

[8] Typically Korean firms hire male college graduates only when they have finished military service of at least 18 months. As a result, most young men who enter colleges serve for the military while they are enrolled, or right after they graduate from colleges. This convention delays the labor market entry of young men with tertiary education up to 7 years compared to high-school graduates. Table 3.4 shows that more people are getting tertiary education in Korea, reinforcing the convention of delayed labor market entrance.

is interpreted as the composition effect, namely the portion explained by the difference in demographic structures between the two countries.

Each demographic group is categorized by gender, age, education level, and marital status. Age group specifications are the same as in the previous subsection. For education levels, we divide all observations into three groups, which are less than secondary school, secondary school completed but not more, and more than secondary school. Additionally, we define the fourth group of 'still enrolled in education' for the young, because many of the younger generation do not finish their education by the age of 24.[9] Marital status is specified as either married or single. In total, 40 subgroups are defined for each country.

Table 3.1: Contribution of each demographic group to differences in weekly hours worked per adult (Korea with respect to the US, %)

Year		1986	1990	1995	2000	2005	2010	2015
Gender	Male	83.1	74.6	75.5	84.9	78.3	87.2	72.8
	Female	16.9	25.4	24.5	15.1	21.7	12.8	27.2
Age	16-24	6.4	5.5	3.9	-8.7	-6.3	-12.3	-8.0
	25-59	61.0	62.3	61.8	69.2	74.2	89.7	75.2
	60+	32.5	32.1	34.2	39.5	32.1	22.5	32.8
Education	<Secondary	62.4	52.9	45.2	54.7	43.3	37.7	29.5
	=Secondary	44.4	43.5	45.1	56.8	58.2	67.2	62.3
	>Secondary	1.9	11.3	16.8	3.5	11.7	8.2	16.1
Marital Status	Married	67.0	53.6	56.8	64.7	57.9	55.9	55.2
	Single	33.0	46.4	43.2	35.3	42.1	44.1	44.8
Composition		34.7	26.9	23.6	36.2	33.6	38.3	32.3
Total Difference (Hours)		-5.2	-6.4	-6.8	-3.5	-3.6	-3.2	-3.5

Notes: Contribution of each category except for education (gender, age, and marital status) adds up to 100%. Contribution of each group in education category does not add up to 100% because of the existence of 'still enrolled in education' category for the young.
Sources: Economically Active Population Survey (Korea), CPS MORG (US)

Table 3.1 shows that male, prime-aged, and married workers have constantly shown high contribution in explaining the gap of hours worked between Korea and the US. The

[9] Shares of the young who are still enrolled in education in two countries are over 40%, and have shown upward trends.

(%)	1986	1990	1995	2000	2005	2010	2015
Korea	44.3	49.9	49.8	56.4	57.9	68.0	65.2
US	38.3	41.5	45.5	47.9	50.4	54.7	52.8

contribution of male has been consistently over 70% for the whole sample period. This is in contrast to the general observation from other OECD countries. For example, Chakraborty, Holter, and Stepanchuk (2015) documents that the contribution to the difference with respect to the US is larger for women in Central and Southern Europe, and Duval-Hernández, Fang, and Ngai (2019) finds that low-skilled women is the key group that causes the cross-country differences in market hours of work in 17 OECD countries. The prime-aged has been the most dominant age group, with the old also taking up a significant portion. The main education group causing the difference in hours of work has shifted from less than secondary to secondary school completed. In addition, married people have exhibited higher contribution than singles, but the gap has declined recently.

Based on these findings, we pick education costs and pension benefits as potential candidates for driving the differences in hours worked between Korea and the US. Education costs matter to married, male, and prime-aged workers with children, and pension benefits are crucial sources of income for the old. In the following subsections, we provide suggestive evidence to establish the importance of these two factors.

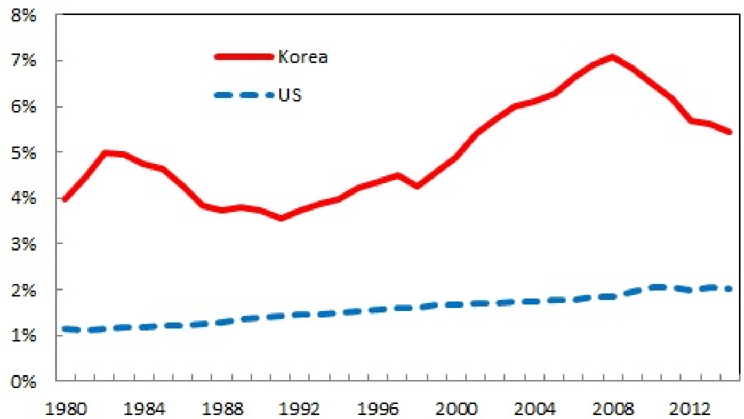
3.2.3 Education Costs

The share of education costs to household disposable income has been constantly higher in Korea than in the US, as Figure 3.4 exhibits. There are two main reasons for this. Firstly, private after-school education is more prevalent in Korea. Secondly, the share of students enrolled in tertiary education is rising, but the opportunity for getting a student loan is more scarce.

Table 3.2 shows that a majority of students in primary, middle, and high school attend private after-school education, and the expenditure for private after-school education amounted to 8% of household disposable income in Korea in 2010. There is no internationally comparable data on the share of spending for private after-school education. But the proportion of students attending after-school lessons is higher than other countries in Korea, which is confirmed by Table 3.3. These statistics are in line with the hypothesis that private education spending takes up higher portion of household income in Korea.

Households with college students also have to face high expenditure on education. Table 3.4 provides statistics on tertiary education in Korea. The ratio of tuition fees to GDP per capita in Korea is similar to the US, but less students benefit from student loans. These facts imply that higher proportion of households are likely to experience liquidity constraints due to financing of tuition fees. Moreover, more people in younger generation have completed tertiary education than the past. Therefore, household spending in tertiary education could

Figure 3.4: Shares of household education costs to household disposable income in Korea and the US



Notes: The shares are calculated by dividing household final consumption expenditure on education by gross household disposable income. Gross household disposable income is obtained by multiplying gross household disposable income per capita in US dollars, population, and purchasing power parities for GDP.
Source: OECD (National Accounts Statistics)

be another important source of long hours worked in Korea.

Higher education costs tighten budget constraints of households with children from primary to tertiary education, inducing households to work more. In this aspect, it could be a strong candidate behind long hours worked in Korea, especially for prime-aged, married men.

3.2.4 Pension Benefits

Table 3.5 suggests that the level of pension benefits in Korea is lower than in the US. Due to a difference in pension scheme, it is hard to find a measure for pension benefits that is comparable between the two countries.[10] We infer the level of pension benefits from the fractions of total and public pension spending to GDP and the mandatory contribution for an average worker. These proxies have been lower in Korea since the mid-1990s, supporting the claim that Koreans receive lower pension than Americans.

As a result, the old in Korea retire after they become 70 on average and rely a sizable portion of their income on their own work, rather than on public transfers or capital income. Although the normal and early retirement ages stipulated in the national pension scheme are relatively lower, the average effective age of labor market exit in Korea is the highest across OECD countries for both genders. It means many Koreans over the age of 64 are still

[10]Korean pension scheme is based on the fully-funded system, while US scheme is closer to the pay-as-you-go system.

