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Essays on the Impact of Technological Progress on the U.S. Labor Markets

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by

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Abstract of the Dissertation

Essays on the Impact of Technological Progress
on the U.S. Labor Markets

by

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This dissertation studies the impact of technological progress on various aspects of the U.S. labor markets such as the recent decline in the labor's share of income, job and wage polarization, rising income and wealth inequalities and skill accumulation.

Chapter 1, "Capital-Task Complementarity and the Decline of the U.S. Labor Share of Income," studies how changes in occupational composition of the labor force contributes to the recent decline of the US labor share of income. Following the job polarization literature and classifying labor by tasks performed, I estimate unitary elasticity between equipment capital and labor performing non-routine tasks. This implies that income loss of labor employed in routine task occupations is the main driver of the decline of the aggregate labor share. For a given path of technological change, decline of the labor share is larger when: (i) the substitutability between equipment capital and routine tasks is stronger, and (ii) equipment capital has a larger weight in production. Furthermore, a dynamic general equilibrium model shows that the impact of permanent technology shocks on the labor share gets smaller as the fraction of routine task labor declines. Consistent with this, the model predicts that the labor share should stabilize at around 55% in the long-run even if technological progress continues at its current pace. The model also documents that the fall in relative equipment capital prices alone can explain 72% of the decline of the labor share for the 1967-2013 period. Finally, repeating the analysis by disaggregating labor into educational groups reveals that

the theory based on capital-task interactions improves on the capital-skill complementarity theory in explaining the decline of the labor share.

Chapter 2, “Impact of Information Technology on the Labor Share: Evidence from the U.S. Sectoral Data,” contributes to the debate over the relationship between capital deepening and the aggregate labor share from a sectoral perspective. The study focuses on a specific group of equipment capital: information and communication technology (ICT) capital and exploits various sectoral heterogeneities to characterize the conditions under which the surge in ICT capital cause the labor share to fall. First, I document significant capital-task complementarity at each sector. Second, decline in ICT capital prices turns out to have a positive impact on the labor share. However, gains of labor devoted to non-routine task occupations are offset by the losses of labor employed in routine task occupations when a sector has: (i) initially high load of employment in routine task occupations, and (ii) weak absolute complementarity between ICT capital and labor working in occupations associated with non-routine tasks. Since sectors satisfying these two conditions have compromised the majority of the economy, the aggregate labor share has exhibited a downward trend so far, leading to the illusion that information technology has been driving the labor share downwards. However, there are two promising facts concerning the future: in one hand, the share of these sectors in value added is persistently falling and on the other hand, the share of routine task employment continues to fall at every sector. Thus, once the structural shifts and within sectoral adjustments are completed, the decline in the labor share should revert back.

Chapter 3, “Job Polarization, Skill Accumulation and Wealth Inequality,” is one of the first attempts in literature to incorporate the job polarization idea into an otherwise standard incomplete markets model with heterogeneous agents in two dimensions: skills and idiosyncratic productivity shocks. This set up allows us to contribute to the existing literature in two ways: (i) linking job polarization with rising wealth concentration, and (ii) modeling the continuous rise in skill supply in response to technological progress and job polarization accompanying it over time. When calibrated and solved for the years 1981 and 2011, the model shows that the decline in relative computer (ICT) capital prices alone accounts for a significant portion of the increases in employment share and relative wages of high skill occupations, as well as the increase in the supply of labor with a college or above-college degree. Consistent with the routinization hypothesis, the model also shows that advances in computer technology can account for most of the decline of the employment share and relative wage of middle class over the three decades between 1981 and 2011. Furthermore, the model successfully captures the erosion of middle-class wealth, whereas wealth concentration rises substantially at the right tail and slightly at the left tail of the wealth distribution.

The dissertation of Musa Orak is approved.

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To my beloved mom,

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Vita

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CHAPTER 1

Capital-Task Complementarity and the Decline of the U.S. Labor Share of Income

1.1 Introduction

> "... the stability of the proportion of the national income dividend accruing to the labor is one of the most surprising yet best established facts in the whole range of economic statistics."
>
> *J. M. Keynes, 1939*

Since Kaldor (1957) documented Keynes' seminal observation, labor's share of income (henceforth, the labor share) had not been at the center of interest for economists. However, this received wisdom of a constant labor share has been challenged by the recent decline in the US labor share, which inspired the interest in this topic.[1] Understanding what drives the decline of the labor share has important implications for socio-economic issues like the rise of wealth and income inequalities, which in turn, as Piketty (2014) argues, cause economic and political instability and may lower economic growth in the long run.

Much of the existing literature trying to shed light on the causes of this recent phenomenon has focused on technological progress and the accompanying increase in the capital to labor ratio. However, no consensus over the link between capital deepening and the labor share has been reached yet. Furthermore, the existing studies are unable to identify the role

[1] Some studies documenting the decline in the labor share are Elsby et al. (2013), Karabarbounis and Neiman (2014b) and Armenter (2015).

played by the changes in skill and task composition of the labor in labor share movements. Taking a more disaggregated view of the economy than the existing literature and exploiting the differing interactions between technological progress and various groups of labor, this paper, however, measures and compares the contributions of changes in skill and occupational composition of the labor force to the decline of the labor share.

In particular, this paper explains the recent decline in the labor share as a consequence of equipment-specific technological change, which has been mainly driven by the rapid advances in computer, software and communication technology, and the resulting shifts in the task composition of the labor force.[2] This type of technological progress makes equipment capital relatively cheaper and hence, changes the distribution of capital used in production in favor of this particular type of capital. Since equipment capital has differing complementarities with different types of labor, this also affects the relative wages and employment and income shares of labor types as well as the aggregate labor share.