Table 3.2: Private after-school education in Korea in 2010

	Total	Primary School	Middle School	High School	General	Vocational
Participation rate (%)	73.6	86.8	72.2	52.8	62.0	33.7
• All students						
Expenditure per student	240	245	255	218	265	67
(Share of income, %)	(7.9)	(8.1)	(8.4)	(7.2)	(8.7)	(2.2)
• Participating students						
Expenditure per student	325	282	352	408	433	246
(Share of income, %)	(10.7)	(9.3)	(11.6)	(13.4)	(14.3)	(8.1)
Total expenditure	20.8	9.7	6.0	5.1	4.8	0.4
(Share of GDP, %)	(1.8)	(0.8)	(0.5)	(0.4)	(0.4)	(0.0)

Notes: Expenditure per student is expressed in thousand won per month. Total expenditure is expressed in trillion won. Share of income represents the share of private education costs to average household disposable income based on 2.84 persons per household.
Source: OECD (Economic Surveys of Korea, 2012)

Table 3.3: Share of students attending after-school lessons

(%)	Mathematics			Language		
	Korea	US	OECD	Korea	US	OECD
Less than 4 hours per week	39.7	23.8	30.0	42.8	20.2	22.1
4 hours or more per week	26.3	5.9	7.9	9.8	5.1	5.3
Total	66.0	29.7	37.9	52.6	25.3	27.4
(%)	Science			Other subjects		
	Korea	US	OECD	Korea	US	OECD
Less than 4 hours per week	32.3	19.5	21.8	44.3	23.1	28.2
4 hours or more per week	6.9	5.0	4.6	20.2	9.7	8.5
Total	39.2	24.5	26.4	64.5	32.8	36.7

Source: OECD (PISA 2012 Results: What Makes Schools Successful?)

participating in the labor market. This is the reason why we do not impose an upper limit on the working age population in the earlier part.

3.2.5 Savings

The share of household savings to disposable income in Korea and the US does not differ a lot, as depicted in Figure 3.5. The average saving rates from 2005 to 2014 are 5.0% and 5.2% for Korea and the US, respectively. Considering that the prime-aged in Korea have paid more for their children's education, the longer hours worked of Koreans could be a

Table 3.4: Selected statistics on tertiary education

	Korea	US
• Tuition fees at bachelor's or equivalent (PPP,$)		
- Public (2011/12 for US,2014 for Korea)	4,773	8,202
- Private (2011/12 for US,2014 for Korea)	8,554	21,189
• Share of full-time students enrolled (%)		
- Public (2011/12 for US,2014 for Korea)	19	68
- Private (2011/12 for US,2014 for Korea)	81	32
• Weighted average of tuition fees/GDP per capita (%)	22	25
• Proportion of students with a loan in tertiary education (%)		
- BA (2013/14)		62
- MA (2013/14)	19	67
- PhD (2013/14)		32
• Proportion of labor force with tertiary education (%)		
- 25-64 years old (2005)	32	39
- 25-64 years old (2015)	45	45
- 25-34 years old (2005)	51	39
- 25-34 years old (2015)	69	47

Note: GDP per capita is obtained by dividing real GDP by population for corresponding years.
Sources: OECD (Education at a Glance 2016), Penn World Table 9.0

factor that generates similar saving rates between the two countries. The savings data also has an implication to hours worked of the old. The wealth of the old in Korea is likely to be lower than in the US since they receive lower pension benefits and have similar levels of savings. Therefore, they tend to work longer or retire later. In sum, similar saving rates in conjunction with higher education costs and lower pension benefits are consistent with longer hours worked for both age groups in Korea.

3.3 The Model

3.3.1 Setup

Households. A representative agent lives for three periods. In period $t-1$ (young), she gets education to be able to work in period t, but she is not involved in any economic activities besides education. Education does not add anything to their productivity.[11]

[11] The estimated returns to schooling by Montenegro and Patrinos (2014) were 13.2% and 13.3% in 2010 in Korea and the US, respectively, which are almost identical. Therefore, it seems innocuous to make this assumption.

Table 3.5: Selected statistics on pension scheme and old-age income

	Korea	US
• Fraction of total pension spending to GDP (%)		
- Mid-1990s	1.5	9.1
- Mid-2000s	2.0	9.3
- Circa 2014	3.4	11.2
• Fraction of public pension spending to GDP (%)		
- Mid-1990s	1.3	6.1
- Mid-2000s	1.7	5.7
- Circa 2014	2.4	6.7
• Mandatory contribution for an average worker (%)		
- Mid-1990s	6.0	12.4
- Mid-2000s	9.0	12.4
- Circa 2014	9.0	12.4
• Official normal retirement age (2014)	61	66
• Official early retirement age (2014)	55	62
• Average effective age of labor market exit		
- Male (2014)	72.9	65.9
- Female (2014)	70.6	64.7
• Sources of income of the over 65s (%)		
- Public transfers (Late 2000's)	16.3	37.6
- Work (Late 2000's)	63.0	32.2
- Capital (Late 2000's)	20.8	30.2

Notes: Official normal and early retirement ages denote corresponding ages stipulated by each public pension system. Public transfers include public pension benefits and safety-net benefits, and capital income include private pension benefits and returns on non-pension savings.
Sources: OECD (Pensions at a Glance 2013, Pensions at a Glance 2015)

In period t, the prime-aged representative agent solves the following problem:

$$\max_{c_{1,t},c_{2,t+1},h_{1,t},h_{2,t+1},s_t} u(c_{1,t}, 1-h_{1,t}) + v(G_t) + \beta[u(c_{2,t+1}, 1-h_{2,t+1}) + v(G_{t+1})], \tag{3.3}$$

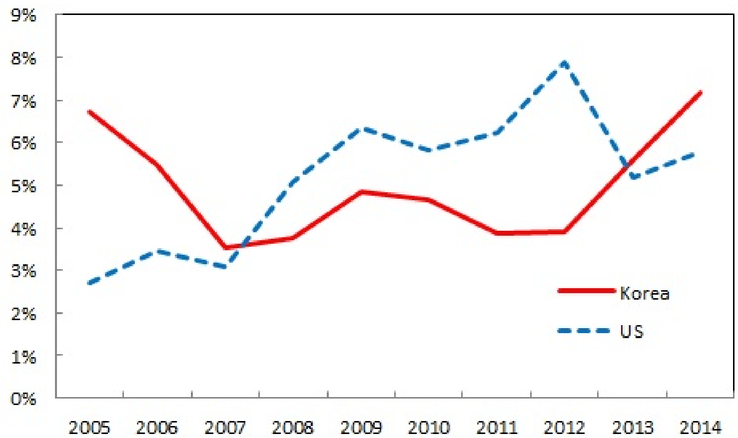
subject to

$$c_{1,t} + s_t = (1-\tau_{l,t})w_t h_{1,t} - E_t + T_t, \tag{3.4}$$

$$c_{2,t+1} = (1-\tau_{l,t+1})w_{t+1}h_{2,t+1} + (1+r_{t+1})s_t + P_{t+1} + T_{t+1}, \tag{3.5}$$

where $c_{1,t}$ is the period t consumption as the prime-aged; $c_{2,t+1}$ is the agent's consumption as the old in period $t+1$; $h_{1,t}$ and $h_{2,t+1}$ are the hours worked when prime-aged and old;

Figure 3.5: Shares of household savings to household disposable income in Korea and the US



Source: OECD (National Accounts Statistics)

G_t is the government consumption; β is the discount rate; s_t represents the savings; $\tau_{l,t}$ is the effective tax rate on labor income; w_t is the wage rate; E_t denotes the education costs; T_t is the lump-sum transfers; r_{t+1} is the return on savings; and P_{t+1} indicates the pension benefits. Both generations pay labor income taxes and receive lump-sum transfers from the government.

The utility function takes the form of log in both consumption and leisure and is the same for all periods:

$$u(c_{1,t}, 1 - h_{1,t}) + v(G_t) = \ln c_{1,t} + a \ln(1 - h_{1,t}) + v(G_t), \tag{3.6}$$

where a denotes the relative weight of leisure in the utility function and $v(\,\cdot\,)$ is an arbitrary function which is increasing in G_t.

For simplicity, it is assumed that there is no population growth, and all generations are of the same measure.[12] In addition, individuals are born with no endowments.[13] Education costs are taken as lump-sum payments by households when they are prime-aged.[14] We posit that all prime-aged workers have children and pay for their children's education costs, but

[12]The average annual population growth rates for 1980-2013 were 0.8% (Korea) and 1.0% (US), which were not very far from 0. The demographic structures in the two countries are broadly similar as well. The prime-aged consist of around 60% of the adult population, and the old take up around 20% to 25% in both countries.

[13]In Korea, the fraction of total value of inherited property subject to inheritance taxes to total compensation of employees was 1.5% for 2009-2014, which is relatively small.

[14]They will be treated as a fraction of household disposable income of the prime-aged ex-post in the calibration. See the next section for details.

this behavior does not affect their utility at all.[15] Another difference between the budget constraints of the prime-aged and the old is that the old receive pension benefits. As mentioned earlier, there is a difference in the pension schemes between Korea and the US.[16] We abstract away from the difference of pension schemes by assuming that the old receive a fraction of the government's tax revenues as pension benefits.

Firms. In each period t, the firm maximizes its profits by producing a unique good in the economy:

$$\underset{K_t,H_t}{max} Y_t - w_t H_t - r_t K_t, \tag{3.7}$$

subject to

$$Y_t = K_t^{\alpha}(A_t H_t)^{1-\alpha}, \tag{3.8}$$

where Y_t represents the output; w_t is the unit cost of labor; r_t is the unit cost of capital; A_t is the technology level; and H_t and K_t are units of labor and capital that the firm hire.

Savings by the representative household are lent to the firm as capital. Capital is assumed to be fully depreciated in each period.

Government. In each period t, the following government budget constraint is satisfied[17]:

$$\tau_{l,t} w_t (h_{1,t} + h_{2,t}) = P_t + 2T_t + G_t. \tag{3.9}$$

The government provides pension benefits to the old, pays out lump-sum transfers to the prime-aged and the old, and consumes for the household out of the revenue from labor income taxes. Government consumption affects the utility of two generations separately with private consumption.

3.3.2 The Steady State Equilibrium

In this chapter, we focus on the steady state equilibrium. A competitive steady state equilibrium consists of factor prices (w, r), hours worked (h_1, h_2), consumption (c_1, c_2), capital (K), and lump-sum transfers (T) such that:

[15] The shares of government education spending to total tax revenue for 2007-2014 were 15.8% (Korea) and 16.2% (US), which are also similar.

[16] Korean public pension system was introduced in 1988 for workplaces employing more than 10 workers, and became mandatory for all employees living in urban areas in 1999. Due to short contribution histories, the level of pension benefits for the current old are generally lower.

[17] We abstract from the government's utility maximization problem because it is hard to obtain information for the functional form of $v(G_t)$. We assume that the government is a machine that meets the budget constraint without any desire. In order to pinpoint the level of T_t, we utilize an additional information for consumption level in the quantitative analysis. See the next section for details.

1. Given factor prices, the household solves the problem (3.3) subject to (3.4)-(3.6) and the firm solves the problem (3.7) subject to (3.8);

2. The government's budget constraint (3.9) is satisfied;

3. The factor prices clear the goods, labor, and capital markets;

$$c_1 + c_2 + G = Y - E, \tag{3.10}$$

$$H = h_1 + h_2, \tag{3.11}$$

$$K = s. \tag{3.12}$$

The household's utility maximization generates the following first order conditions:

$$c_2 = \beta(1+r)c_1, \tag{3.13}$$

$$1 - h_2 = \beta(1+r)(1-h_1), \tag{3.14}$$

$$c_1 = \frac{1}{a}(1-\tau_l)w(1-h_1). \tag{3.15}$$

The life-time budget constraint for the household can be expressed as:

$$c_1 + \frac{c_2}{1+r} = (1-\tau_l)wh_1 - E + T + \frac{1}{1+r}[(1-\tau_l)wh_2 + P + T]. \tag{3.16}$$

If we plug in (3.13)-(3.15) for (3.16), we can obtain the expressions for hours worked of the prime-aged and the old:

$$h_1 = 1 - \frac{a}{(1+\beta)(1+a)}\frac{2+r}{1+r} - \frac{a}{(1+\beta)(1+a)(1-\tau_l)w}[\frac{2+r}{1+r}T + \frac{P}{1+r} - E], \tag{3.17}$$

$$h_2 = 1 - \frac{a\beta(2+r)}{(1+\beta)(1+a)} - \frac{a\beta(1+r)}{(1+\beta)(1+a)(1-\tau_l)w}[\frac{2+r}{1+r}T + \frac{P}{1+r} - E]. \tag{3.18}$$

These mean that the hours worked of both generations rise when τ_l falls, E goes up, and P declines, given fixed w and r. If we just consider the labor supply of the household, our model can incorporate the potential impacts of education costs and pension benefits on hours worked, as well as the existing mechanism that the higher labor income tax rate lowers hours of work.

We can alternatively solve for c_1 and c_2 using the household's first order conditions and the consolidated budget constraint:

$$c_1 = \frac{1}{(1+\beta)(1+a)}[\frac{2+r}{1+r}((1-\tau_l)w+T)+\frac{P}{1+r}-E], \tag{3.19}$$

$$c_2 = \frac{\beta(1+r)}{(1+\beta)(1+a)}[\frac{2+r}{1+r}((1-\tau_l)w+T)+\frac{P}{1+r}-E]. \tag{3.20}$$

Then K is determined by the household's budget constraint and the capital market clearing condition:

$$K = (1-\tau_l)w - \frac{1}{1+\beta}[\frac{2+r}{1+r}((1-\tau_l)w+T)+\frac{P}{1+r}-E]-E+T. \tag{3.21}$$

The firm's profit maximization conditions, combined with the market clearing conditions, are as follows:

$$w = (1-\alpha)K^{\alpha}A^{1-\alpha}(h_1+h_2))^{-\alpha}, \tag{3.22}$$

$$r = \alpha K^{\alpha-1}(A(h_1+h_2))^{1-\alpha}. \tag{3.23}$$

The steady state equilibrium is characterized by (3.17)-(3.23) and the government's budget constraint (3.9) without time subscripts.