Consistent with the job polarization literature, this paper assigns labor into one of the three occupations, which are classified by the type of tasks associated with them: (non-routine) cognitive, routine, and (non-routine) manual.[3][4] When there is capital-task complementarity, which I define as equipment capital being more substitutable with routine tasks than non-routine tasks, technological progress necessarily reduces the relative demand for labor devoted to routine tasks and drives its share of income downwards. On the other hand, the demand for labor working in non-routine tasks -whether cognitive or manual- increases,

[2]Here, equipment-specific technological change refers to technological progress embodied in the form of new equipment capital goods (Gort et al. (1999)).

[3]Job polarization refers to the growth of the employment shares of high skill (cognitive) and low skill (manual) occupations, while that of middle skill (routine) occupations erodes.

[4]Cognitive occupations are high skill managerial and professional jobs, while routine occupations represent middle skill jobs that are codifiable and thus, vulnerable to automation. Examples of low skill manual occupations are personal services such as child care and home health care.

which raises the relative wage rate and/or employment share of labor in these occupations, thereby driving the income share of this group upwards. How these two opposing forces translate into the aggregate labor share depends on their relative magnitudes, which in turn are determined by the elasticities of substitution between equipment capital and each type of labor. Therefore, I first estimate a general production function that allows for job polarization to measure these key elasticities, which are not available in related literature.[5] Then, the estimated production function is nested into a dynamic general equilibrium model to quantify the contribution of equipment-specific technological change to the decline of the labor share.

The estimation analysis reveals that there is unitary elasticity between equipment capital and labor devoted to non-routine tasks. This Cobb-Douglas relationship is crucial in the sense that it implies that equipment capital and labor working in non-routine task occupations capture constant shares of the income lost by labor performing routine tasks. This guarantees that the income losses of this group always dominate the gains of labor in non-routine task occupations, thereby making the decline in the aggregate labor share an inevitable outcome of equipment-specific technological progress and the accompanying job polarization process. For a given level of equipment-specific technological change, the magnitude of the decline in the aggregate labor share, on the other hand, depends on three factors. First, the stronger the substitutability between routine tasks and the composite output of equipment capital and non-routine tasks, the easier it is to switch from routine tasks to other factors and thus the larger the change in the labor share. Second, given this elasticity, the larger the weight of equipment capital in production, the more sensitive the labor share is to equipment-specific technological progress. Finally, the higher the fraction of the labor force employed in occupations associated with routine tasks, the more rapid the decline of the labor share is for a given level of technological progress.

[5] I used a two-stage Bayesian estimation methodology that is adapted from the works of Krusell et al. (2000) and Polgreen and Silos (2009). However, unlike the aforementioned papers, rather than fitting the labor share in my estimation process, I kept it as one of the estimation outcomes.

Whereas this paper focuses on capital-task complementarity, most of the literature points out capital-skill complementarity as one of the potential stories behind the decline of the labor share.[6] To assess the marginal contribution of the task-based story in explaining the decline of the labor share, I repeat the estimation process using an education-based skill classification as opposed to the task-based one. The model, in this case, is unable to capture the recent acceleration in the decline of the labor share in a manner consistent with other labor market trends. Furthermore, the task-based classification simplifies the modeling of the labor share to a great extent as it allows us to pin down the changes in the labor share on the changes in the wage-bill ratio, which is defined as the ratio of wage income of labor doing non-routine tasks to that of labor devoted to routine tasks. Thus, the explanation based on the interactions between equipment capital and task groups of labor considerably improves and simplifies our understanding of the link between technological progress and the labor share.

This paper differs from the existing explanations such as Karabarbounis and Neiman (2014a), Karabarbounis and Neiman (2014b), Piketty and Zucman (2014) and Lawrence (2015) in the sense that it shows that it is not labor per se that is being substituted away. Once we follow the job polarization literature and classify labor by the tasks performed, we find that substitution is solely away from routine tasks to both equipment capital and non-routine tasks, and the income losses of this group account for the entire decline of the labor share for the 1967-2013 period. This has two kinds of new implications. First, potential policy implications are different. Whereas the existing explanations would require policies such as taxing capital or subsidizing employment, my model implies that the policies helping the labor acquire skills compatible with the non-routine cognitive tasks would be the most appropriate choices. Secondly, this paper has a different prediction about the future course of the labor share. The existing studies based on the substitutability between aggregate capital and labor do not predict a lower bound for the labor share if technological progress keeps

[6] Capital-skill complementarity is a concept similar to capital-task complementarity when labor is grouped on the basis of years of education rather than tasks associated with their occupations.

its current pace. My explanation built on capital-task complementarity, however, predicts a slowdown in the decline of the labor share as the economy completes its transition to a new steady state with a very low share of employment of labor in routine task occupations.

The estimation part revealed the theoretical channel behind the decline in the labor share. In the second half of the paper, the estimated elasticities are used in a dynamic general equilibrium model that generates job polarization characteristics to quantify the impact of equipment-specific technological change and capital-task complementarity on the labor share. This model also enables us to project the lower bound for the labor share and conduct counterfactual analysis. When the non-estimated parameters of the model are calibrated to the US data, I find that equipment-specific technological change can account for around 72% of the trend decline in the labor share between the years 1967 and 2013. The acceleration of technological progress during the 1996-2003 period alone accounts for around 22% of the decline. Finally, the model shows that the initial response of the labor share to permanent technology shocks gets smaller as the employment share of labor working in routine task occupations declines over time. Consistent with this, the model projects that even if technological progress continues at its current pace, the fall in the labor share would cool down in the medium-run before flatting somewhere around 55% in the very long run.