3.4 Quantitative Analysis

3.4.1 Calibration

In this section, we calibrate the model to match the data of the US in 2010 and 2011 and produce hours worked in Korea. We measure how much of the gap in hours worked between the two countries is explained by the model. Then we perform counterfactual exercises to compare the contribution of each factor in accounting for the gap.

We choose 2010 and 2011 as the sample period due to availability of the data. There is a possibility that the Great Recession could have influenced hours worked in both countries. Figures 3.3 show that hours worked in both countries have declined right after the Great Recession, with the fall being larger in the US. But there seems to be no further drop from 2010 and hours worked in both countries have been stable in 2010 and 2011. Moreover, the official business cycle troughs of the US and Korean economy were June 2009 and February 2009, respectively.[18] Thus this period is relatively free from the direct aftermath of the Great Recession.

[18] The business cycle troughs of the US and Korea are announced by the NBER and the Statistics Korea, respectively. The next business cycle trough for Korea was March 2013.

Table 3.6: Average age of parents when their kids finish colleges

	Korea	US
• Mean age of mothers at birth (A, 2006-2014)	31.2	27.8
• Difference between mean age of mothers and fathers at first birth (B, 2006-2014)	2.9	2.3
• Estimated mean age of fathers at birth (C=A+B, 2006-2014)	34.1	30.1
• Usual age of entrance for college (D)	19	18
• Average duration of college education (E, years)	4 - 7	4
• Average age of parents when their kids finish colleges ((A+C)/2+D+E)	55.7 - 58.7	50.9

Notes: The difference in mean age of the first marriage between men and women is used as a proxy for the difference between mean age of mothers and fathers at first birth (B) in Korea. When estimating the mean age of fathers at birth (C), we assume that the mean age difference between mothers and fathers are close to the difference between mean age of mothers and fathers at first birth. Usual ages of entrance for college (D) for both countries and average duration for college education (E) in the US are standard figures. The average duration of college education (E) in Korea for 2007-2014 is around 4 years, but it could take up to 7 years for men eligible for military service.
Sources: Statistics Korea (Korea), Centers for Disease Control and Prevention, The National Survey of Family Growth (US)

We categorize the prime-aged and the old as people aged 15-59 and over 60, respectively, based on the calculation in Table 3.6. The average age of parents when their kids finish colleges is 55.7 to 58.7 years old in Korea, whereas it is much younger in the US. Since our purpose is for the prime-aged generation to encompass households paying for their children's education as much as possible, we set the upper limit of the prime-aged to be 59 years old. Also, considering the fact that the official normal retirement age in Korea is 61 years old and that the old receive pension in our model, it would be reasonable to classify people over 60 as the old.[19]

Policy Parameters. We obtain the policy related parameters for the US and Korea from various sources of data. There are six of them in this model, namely, τ_l, E, A, P, G, and T. McDaniel (2011) formulates the effective tax rate on labor income τ_l as $(\tau_{ss} + \phi\tau_{inc} + \tau_c)/(1 + \tau_c)$, where τ_{ss} represents the average payroll tax rate, τ_{inc} is the average tax rate on household income, and τ_c denotes the average tax rate on consumption expenditure. She assumes $\phi = 1.6$ following Prescott (2004). The data from Cara McDaniel is used to acquire τ_l for the average between 2010 and 2011.[20]

[19]The official normal retirement age in the US is 66 years old, but the early retirement age is 62 years old.
[20]This data is computed based on the methodology of McDaniel (2007).

The household treats E as a lump-sum payment, but we think of E as a fraction of household's disposable income ex-post for the ease of obtaining the relevant data. It means $E = e(1 - \tau_l)wh_1$, but the household perceives E as a constant. e is derived from doubling the share of education costs to disposable income in Figure 3.4, because the old who take up a half of the economy does not spend education costs in the model.

We normalize Y to 1 instead of calibrating the level of technology A. Since A is a scaling factor for w and r, the level of A practically determines the income level of the economy. Since our main claim is that the difference in hours worked cannot be entirely attributed to the difference in income, we fix the output to 1 for both economies to abstract away from the income differences. Another advantage of this normalization is that we can consider all variables as fractions of Y.

P is the fraction of public pension spending to GDP, and G is the share of government consumption to GDP. P is available from OECD and G can be obtained from the Penn World Table 9.0. In addition, we use the fraction of private consumption to GDP $\hat{c}$ to match the level of c_1 and c_2 calculated by the model. This is because we need an extra target to be able to determine the level of lump-sum transfers T. We also get the figures for $\hat{c}$ from the Penn World Table 9.0.

Calibrated Parameters. Three parameters (α, β, a) need to be calibrated in the model. α is the capital share of income in the production function. We get $\alpha = 0.286$ from the estimate of the US in 2010 by Piketty and Zucman (2014).[21]

The discount factor $\beta = 0.005$ and the weight on leisure in the utility function $a = 3.068$ are jointly calibrated to match the average hours worked of the prime-aged (h_1) and the old (h_2) for 2010-2011 in the US. h_1 and h_2 are expressed as fractions of a 99 hour week, since hours worked in CPS cannot exceed 99 hours per week.[22] The estimated β seems extremely small, but given that the length of period 1 is 35 years, the value of implied yearly discount factor is around 0.86.[23] If we instead fix a higher value for β and calibrate α and a to jointly match the target of h_1 and h_2, the calibrated value of α becomes smaller, but the model prediction does not change much.

Table 3.7 summarizes the policy related and calibrated parameters.

[21] Using the same method, Lee and Yoon (2015) estimates that α is around 0.32 in Korea in 2010, which is not far from the US level.

[22] Hours worked for the Economically Active Population Survey in Korea is top-coded to 112 hours per week. The number of observations that report hours of work longer than 99 are less than 0.1% of the whole sample, so the impact of top-coding to 99 hours is minimal.

[23] Since period 1 is from age 25 to 59, the length of period 1 is 35 years.

Table 3.7: Summary of parameters

Parameters	Values	Sources/Targets
• Policy related variables		
τ_l	0.293, 0.334	Cara McDaniel's tax data set
e	0.041, 0.126	Share of education costs to disposable income (OECD)
Y	1, 1	Normalization
P	0.067, 0.022	Share of public pension spending to GDP (OECD)
G	0.127, 0.149	Share of government consumption to GDP (PWT 9.0)
$\hat{c}$	0.711, 0.499	PWT 9.0
• Calibrated parameters		
α	0.286	Piketty and Zucman (2014)
β	0.005	Hours worked of the prime-aged and the old
a	3.068	Hours worked of the prime-aged and the old

Notes: Figures in the upper panel are the averages for 2010-11 in the US and Korea, respectively. Parameters in the lower panel are calibrated using the averages for 2010-11 in the US, except for α where it is the estimate for 2010.

3.4.2 Quantitative Results

We feed the policy related parameters for Korea in the model to generate the level of hours worked in Korea. Table 3.8 shows the results, along with the actual hours worked in Korea and the US. The actual gap in hours worked for the prime-aged is 4.7 hours per week, but the model produces a gap of 8.3 hours. For the old, hours of work in Korea is predicted to be higher than in the US by 1.2 hours per week by the model, while the actual gap is 5.1 hours. The model over-achieves the gap of hours worked for the prime-aged and closes 23% of the actual gap in hours worked of the old between the two countries. However, the model replicates longer hours worked for both generations in Korea compared to the US, confirming our hypothesis that higher education costs and lower pension benefits contribute to longer hours worked.

Table 3.8: Actual and model generated weekly hours worked

	Actual			Model		
	Korea	US	Gap	Korea	US	Gap
h_1	33.2	28.4	4.7	36.8	28.4	8.3
h_2	14.1	9.0	5.1	10.2	9.0	1.2

Next, we perform counterfactual exercises to check the impacts of the key policy related variables (τ_l, e, and P) on hours worked. Each counterfactual imposes the level of each variable to be the same as the level in the US. By comparing the results with the baseline, we can verify how each factor affects the hours worked of the prime-aged and the old.

The results for counterfactual exercises are shown in Table 3.9. The direction of the impact of labor tax rate on hours worked is as expected from the previous literature. In the baseline, higher effective tax rates on labor income in Korea reduce hours worked of both generations due to lower after-tax wages.

Higher education costs in Korea contribute to longer hours worked of the prime-aged but to shorter hours worked by the old.[24] h_1 increases because of the tighter budget constraint of the prime-aged. h_2 falls despite the higher education costs mainly because the decrease in period 2 consumption due to lower permanent income dominates the fall in total returns from savings.

Lower pension benefits in Korea lead to less hours of work for the prime-aged and more hours of work for the old. It is natural that the old work longer with lower pension benefits, but it seems somewhat counter-intuitive that the prime-aged work less. The reason why h_1 falls is that lower pension benefits imply higher lump-sum transfers according to the government budget constraint, and the increase in lump-sum transfers is larger than the increase in savings needed to prepare for lower income in period 2.

Table 3.9: Counterfactual exercises

		Actual	Baseline	Counterfactual		
				τ_l	e	P
Hours worked (hours)	h_1	33.1	36.8	37.7	35.6	38.5
	h_2	14.1	10.2	11.4	11.4	8.5
Gap with the US (hours)	h_1	4.7	8.3	9.3	7.1	10.1
	h_2	5.1	1.2	2.4	2.4	-0.5
τ_l			0.334	0.293		
e			0.126		0.041	
P			0.022			0.067

Notes: Other policy related parameters not shown in the table are assumed to be the same as Korean levels. In each case, the level of $\hat{c}$ is assumed to be fixed.

Since the hours worked of two generations move in opposite directions as a result of the change in each factor, it is hard to determine which factor shows higher contribution

[24] In the earlier section, we show that the hours worked of both generations go up when E increases. The reason why the hours worked of the prime-aged and the old move in the opposite direction here is because the counterfactual exercises are implemented under the assumption that $\hat{c} = c_1 + c_2$ is fixed to the actual level. This assumption creates a trade-off between h_1 and h_2. Even with this caveat, the changes in education costs and pension benefits generate expected responses to hours worked of the relevant demographic group for each factor, which are the prime-aged and the old, respectively.

in explaining hours worked in Korea. But if we just focus on the behavior of the more relevant demographic group, the lower pension benefits appear more influential than the higher education costs. Hours worked of the old rises by 1.7 hours per week in the baseline due to lower pension benefits, whereas higher education costs raise hours worked of the prime-aged increases by 1.2 hours per week. Both in absolute and relative terms, the contribution of pension benefits is higher in rationalizing the long hours worked in Korea.

3.5 Conclusion

In this chapter, we provide an answer to the question of why hours worked in Korea are longer than the US even though the effective tax rate on labor income is higher and family care subsidies are not high. We propose high education costs paid by the prime-aged and low pension benefits paid to the old as potential explanation to this observation. Higher education costs and lower pension benefits restrict budget constraints of the prime-aged and the old, respectively, leading each generation to work more. Using a two-period OLG model encompassing these variables, we show that the model can quantitatively produce longer hours worked in Korea. The performance of pension benefits are stronger than that of education costs in generating long hours worked of the relevant demographic group.

3.6 References

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Appendix A

Appendices to Chapter 1

A.1 Fixed Effects Regression Results

Table A.1: Fixed effects regression results

Dependent variable: Female hours share of each occupation in current year (1998-2017)						
	(1)	(2)	(3)	(4)	(5)	(6)
Service offshoring	-0.559		-0.492		-1.145	-0.990
(lagged)	(0.838)		(0.968)		(0.886)	(0.989)
Material offshoring		-0.163		-0.122	-0.316	-0.265
(lagged)		(0.189)		(0.253)	(0.214)	(0.273)
ICT intensity			0.652	0.600		0.645
(lagged)			(0.524)	(0.496)		(0.517)
Manufacturing share			-0.036	-0.029		-0.027
			(0.094)	(0.100)		(0.101)
Female hours share	0.648***	0.648***	0.611***	0.612***	0.641***	0.605***
(lagged)	(0.090)	(0.095)	(0.102)	(0.106)	(0.097)	(0.110)
Number of obs.	340	340	306	306	340	306
R^2	0.457	0.457	0.420	0.420	0.460	0.422
Dependent variable: Female hours share of each occupation in current year (1990-1997)						
	(1)	(2)	(3)	(4)	(5)	(6)
Service offshoring	5.375		5.938		5.190	5.782
(lagged)	(5.477)		(5.207)		(6.254)	(6.319)
Material offshoring		-0.157		-0.170	-0.060	-0.037
(lagged)		(0.258)		(0.261)	(0.336)	(0.350)
ICT intensity			0.484	-0.323		0.438
(lagged)			(0.808)	(0.940)		(0.739)
Manufacturing share			0.027	0.007		0.029
			(0.109)	(0.121)		(0.114)
Female hours share	0.496***	0.512***	0.503***	0.508***	0.493***	0.501***
(lagged)	(0.106)	(0.087)	(0.115)	(0.088)	(0.095)	(0.103)
Number of obs.	136	136	136	136	136	136
R^2	0.352	0.339	0.353	0.339	0.352	0.353

Notes: All regressions contain occupation and year fixed effects. Standard errors are clustered by each occupation. ***, **, * indicate that the coefficients are statistically significant at 1%, 5%, and 10% level, respectively.

A.2 Proofs for Lemmas and Propositions

Lemma 1. *If $w^D(0) < \beta_j \tau(0) w^*$, $w^D(1) > \beta_j \tau(1) w^*$, and $\partial w^D(k)/\partial k > \partial(\beta_j \tau(k) w^*)/\partial k$ for all k, then there exists a unique cutoff K_j that satisfies the following conditions:*

1. *$w^D(K_j) = \beta_j \tau(K_j) w^*$,*
2. *$L_j^D(k) > 0$ and $L_j^*(k) = 0$ for $0 \le k \le K_j$,*
3. *$L_j^D(k) = 0$ and $L_j^*(k) > 0$ for $K_j < k \le 1$.*

Proof. Define $h_j(k) = w^D(k) - \beta_j \tau(k) w^*$. Then $h_j(k)$ is a continuous function of k and $min(h_j(0), h_j(1)) = h_j(0) < 0 < h_j(1) = max(h_j(0), h_j(1))$. By the intermediate value theorem, there exists $K_j \in [0,1]$ such that $h_j(K_j) = 0$. $\partial h_j(k)/\partial k = \partial w^D(k)/\partial k - \partial(\beta_j \tau(k) w^*)/\partial k > 0$ for all k, so $h_j(k)$ is a monotonically increasing function on [0, 1]. This guarantees the existence of a unique K_j.