The model has two additional corollary results. First, an extension of the model, enables us to explain the substantial sectoral differences in the labor share trends. There is only a very limited number of papers seeking an explanation for this sectoral heterogeneity. For instance, in a recent paper, Alvarez-Cuadrado et al. (2015) account for these differences by varying the substitutabilities of capital and labor across sectors. In contrast, my model does not rely on sectoral differences in substitution possibilities among the factors of production. Rather, it has the implication that the differences in the importance of equipment capital in production across sectors explain this phenomenon in a manner consistent with the capital-task complementarity explanation provided for the aggregate economy.

Second, this paper also has relevance to debate on the substitutability between aggregate capital and labor. While there are numerous other studies providing estimates of elasticity of substitution at the aggregate level, this paper does have an advantage over the existing studies in the sense that it can be used in estimating an aggregate elasticity measure that is consistent with both the decline of the aggregate labor share and other labor market trends such as job and wage polarizations. Using the aggregated factor and price series simulated by my disaggregated model, I measure the aggregate elasticity of substitution between capital and labor to be 1.06. This estimate lies in between two opposite extreme views in related literature.

By incorporating the task composition of the wage bill into the analysis of labor share, this paper is the first one to bring three strands of literature - namely, labor share, capital-skill complementarity, and job polarization- together. In next section, I will briefly sum up the contributions to each of these. The literature survey is followed by Section 1.3 that presents the data sources and motivating facts. Section 1.4 is the empirical part of the paper, where I present the structural model to be estimated, estimation methodology and results. Then I describe the general equilibrium model in Section 1.5 before presenting the quantitative findings of the model in Section 1.6. Section 1.7 extends the model into three sectors and discusses the implications of the model for the sectoral differences. Finally, Section 1.8 concludes the paper.

1.2 Related Literature

This paper is related to three literatures. First is the labor share literature that seeks for an explanation for the decline in the labor share. Among the proposed explanations, most of this literature focuses on the decline in capital prices, which is used as the proxy for technological change. So far, no agreement has been reached regarding the impact of capital prices on the labor share. The second line of literature is the capital-skill complementarity literature, which mostly focuses on the causes of the rise in skill premium and income inequality. Finally, this study is also related to the literature on job polarization, which can be considered as a special case of capital-skill complementarity with information, communication and software technology (ICT) capital and task content of occupations at the center of interest. So far, the last two literatures have ignored the labor share.

1.2.1 Labor share

The decline in the labor share in most of the countries and sectors is well documented by many studies including Guerriero (2012) and Karabarbounis and Neiman (2014b). Similarly, Elsby et al. (2013) provide a detailed examination of the trend in the labor share and confirm the decline in the US. Nevertheless, they claim that one third of the decline is an artifact of a progressive understatement of the labor income of the self-employed. In his recent paper, Armenter (2015) constructs a wide range of alternative definitions of the labor share to address the measurement issues and confirms the overall trend decline. There are contradicting views as well. Bridgman (2014) claims that the US labor share has not fallen as much once the items that do not add to capital, depreciation and production taxes are netted out. Similarly, Rognlie (2015) shows that the recent rise in the share of capital income is due only to the housing sector. Finally, Koh et al. (2015) claim that capitalization of intellectual property products entirely explains the decline of the US labor share.

Most of the studies in this literature come to the conclusion that factor prices alone cannot account for the labor share's decline. Leon-Ledesma et al. (2010) provide a detailed review of studies estimating elasticity of substitution between capital and labor and report that most of the estimates range between 0.5 and 0.8.[7] In a recent paper, Oberfield and Raval (2014), document a similar aggregate elasticity and thus, conclude that capital prices must have played a positive impact on the labor share, if any. Hence, attempts to explain the decline in the labor share using the factor prices require extending the dimension of the

[7]See Table 1 in Leon-Ledesma et al. (2010) for empirical estimates of the aggregate elasticity of substitution between capital and labor from various studies. They also find in Leon-Ledesma et al. (2015) this elasticity to be 0.7.

story to include other factors such as automation.[8]

Nonetheless, there are a few recent exceptions such as Karabarbounis and Neiman (2014a), Karabarbounis and Neiman (2014b) and Piketty (2014) that attribute the decline in the labor share to the changes in factor prices, namely, falling relative price of capital. In their pioneering paper, Karabarbounis and Neiman (2014b) use cross-sectional variation across countries in terms of the labor share trends and capital prices and estimate the elasticity of substitution between capital and labor as 1.25. They find that the relative price of investment goods explains almost half of the decline in the labor share. However, Elsby et al. (2013) criticizes their explanation for not being consistent with the coexistence of recent acceleration in the labor share decline and historically slow capital investment. More importantly, even though they also check the robustness of their findings to the changes in skill composition, their methodology does not allow them to identify the role played by the changes in the stock of skill in labor share movements. What differentiates this paper from the work of Karabarbounis and Neiman (2014b) is its focus on compositional changes of the labor force.

The conflicting results in the literature mainly stems from methodological and data differences. This paper bridges the gap between these two views by identifying the key interaction between capital and various types of labor and how this drives the aggregate decline in the labor share. In this context, what matters for explaining the labor share decline is not the aggregate elasticity of substitution between capital and labor. Rather, the elasticity of substitution between equipment capital and labor devoted to routine tasks plays the key role. Nevertheless, I also estimate an elasticity of substitution between aggregate capital and labor from my model generated data. My estimation lies somewhere between two opposite views, while still preserving consistency with other labor market trends, such as job and

[8] However, taking the general view on the complementarity of capital and labor as given, Lawrence (2015) argues that this complementarity does not contradict the decline in the labor share as he claims that effective capital-labor ratios have actually fallen in the sectors and industries that account for the largest portion of the declining labor share in income since 1980.

wage polarizations.