For $0 \le k \le K_j$, $h_j(k) \le 0$, i.e., $w^D(k) \le \beta_j \tau(k) w^*$. Therefore, firms only hire the cheaper labor input, which is the domestic labor. For $K_j < k \le 1$, $h_j(k) > 0$, i.e., $w^D(k) > \beta_j \tau(k) w^*$, implying that firms choose to employ the offshored labor in this range. □

Lemma 2. *When Lemma 1 holds,*

$$\frac{\partial K_j}{\partial \beta_j} > 0.$$

Proof. Since

$$\beta_j = \frac{w^D(K_j)}{w^* \tau(K_j)},$$

$$\frac{\partial \beta_j}{\partial K_j} = \frac{[\frac{\partial w^D(K_j)}{\partial K_j} \tau(K_j) - w^D(K_j) \frac{\partial \tau(K_j)}{\partial K_j}]}{w^* [\tau(K_j)]^2}.$$

Using the expression for β_j, we can rewrite:

$$\frac{\partial \beta_j}{\partial K_j} = \frac{\tau(K_j)[\frac{\partial w^D(K_j)}{\partial K_j} - \beta_j w^* \frac{\partial \tau(K_j)}{\partial K_j}]}{w^* [\tau(K_j)]^2}.$$

Because the numerator is positive by the assumption in Lemma 1,

$$\frac{\partial \beta_j}{\partial K_j} > 0,$$

confirming

$$\frac{\partial K_j}{\partial \beta_j} > 0.$$

$\square$

Proposition 1. *When (1.14) and (1.21) holds, $K_g < K_s$, and $\alpha'(k) > 0$, the female to male hours ratio in the goods sector is lower than the ratio in the service sector:*

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \frac{\int_0^{K_s} L_{fs}(k)dk}{\int_0^{K_s} L_{ms}(k)dk}.$$

Proof. Under (1.21), we can verify that the claim is equivalent to

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk}.$$

Using (1.14) we can write

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} = \int_0^{K_g} \varphi(k)^{\varepsilon} x^{-\varepsilon} \frac{L_{mg}(k)}{\int_0^{K_g} L_{mg}(k)dk} dk.$$

This is a weighted average of $\varphi(k)^{\varepsilon} x^{-\varepsilon}$ and lies between the minimum and maximum of $\varphi(k)^{\varepsilon} x^{-\varepsilon}$ on $[0, K_g]$. Since $\varphi'(k) > 0$,

$$\varphi(0)^{\varepsilon} x^{-\varepsilon} < \frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \varphi(K_g)^{\varepsilon} x^{-\varepsilon}.$$

Similarly,

$$\varphi(K_g)^{\varepsilon} x^{-\varepsilon} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk} = \int_{K_g}^{K_s} \varphi(k)^{\varepsilon} x^{-\varepsilon} \frac{L_{ms}(k)}{\int_{K_g}^{K_s} L_{ms}(k)dk} dk < \varphi(K_s)^{\varepsilon} x^{-\varepsilon}.$$

Therefore,

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \varphi(K_g)^{\varepsilon} x^{-\varepsilon} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk}.$$

$\square$

Proposition 2. *If Proposition 1 holds, the aggregate female to male hours ratio rises over time as $\gamma_g > \gamma_s$.*

Proof. If we differentiate FM with respect to R_{sg} and rearrange terms,

$$\frac{\partial FM}{\partial R_{sg}} = \frac{1}{R_{sg}} \frac{\int_0^{K_g} L_{fg}(k)dk \int_0^{K_s} L_{ms}(k)dk - \int_0^{K_s} L_{fs}(k)dk \int_0^{K_g} L_{mg}(k)dk}{[R_{sg} H_{sg}^{\rho-\eta} \int_0^{K_g} \varphi(k)^{-\varepsilon} L_{fs}(k)dk + \int_0^{K_s} \varphi(k)^{-\varepsilon} L_{fs}(k)dk]^2 x^{2\varepsilon}} < 0,$$

by Proposition 1. Since R_{sg} decreases as $\gamma_g > \gamma_s$, FM goes up when the labor productivity growth is higher in goods. $\square$

Proposition 3. *If Proposition 1 holds and $\eta > \rho$, the aggregate female to male hours ratio falls as β_s goes down and $\beta_g < \beta_s$ is still satisfied after the change.*

Proof.

$$\frac{dFM}{d\beta_s} = \frac{\partial FM}{\partial \beta_s} + \frac{\partial FM}{\partial K_s}\frac{\partial K_s}{\partial \beta_s}.$$

If we differentiate FM with respect to β_s and rearrange terms,

$$\frac{\partial FM}{\partial \beta_s} = \frac{\partial H_{sg}}{\partial \beta_s}\frac{\rho - \eta}{H_{sg}}\frac{\int_0^{K_g} L_{fg}(k)dk \int_0^{K_s} L_{ms}(k)dk - \int_0^{K_s} L_{fs}(k)dk \int_0^{K_g} L_{mg}(k)dk}{[R_{sg}H_{sg}^{\rho-\eta}\int_0^{K_g}\varphi(k)^{-\varepsilon}L_{fs}(k)dk + \int_0^{K_s}\varphi(k)^{-\varepsilon}L_{fs}(k)dk]^2 x^{2\varepsilon}} > 0,$$

by Proposition 1. The derivative of FM with respect to K_s can be written as

$$\frac{\partial FM}{\partial K_s} = \frac{L_{fs}(K_s)[R_{sg}H_{sg}^{\rho-\eta}\int_0^{K_g}(\varphi(k)^{-\varepsilon} - \varphi(K_s)^{-\varepsilon})L_{fs}(k)dk + \int_0^{K_s}(\varphi(k)^{-\varepsilon} - \varphi(K_s)^{-\varepsilon})L_{fs}(k)dk]}{[R_{sg}H_{sg}^{\rho-\eta}\int_0^{K_g}\varphi(k)^{-\varepsilon}L_{fs}(k)dk + \int_0^{K_s}\varphi(k)^{-\varepsilon}L_{fs}(k)dk]^2 x^{\varepsilon}}.$$

Since $\varphi'(k) > 0$, $\varphi(k)^{-\varepsilon} > \varphi(K_s)^{-\varepsilon}$ for $0 \leq k < K_s$. This implies that $\partial FM/\partial K_s > 0$. Also we know from Lemma 2 that $\partial K_s/\partial \beta_s > 0$. Therefore,

$$\frac{dFM}{d\beta_s} > 0.$$

$\square$

A.3 The Model with Sector-specific Weights on Female Labor

When the weights on female labor in the domestic labor aggregate are different across sectors, the domestic labor is expressed as follows:

$$L_j^D(k) = [\alpha_j(k) L_{fj}(k)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha_j(k)) L_{mj}(k)^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{A.1}$$

where $\alpha_s(k) > \alpha_g(k)$ for all k. This is the only difference with the original model in the setup.

In the domain where firms only employ domestic labor, the wage of hiring a unit of $L_j^D(k)$ is not the same for both sectors anymore:

$$w_j^D(k) = [\alpha_j(k)^\varepsilon w_f^{1-\varepsilon} + (1-\alpha_j(k))^\varepsilon w_m^{1-\varepsilon}]^{\frac{1}{1-\varepsilon}}. \tag{A.2}$$

The cutoff offshorability K_j for each sector j is defined such that $w_j^D(K_j) = \beta_j \tau(K_j)$. In the new setup, Lemmas 1 and 2 also come through with slight modifications.

One caveat to note on the relationship between K_j and β_j is that $\beta_g < \beta_s$ does not necessarily mean $K_g < K_s$ in the new model. This is because $\alpha_j(k)$ also matters in determining K_j in contrast to the original model. If we assume the simplest specification of $\alpha_j(k) = \alpha_k k + \alpha_{cj}$ as in Section 5, $dK_j/d\alpha_{cj}$ is positive when $K_j \geq \alpha_j^{-1}(x/(1+x))$ and negative when $K_j < \alpha_j^{-1}(x/(1+x))$.[1] Given $\alpha_{cs} > \alpha_{cg}$, this means that there is a possibility that K_s is lower than K_g depending on the parameters of $\alpha_j(k)$ even if $\beta_g < \beta_s$. In the calibration, we start from estimating K_s and K_g and back out $\theta_s \equiv \beta_s w^*$ and $\theta_g \equiv \beta_g w^*$ from the equalization of hiring costs. Since we think of K_j as a proxy that indicates the degree of offshoring in the quantitative analysis and the cutoff offshorability in the service sector is higher than in the goods sector for all years in our calibration, we do not stick to the parametric assumption of $\beta_g < \beta_s$ in the augmented model.[2]

The ratio of female to male hours worked in each task, which is governed by (1.14) in the original model, is different in the new model:

$$\frac{L_{fj}(k)}{L_{mj}(k)} = \varphi_j(k)^\varepsilon x^{-\varepsilon}, \tag{A.3}$$

where $\varphi_j(k) \equiv \alpha_j(k)/(1-\alpha_j(k))$, $x \equiv w_f/w_m$, $0 \leq k \leq K_j$, and $j = g, s$. The profit

[1] This result is based on the assumption of Lemma 1 that $\partial w_j^D(k)/\partial k > \partial(\beta_j \tau(k) w^*)/\partial k$ for all k.

[2] In Table 1.4, we can see that the calibrated θ_g is higher than θ_s in 1970.

maximizing condition of L_j slightly changes as well:

$$p_jA_j = \underbrace{[w_f^{1-\eta}\int_0^{K_j}(\alpha_j(k)^{-\frac{\varepsilon}{\varepsilon-1}}I_j(k,x)^{\frac{1}{\varepsilon-1}})^{1-\eta}dk + (\beta_j w^*)^{1-\eta}\int_{K_j}^1 \tau(k)^{1-\eta}dk]^{\frac{1}{1-\eta}}}_{\equiv \widehat{H}(\beta_j,x)}, \tag{A.4}$$

where $I_j(k,x) \equiv w_f L_{fj}(k)/(w_f L_{fj}(k) + w_m L_{mj}(k)) = 1/(1+\varphi_j(k)^{-\varepsilon}x^{\varepsilon-1})$.

The conditions for the household's utility maximization stay the same. Using the utility maximization condition, (A.4), and the market clearing condition, the ratio between labor aggregates in goods and service in equilibrium is obtained:

$$\frac{L_g}{L_s} = \frac{A_s}{A_g}\frac{c_g}{c_s} = [\underbrace{\frac{\widehat{H}(\beta_s,x)}{\widehat{H}(\beta_g,x)}}_{\equiv \widehat{H}_{sg}(\beta_s,\beta_g,x)}\frac{\omega}{1-\omega}]^{\rho}(\frac{A_g}{A_s})^{\rho-1}. \tag{A.5}$$

Still, $\partial\widehat{H}_{sg}(\beta_s,\beta_g,x)/\partial\beta_s > 0$ and $\partial\widehat{H}_{sg}(\beta_s,\beta_g,x)/\partial\beta_g < 0$. The new ratios of hours worked in goods to service are the following:

$$\frac{L_{fg}(k)}{L_{fs}(k)} = \widehat{H}_{sg}(\beta_s,\beta_g,x)^{\rho-\eta}\underbrace{(\frac{A_g}{A_s})^{\rho-1}(\frac{\omega}{1-\omega})^{\rho}}_{\equiv R_{sg}(A_g,A_s)}[\frac{\alpha_g(k)}{\alpha_s(k)}]^{\frac{\varepsilon(\eta-1)}{\varepsilon-1}}[\frac{I_g(k,x)}{I_s(k,x)}]^{\frac{\varepsilon-\eta}{\varepsilon-1}}, \tag{A.6}$$

$$\frac{L_{mg}(k)}{L_{ms}(k)} = \widehat{H}_{sg}(\beta_s,\beta_g,x)^{\rho-\eta}(\frac{A_g}{A_s})^{\rho-1}(\frac{\omega}{1-\omega})^{\rho}[\frac{\alpha_g(k)}{\alpha_s(k)}]^{\frac{\varepsilon(\eta-\varepsilon)}{\varepsilon-1}}[\frac{1-\alpha_g(k)}{1-\alpha_s(k)}]^{\varepsilon}[\frac{I_g(k,x)}{I_s(k,x)}]^{\frac{\varepsilon-\eta}{\varepsilon-1}}, \tag{A.7}$$

for $0 \leq k \leq K_g$.

In the original model, $L_{fg}(k)/L_{fs}(k)$ did not depend on k and was the same as $L_{mg}(k)/L_{ms}(k)$, as (1.21) shows. However, neither of these is true in the new model. The ratio of female hours worked in goods to service differs by each task k and is not equal to the ratio of male hours worked.

It is hard to rigorously prove Proposition 1, which states that the female to male hours ratio is higher in the service sector, under the new setting. Proposition 1 has an intuitive appeal because (A.3) and the assumption of $\alpha_s(k) > \alpha_g(k)$ confirm higher female to male hours ratio in the service sector for each task k. However, these facts do not guarantee that the female intensity in the service sector for the entire range of $[0, K_g]$ is higher than in the goods sector.

But Proposition 1 is highly likely to be satisfied. To show this, we follow the proof similar to the one in Appendix A.2. First,

$$\varphi_s(0)^\varepsilon x^{-\varepsilon} < \frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk} = \int_0^{K_g} \varphi_s(k)^\varepsilon x^{-\varepsilon} \frac{L_{ms}(k)}{\int_0^{K_g} L_{ms}(k)dk} dk < \varphi_s(K_g)^\varepsilon x^{-\varepsilon},$$

and

$$\varphi_s(K_g)^\varepsilon x^{-\varepsilon} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk} = \int_{K_g}^{K_s} \varphi_s(k)^\varepsilon x^{-\varepsilon} \frac{L_{ms}(k)}{\int_{K_g}^{K_s} L_{ms}(k)dk} dk < \varphi_s(K_s)^\varepsilon x^{-\varepsilon},$$

because $\varphi_s(k)$ is increasing in k, which lead to

$$\frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk}.$$

We can also verify that

$$\frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk} < \frac{\int_{K_g}^{K_s} L_{fs}(k)dk}{\int_{K_g}^{K_s} L_{ms}(k)dk}$$

is equivalent to

$$\frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk} < \frac{\int_0^{K_s} L_{fs}(k)dk}{\int_0^{K_s} L_{ms}(k)dk}.$$