There are several other explanations proposed in the literature as well. For example, Elsby et al. (2013) provide evidence that offshoring of labor might be the leading contributor of the decline in the US labor share. Guerriero and Sen (2012), on the other hand, suggest that trade openness and technological innovation have a positive and significant effect on the labor share, while automation seems to be one of the negative drivers. In their recent work, Alvarez-Cuadrado et al. (2015) document that the labor share trends differ between manufacturing and services in many developed economies including the US and show that differences in the degree of capital-labor substitutability across sectors can explain both the structural change and the decline in the labor share. Finally, there are a few studies investigating business and medium cycles properties of the labor share, such as Shao and Silos (2014) and McAdam et al. (2015).

1.2.2 Capital-skill complementarity

The second line of literature this paper fits in is the broad capital-skill complementarity literature. A few of the pioneering papers in this vast literature are Katz and Murphy (1992), Greenwood et al. (1997) and Krusell et al. (2000). Among them, this paper is mostly related to Krusell et al. (2000), who also estimate a production function for the US economy. The elasticities estimated in their paper have continued to be used by most of the studies that have capital-skill complementarity or any variants of it such as Routinization Biased Technical Change. At the time of their study, the decline in the labor share was not an issue yet and their model's predictions seemed to be consistent with both the skill premium and the labor share trends. Later, the skill premium kept rising in a period when the labor share was falling.

When I extend the hours and capital stock data in Krusell et al. (2000) to cover the period until 2013 and use their parameters, I find that their model does remarkably well in terms of predicting the course of the skill premium after 1992, which is the end year of their study. However, the updated data and their estimated parameters predict a significant rise in the labor share since then. When I re-estimate their model, the degree of capital-skill complementarity falls, especially due to a weaker absolute complementarity between equipment capital and skilled labor. This considerably curbs the model-predicted rise in the labor share, yet capital-skill complementarity alone is still incapable of capturing the recent decline in the labor share when skill is defined as having a college degree or not. This paper improves the consistency between rising wage premium and declining labor share by splitting labor into skill groups based on the task content of their occupations so that the automation channel is more emphasized. More on this will be elaborated in Section 1.3.

1.2.3 Job polarization

Job polarization, which is defined as the rise in the shares of high and low skill occupations relative to the share of middle skill occupations, has been documented for the US by many studies.[9] Similar employment shifts have been found for other countries as well.[10] Recently, there is a debate over continuance of the job polarization process. While Beaudry et al. (2013) claim that demand for skills has declined to a significant extent since 2000, Autor (2015) argues that new jobs requiring more skills are still being created rapidly.

Even though job polarization can be considered as a nuanced version of capital-skill complementarity, it differs from it in the sense that labor is divided into skill groups in terms of task content of their occupations. This literature explains the erosion of the employment share and relative wages of the middle class by the advances in computer and related technologies that enable firms to replace their routine task implementing employees with cheaper

[9] A few examples are Autor et al. (2003), Acemoglu and Autor (2011), Acemoglu and Autor (2012) and Autor and Dorn (2013).

[10] See Goos and Manning (2007) and Bisello (2013) for UK; Spitz-Oener (2006), Dustmann et al. (2009) and Kampelmann and Rycx (2011) for Germany; Ikenaga and Kambayashi (2010) for Japan, and Goos et al. (2011), Nellas and Olivieri (2012) and Fernandez-Macias (2012) for other European countries.

computer technology.

This literature mostly focused on the existence, causes, and consequences of job polarization and its implications for wage and income inequalities. Recently, the focus has shifted to the cyclical properties of job polarization.[11] However, to my knowledge, the link between job polarization and the labor share has not been studied yet and this paper will be one of the first, if not first. Furthermore, this paper contributes to this literature by estimating the most appropriate elasticities of substitution consistent with job polarization as well as the decline in the labor share.

1.3 Data and Facts

In this section, I first explain the reasons behind my choice of skill definition. Later, data sources and an outline of the methodology used in calculation of efficiency hours and wages are described. Details of the methodology can be found in Appendix 1.9.3. Finally, some motivating facts from the data are presented.

1.3.1 Rationale for the choice of task-based labor classification

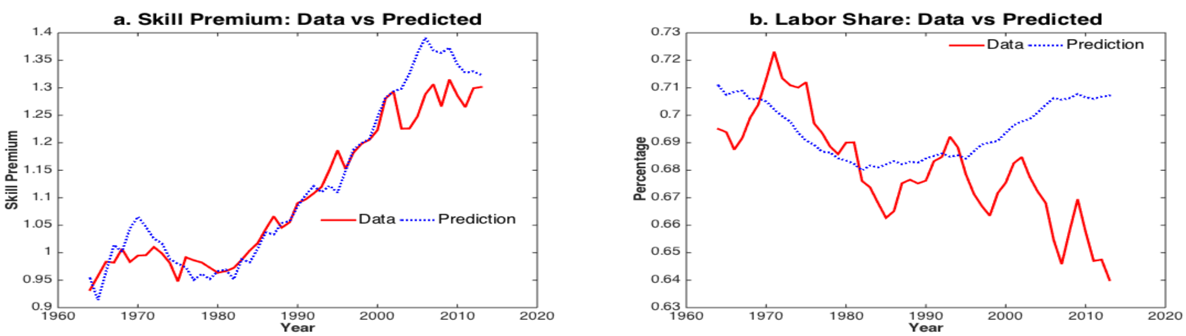
Unlike the standard capital-skill complementarity literature, this paper classifies labor based on the tasks associated with their occupations, rather than them having a college degree or not. Occupations are grouped into three categories following the works of Acemoglu and Autor (2011), Autor and Dorn (2013), Autor et al. (2003), Autor and Dorn (2013) and Jaimovich and Siu (2012) among many others: cognitive, routine, and manual.[12] The main

[11]See, for example, Jaimovich and Siu (2012), Albanesi et al. (2013), Smith (2013) and Foote and Ryan (2014) among several others.

[12]Details of the occupational classification can be found in Appendix 1.9.3. In short, routine tasks are the ones that can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures. These tasks can be replaced by machines, computers or even be offshored. In contrast, when a task requires instant decision making, flexibility, taking initiatives, problem solving, creativity and

reason for this choice is the inability of the education-based skill definition to fully account for the whole trend decline in the labor share. To be more specific, the commonly used elasticities of substitution used in the literature, which are derived for the skill groups based on years of education, are inconsistent with the decline in the labor share. This is depicted in Figure 1.1, where I extend the data set of Krusell et al. (2000) and plot the prediction of their model for the 20 years following their original period of study.[13]

Figure 1.1: Data and Prediction of Krusell et al. (2000)



Note: The figure shows the predicted paths of the skill premium (a) and the labor share (b) by the production function estimated by Krusell et al. (2000) for the period 1963-1992.
Source: Author's calculations using the extended dataset of Krusell et al. (2000) and their original parameters.

Panel (a) of Figure 1.1 shows that the model estimated by Krusell et al. (2000) for the period 1963-1992 can successfully predict the course of the skill premium until recent years- except for a jump up predicted by the model in early 2000s. However, as the panel (b) demonstrates, when the estimated production function is fed with the observed series of

personal interaction, then it is classified as non-routine. Cognitive non-routine occupations mainly consists of cognitive tasks that require extensive mental activity. A few examples in this category are managerial, professional and technical occupations. Furthermore, manual non-routine service jobs that mostly require physical activity but at the same time taking initiatives, flexibility, personal interaction and decision making falls in this category as well.

[13] I am indebted to Professor Lee Ohanian and Professor Gianluca Violante for sharing their code and data.

skilled and unskilled hours, as well as capital series, their model predicts a counterfactual rise in the labor share in last two decades. When I re-estimate their model for the entire period between 1963-2013, the predicted rise in the labor share is trimmed to a large extent. However, this comes at the expense of a worsening of the fit of the skill premium. Furthermore, even though the fit of the labor share improves substantially, it still cannot account for the acceleration in the decline of the labor share in the last decade. In later sections, I show that switching to the task-based definition of skill substantially improves our ability to replicate the trend of the labor share. This is the main reason that this paper seeks the answer to the decline in the labor share in job polarization literature that uses the task-based skill definition.

I also believe that the task-based definition of skill is more dynamic and more responsive to technological advancement than education-based definition. First, we see that the share of college degree attainment had been on the rise even long before the onset of the decline of the labor share and this process still continues with no noticeable trend shift. However, job polarization is a more recent phenomenon and it coincides with the trend decline in the labor share. Furthermore, switching between occupations is a more dynamic choice as it responds to the business cycles and labor market conditions. On the other hand, moving up in the educational ladder takes time, while moving down is practically impossible within a generation. Second, when the Current Population Survey (CPS) data is analyzed, one can see that around 22% of the college graduates already work in less paying, routine occupations.[14] If we assume that wages paid in an occupation reflects the productivity of labor, then years of education does not seem to be a perfect measure of skills possessed by labor. Finally, we see both in data and in my model that the labor share is falling mainly due to the fall in the labor share of workers in routine occupations, while that of the ones in non-routine occupations is on the rise in all sectors. Hence, it is important to separate these two groups

[14]The number is larger for high school or lower degree graduates in non-routine occupations, since these jobs also include the low skill service jobs. Yet, even in managerial positions, there is a significant portion of workers without a college degree.

from each other to identify the causes of the overall decline in the labor share. Bringing all these together, it turns out that occupational skill classification is the most appropriate choice for the purpose of my paper.

1.3.2 Data sources

1.3.2.1 Hours and wage data

The derivation of efficiency hours and wages closely follows from Krusell et al. (2000) and Domeij and Ljungqvist (2006). The main source of wage and occupational composition data is the CPS March Supplement for the years between 1967 and 2013.[15] I used all the person level data, excluding the agents who are younger than 16 or older than 70, self employed, unpaid family workers and working in either agriculture or military. Observations with reported annual working hours less than 260 (quarter of part time work) in last year and hourly wages below half the minimum federal wage rate are dropped to clean out the outliers and misreportings in data. After these adjustments, we are left with annual observations ranging from $55,721$ (1996) to $96,184$ (2001).

The main variables of interest are the nominal hourly wage rates and hours of three types of labor. The details of obtaining the hourly wages and the resulting task premiums are described in Appendix 1.9.3. In short, I first calculated the total hours worked last year by multiplying the usual hours worked by the weeks worked last year.[16] Later, annual wage and salary income is divided by total hours worked last year to obtain the nominal hourly

[15]CPS data is compiled and published by IPUMS (Flood et al. (2015)). For the data between 1967 and 2013, I used CPS files from 1968 to 2014. Even though the capital stock and price series are available for earlier years, I restrict the period of study to start from 1967 since consistent occupational data is available only starting from this year.

[16]These series are not available for CPS years before 1976. For those years, I used hours worked last week instead of usual hours worked and I had to use the intervalled weeks worked last year. Please see the Appendix 1.9.3 for details of how these series are used.

wage rate of each agent. Finally, each agent is assigned to one of 198 groups by age, sex, race, and task.[17] I calculated average hours and wage rates of each group and then aggregated them into three task groups using the group wages of a particular year for the aggregation.[18] Task premium between two task groups is simply obtained by dividing the wage rate of one group by the wage rate of another group.