Therefore, if we show that

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} \leq \frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk},$$

then we can prove

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} < \frac{\int_0^{K_s} L_{fs}(k)dk}{\int_0^{K_s} L_{ms}(k)dk}.$$

By (A.3),

$$\frac{\int_0^{K_g} L_{fg}(k)dk}{\int_0^{K_g} L_{mg}(k)dk} = \int_0^{K_g} \varphi_g(k)^\varepsilon x^{-\varepsilon} \frac{L_{mg}(k)}{\int_0^{K_g} L_{mg}(k)dk} dk, \tag{A.8}$$

and

$$\frac{\int_0^{K_g} L_{fs}(k)dk}{\int_0^{K_g} L_{ms}(k)dk} = \int_0^{K_g} \varphi_s(k)^\varepsilon x^{-\varepsilon} \frac{L_{ms}(k)}{\int_0^{K_g} L_{ms}(k)dk} dk. \tag{A.9}$$

We know $\varphi_g(k) < \varphi_s(k)$ for all k, but the relationship between the weights in the integral ($L_{mg}(k)/\int_0^{K_g} L_{mg}(k)dk$ and $L_{ms}(k)/\int_0^{K_g} L_{ms}(k)dk$) is not straightforward. From the comparison of these two integrals, all we can ensure is that the female intensity in the service sector (A.9) would be higher than in the goods sector (A.8) on $[0, K_g]$ unless the distribution of $L_{mg}(k)$ ($L_{ms}(k)$) is highly skewed to the right (left) so that this skewness overturns the dominance of $\varphi_s(k)^\varepsilon$ over $\varphi_g(k)^\varepsilon$. Even if the female to male hours ratio in the goods sector is higher than in the service sector on $[0, K_g]$, it further needs to be higher than the gender hours ratio in the service sector on $[0, K_s]$ to nullify Proposition 1. Therefore, it is highly likely that Proposition 1 holds in the new model.

We can show that Propositions 2 and 3 are also met if the female intensity is indeed higher in the service sector using a similar proof in Appendix A.2. In the case of Proposition 3, the indirect effect of the change through K_s is reinforced compared to the original model due to the difference between $\alpha_g(k)$ and $\alpha_s(k)$. The effect of a change in β_g on the hours ratio remains ambiguous.

A.4 Calibration

A.4.1 Relationship Between the Labor Productivity Data by BLS and the Sector-specific Productivity in the Model

In this part of the Appendix, we derive the mapping from the labor productivity data by BLS to the sector specific productivity (A_j) in our model. We denote the labor productivity of BLS by LP_j. It is defined by output per hour of work. In our framework, it is expressed as follows:

$$LP_j = \frac{Y_j}{\int_0^{K_j} (L_{fj}(k) + L_{mj}(k))dk}. \tag{A.10}$$

If we plug in the connection between female and male hours of task k in (A.3) for the domestic labor aggregate in (A.1), we obtain the following relationships:

$$\frac{L_j^D(k)}{L_{fj}(k)} = [\frac{\alpha_j(k)}{I_j(k,x)}]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{A.11}$$

$$\frac{L_j^D(k)}{L_{mj}(k)} = [\frac{\alpha_j(k)}{I_j(k,x)}]^{\frac{\varepsilon}{\varepsilon-1}} \varphi_j(k)^{\varepsilon} x^{-\varepsilon}, \tag{A.12}$$

where $I_j(k,x) \equiv w_f L_{fj}(k)/(w_f L_{fj}(k) + w_m L_{mj}(k)) = 1/(1+\varphi_j(k)^{-\varepsilon} x^{\varepsilon-1})$ and $\varphi_j(k) \equiv \alpha_j(k)/(1-\alpha_j(k))$ as specified before. Substituting these expressions for (A.10) generates:

$$LP_j = \frac{Y_j}{\int_0^{K_j} (1+\varphi_j(k)^{-\varepsilon} x^{\varepsilon})[\frac{\alpha_j(k)}{I_j(k,x)}]^{\frac{\varepsilon}{1-\varepsilon}} L_j^D(k)dk}. \tag{A.13}$$

A first order condition from firm's profit maximization problem is expressed as:

$$p_j A_j L_j^{\frac{1}{\eta}} L_j^D(k)^{-\frac{1}{\eta}} \alpha_j(k) L_j^D(k)^{\frac{1}{\varepsilon}} L_{fj}(k)^{-\frac{1}{\varepsilon}} = w_f. \tag{A.14}$$

Rearranging this condition using (A.4) and (A.11), we can derive the relationship between $L_j^D(k)$ and L_j:

$$\frac{L_j}{L_j^D(k)} = [\frac{w_f}{\hat{H}(\beta_j,x)} \alpha_j(k)^{\frac{\varepsilon}{1-\varepsilon}} I_j(k,x)^{\frac{1}{\varepsilon-1}}]^{\eta}. \tag{A.15}$$

Taking into account the facts that $A_j = Y_j/L_j$, L_j is independent of k, and $w_f = x$ because w_m is a numeraire, we obtain the following mapping from A_j to LP_j:

$$LP_j = A_j \frac{[x/\hat{H}(\beta_j,x)]^{\eta}}{\int_0^{K_j} (1+\varphi_j(k)^{-\varepsilon} x^{\varepsilon})[\alpha_j(k)]^{\frac{\varepsilon(\eta-1)}{\varepsilon-1}} [I_j(k,x)]^{\frac{\varepsilon-\eta}{\varepsilon-1}} dk}. \tag{A.16}$$

Then using the labor productivity data from BLS and calibrated parameters we can back out A_j of each year and calculate the annual growth rates for each period.

To avoid an issue of potential connection between A_j and K_j, we assume that there has been no offshoring from 1970 to 2016 to calculate the common A_j for every scenario in our analysis.

A.4.2 Parameters from the Household's Side

We import the number for the elasticity of substitution between goods and service consumption $\rho = 0.002$ from the estimate by Herrendorf, Rogerson, and Valentinyi (2013).

For the calibration of ε_l, α_l, and δ, we need the data for leisure of each year and gender. We get these figures using the actual hours worked for each year and gender from the CPS and total time endowment calculated based on Valerie Ramey's data. We treat the time endowment as the total time allocated to work and leisure, except for home production. Since we abstract away from home production in our model, it is necessary to make this adjustment to avoid women's leisure surpassing men's leisure excessively. The total time endowments of each gender and year are computed by subtracting the hours for home production provided by Valerie Ramey from the total time allocation of 88.5 hours per week.

(1.17) suggests that the elasticity of substitution between male and female leisure ε_l shows the elasticity of the gender leisure ratio (L_{fl}/L_{ml}) with respect to the gender wage ratio. We run a simple regression of log L_{fl}/L_{ml} on log x from 1970 and 2016, and set the slope coefficient as $\varepsilon_l = 0.210$. Then using the data in 1970 and ε_l, we can get the value for women's weight in the labor aggregate $\alpha_l = 0.329$ from (1.17). Given these parameter values, the relative weight of the leisure aggregate in the utility function $\delta = 1.404$ can be acquired through (1.18).