CPS income data is topcoded, meaning that the observations above a certain threshold are censored to ensure confidentiality. Topcoding practice has changed from time to time, thereby causing jumps in the task premium series. Fortunately in 2012, the Census Bureau released a series of revised income topcodes files that reconciled the topcoded income values between the CPS years 1976 and 2010 with the topcoded values based on the Income Component Rank Proximity Swap methodology that was introduced in year 2011.[19] Having a consistent topcoding method throughout 1975-2013 period enabled us to eliminate the jumps resulting from the switches in topcoding methodology. For earlier years, no adjustments are made to topcoded values.[20]

1.3.2.2 Capital stock and price series

Construction of structural capital series is straightforward. First, nonresidential structural capital investment series from the NIPA Table 5.2.5 are deflated and, using these series and a depreciation rate of 0.0275, I recursively construct structural capital stock series. The initial structural and equipment capital stock series are chosen to match the work of Krusell

[17] Alternatively, I doubled the size of groups by controlling for education as well. This did not affect key findings of the paper.

[18] Here, there is an assumption that the groups within a class are perfect substitutes (Krusell et al. (2000)).

[19] IPUMS (Flood et al. (2015)) published these swap values along with IPUMS identifiers and income variable names.

[20] I also multiplied the topcoded values by 1.45 as suggested by Krusell et al. (2000) and the key findings of the paper remained intact.

et al. (2000), who start from a value of capital that matches the investment/capital ratio as in Gordon (1990).

To obtain investment in equipment capital in efficiency units, we need to use quality adjusted measures of equipment capital prices. Fortunately, capital price series of Krusell et al. (2000) are updated and published by DiCecio (2009) until the year 2013. These price series are used in deflating the investment in nonresidential equipment capital and intellectual property products in NIPA Table 5.2.5. The efficient equipment capital stock is then constructed in the same way as structural capital series, using a calibrated depreciation rate of 0.1460.

1.3.2.3 Aggregate and disaggregated labor shares

I follow Krusell et al. (2000) and calculate the aggregate labor share as the ratio of labor income to the sum of labor income and capital income (depreciation, corporate profits, net interest and rental income of people) from NIPA Table 1.10. Unfortunately, it is not possible to measure the labor shares of different task groups using the NIPA tables. To approximate those, I calculated the total wage bill of three groups of labor using the CPS data and obtained share of each group in total wage bill.[21] These shares are used as the weights of each group in the aggregate labor share. This follows from the assumption that non-wage labor income across groups are proportional to the wage income of each group.

Even though the sectoral story is not the central focus of this paper, the sectoral data is used in calibration, as well as testing some of the predictions of the model. The sectoral labor shares are calculated from the labor file of World-KLEMS dataset of Jorgenson (2012), while sectoral capital stock and compensation series are taken from the capital files of EU-KLEMS data set constructed by O'Mahony and Timmer (2009). I combine this data with

[21] I used a wider CPS sample than the one used for obtaining efficiency hours and wages. In particular, I did not exclude even the agents who reported below 260 hours in calculation of hours. Furthermore, I used raw hours here rather than the efficiency hours since the aim here is to calculate the wage bill of each group.

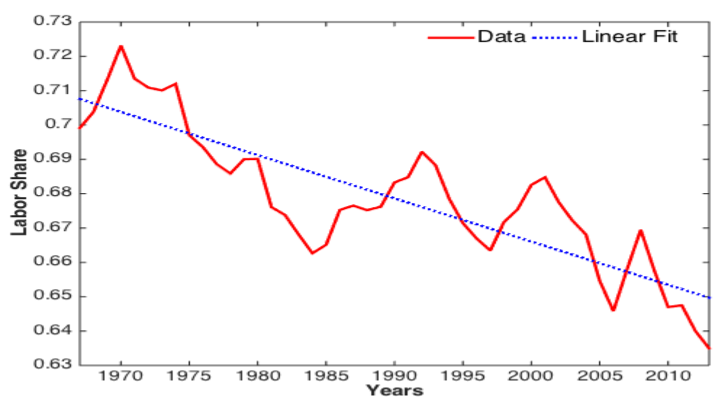
my calculations of hours and wage - and hence task specific labor shares- data from CPS. EU-KLEMS and World-KLEMS data sets provide capital stock and the labor share series for up to 72 industries. I aggregate those sectors into 27 groups, excluding agriculture, public administration and military and real estate activities.[22]

1.3.3 Facts from the data

In this subsection, basic facts from the data that motivated this paper are presented.

Fact 1: The aggregate labor share has declined substantially in last few decades. The total decline in the labor share between the years 1967 and 2013 accumulates up to 9.6%. The trend coefficient of the labor share depicted in Figure 1.2 corresponds to 0.13% decline per year.

Figure 1.2: The US Labor Share of Income



Source: Author's calculations from NIPA tables.

[22]Sectoral classification of CPS data and EU-KLEMS data do not match one-to-one as the former is based on NAICS classification while the latter uses ISIC Rev. 4 to classify the industries. To match these two, I took the EU-KLEMS aggregations and aggregated the CPS sub-industries at three-digit level into two-digit level consistent with ISIC classification.

Fact 2: Most of the trend decline in the labor share has taken place in two periods: 1967-1984 **and** 2003-2013**.** The latter period follows the ICT boom years that occurred between 1996-2003. As Figure 1.3 demonstrates, during this period, the average annual percentage decline in equipment capital prices doubled from around 3.5% to above 7%, while the rise in equipment capital stock reached historically high levels. The acceleration in the decline in labor share following the ICT boom strengthens the conjecture that the decline in the labor share might be closely related to equipment-specific technological progress and its interaction with various task groups.

Figure 1.3: Growth of Relative Price and Stock of Equipment Capital

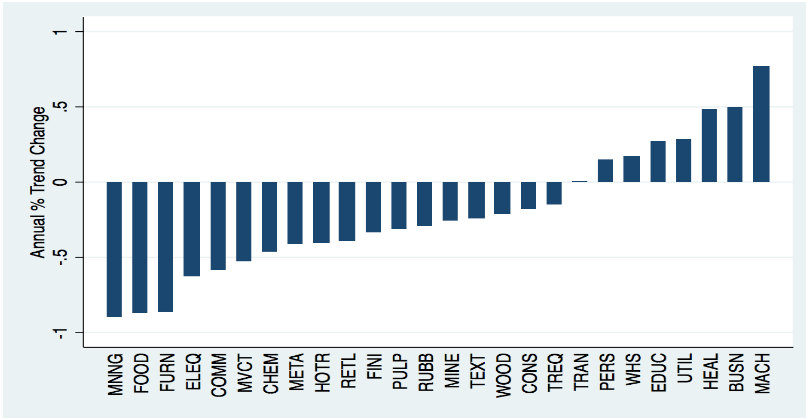
Note: Both the price and stock data are relative to structural capital.
Source: Author's calculations from the data set of DiCecio (2009) and NIPA tables.

Fact 3: The decline in the labor share mainly stems from within sector changes and hence cannot be attributed to the sectoral shifts in the economy. Even though the share of traditionally high labor share sectors such as manufacturing in value added had been persistently falling, the labor share had been declining in most of the sectors. As a matter of fact, manufacturing industries in general experienced the largest decline in the labor share. This can be seen clearly in Figure 1.4 that plots the labor share trend coefficients for each sector and also in time series plots for each sector that is presented in Figure 1.16.[23][24]

[23]See Table 1.9 in Appendix 1.9.1 for the abbreviations.

[24]Figure 1.4 excludes Coke and Refined Petroleum Products industry as it has three times larger trend

Figure 1.4: The Labor Share Trend Coefficients by Sectors



Note: The y-axis shows the coefficient of the regression of logarithm of the labor share on a constant and a time variable. In this sense, this coefficient shows the annual growth rate of the labor share.
Source: Author's calculations from labor and output files of World-KLEMS data set.

To prove more formally that the decline in the labor share cannot be accounted for by the structural transformation in the economy, I conducted a standard decomposition analysis of the labor share. The within/between decomposition formula used follows from Karabarbounis and Neiman (2014b):

$$\Delta LS_{agg} = \sum_i \left(\bar{\omega}_i \Delta LS_i\right) + \sum_i \left(\bar{LS}_i \Delta\omega_i\right)$$

where, i represents 25 non-agricultural and non-public sectors, data for which is compiled from World-KLEMS data set.[25] The sectors included can be found in Table 1.9. LS denotes the labor share while ω_i is the share of the value added of the sector i in total value added. Variables with a bar stand for the average value for the entire period between 1967 and 2010. The first component on the right hand side measures the within component of the decline in the labor share, while the second term represents the between component.

coefficient than the next sector with largest trend coefficient.

[25]The aggregate labor share I calculated from NIPA Tables and the series I obtained from World-KLEMS data set are different and hence not directly comparable. However, they both foresee a similar decline at the aggregate level. Therefore, since World-KLEMS is the only detailed source of the labor share at the sectoral level and what matters for the purpose of this study is the general trends at the sectoral level, I used them in sectoral analysis as a proxy to NIPA tables.

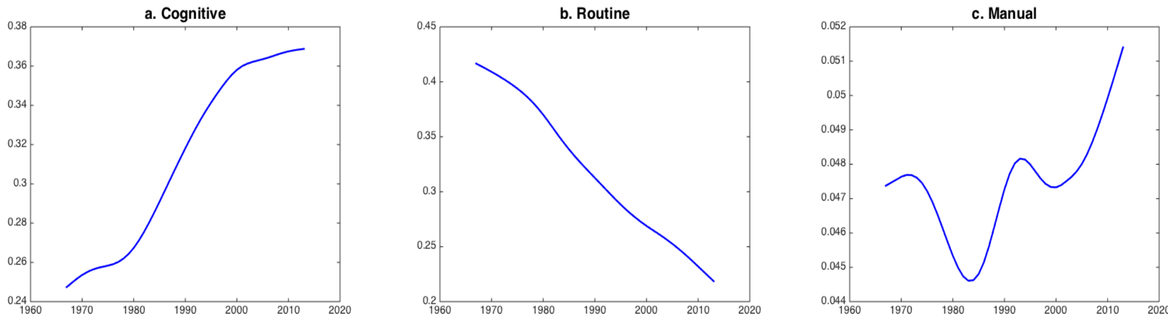
Table 1.1 shows that 73.7% of the decline in aggregate labor share in US stems from the within sector changes during the entire period of study. This number rises to 95% for the second half of the study. However, for the earlier periods, the between sector component drives the entire fall in the labor share. Thus, since it does not encompass sectoral shifts, my model is expected to be more successful in explaining the decline in the labor share in post-1990 period.

Table 1.1: Decomposition of the Labor Shares for Various Periods

Period	**Within**	**Between**
1967-1989	−36.8%	136.8%
1990-2010	95.0%	5.0%
1967-2010	73.7%	22.3%

Fact 4: The decline in the aggregate labor share is driven solely by the decline in the share of labor working in routine task occupations in aggregate income, while labor devoted to non-routine tasks enjoyed a substantial rise in their share of income. Figure 1.5 splits the aggregate labor share into three groups: cognitive, routine and manual. These plots are obtained by calculating the wage bills of each group from CPS and using their share in the total wage bill as their weight in the aggregate labor share. As it is clear from panel (b) Figure 1.5, routine task labor experienced a substantial and a continuous fall in labor share, which accumulates up to 50% in last 47 years. Panel (a) shows that the cognitive labor share rapidly rose between 1980 and 2000 and slowed down since then. This is consistent with the findings of Beaudry et al. (2013), who documented that the demand for skill has recently declined. Finally, as depicted in panel (c), manual service labor, on the other hand, experienced only a limited rise in its share of income. Moreover, Figure 1.17, which is constructed in the same way as Figure 1.4, shows that the fall in routine and gain in non-routine labor shares are common across all sectors.

Figure 1.5: The Labor Share by Tasks



Note: The series are HP-trends.

Source: Author's calculations from CPS and NIPA.

1.4 Empirical Analysis: Estimation and Implications

In this section, the structural partial equilibrium model used in estimation is introduced first. Later, the estimation strategy is presented. This is followed by an overview of the algorithm. Finally, the estimation results and its implications are discussed.

1.4.1 Partial Equilibrium Model

1.4.1.1 Model environment

Two of the equations employed in estimation come from the profit maximization decision rules of a representative firm that produces using a general production function, which allows, but does not enforce job polarization characteristics. The firm chooses between five factors of production: structural capital, equipment capital, and three type of hours in efficiency units: cognitive, routine, and manual. The elasticities of substitution between equipment capital and each type of labor are allowed to differ.

Even though not modeled explicitly, two other sectors give input to our model equations. First, a household sector is assumed to own the two types of capital used in production. The investment decision rules of the household between two types of capital provide us with a no-arbitrage condition between the returns on them. Combined with firm's first order conditions, this constitutes our third equation used in estimation. Second, I implicitly assume that there are perfectly competitive firms producing equipment capital and their profit maximization decision allows us to model technological advancement as a decline in the relative price of equipment capital. All these sectors are introduced in more detail in the upcoming subsections.

1.4.1.2 Final good production technology

The final good, Y_t, is produced using five factors of production:

$$Y_t = A_t G\left(K_{str,t}, K_{eq,t}, h_{c,t}, h_{r,t}, h_{m,t}; \varphi_{c,t}, \varphi_{r,t}, \varphi_{m,t}; \Upsilon\right)$$

where, K_{str} is structural capital, K_{eq} is equipment capital, and h_c, h_r and h_m are raw hours worked in cognitive, routine, and manual task occupations, respectively. Similarly, φ_c, φ_r and φ_m are efficiencies of these labor groups. Furthermore, A denotes for the neutral technological change. Finally, Υ is the set of model parameters, most of which will be estimated.

Below is the specific functional form used in baseline estimation.

$$Y_t = A_t K_{str,t}^{\alpha} \left(\mu L_{r,t}^{\sigma} + (1-\mu) \left(\theta \left[\lambda K_{eq,t}^{\rho} + (1-\lambda) L_{c,t}^{\rho} \right]^{\frac{\beta}{\rho}} + (1-\theta) L_{m,t}^{\beta} \right)^{\frac{\sigma}{\beta}} \right)^{\frac{1-\alpha}{\sigma}} \tag{1.1}$$

Here, L_c, L_r and L_m denote the efficiency hours for the respective task groups, which are defined as follows:

$$L_{i,t} = e^{\varphi_{i,t}} h_{i,t} \qquad \forall i \in \{c, r, m\} \tag{1.2}$$

This production function differs from that in Krusell et al. (2000) in the sense that it has three skill groups rather than two. I tried several alternative functional forms differing especially in the position of manual service hours.[26] Since it generated the best fit of the data among all other alternatives, and also is consistent with the job polarization literature

[26] Among several others, two main alternative functional forms estimated are as follows:
(1) $G(.) = A_t K_{str,t}^{\alpha} \left(\mu \left[\theta L_r^{\beta} + (1-\theta) L_m^{\beta} \right]^{\frac{\sigma}{\beta}} + (1-\mu) \left[\lambda K_{eq}^{\rho} + (1-\lambda) L_c^{\rho} \right]^{\frac{\sigma}{\rho}} \right)^{\frac{1-\alpha}{\sigma}}$, and
(2) $G(.) = A_t K_{str,t}^{\alpha} \left(\mu L_r^{\sigma} + (1-\mu) \left[\lambda K_{eq}^{\rho} + (1-\lambda) L_c^{\rho} \right]^{\frac{\sigma}{\rho}} \right)^{\frac{1-\alpha-\beta}{\sigma}} L_m^{\beta}$.

in the sense that manual tasks are weakly complementary to equipment capital, equation 1.1 is chosen as the baseline functional form.[27]

The complete set of parameters are $\Upsilon \in \{\sigma, \rho, \beta, \alpha, \mu, \lambda, \theta\}$. The last three are weight parameters and thus not at the center of our focus. The first three, on the other hand, are the key parameters governing the elasticities of substitution between equipment capital and different task groups. Using the definition of Krusell et al. (2000), the elasticity of substitution between routine (unskilled) hours and the composite product of equipment capital and non-routine hours (cognitive and manual) is $\frac{1}{1-\sigma}$, while the elasticity of substitution between equipment capital and cognitive (skilled) hours is defined as $\frac{1}{1-\rho}$.[28] Similarly, $\frac{1}{1-\beta}$ is the elasticity of substitution between manual task and the combined output of cognitive task and equipment capital. Finally, the parameter α determines the share of structural capital compensation in value added and can easily be calibrated from the data.

I define capital-task complementarity as $\sigma > \rho$ (equivalently, $\frac{1}{1-\sigma} > \frac{1}{1-\rho}$). Therefore, capital-task complementarity implies that when there is equipment-specific technological improvement, which is proxied by a fall in the relative price of equipment capital, and hence equipment capital intensity in production increases, we would expect the share of routine hours in total hours to fall, while that of non-routine hours is expected to rise. Meanwhile, if the increase in the relative supply of non-routine labor does not keep up with the rise in the relative demand for non-routine labor, we would expect the task premium and the wage-bill ratio (defined as the ratio of total wage bill of non-routine labor to the total wage bill of routine labor) to rise as well. Considering the large decline in equipment capital prices

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[27]Basically, the elasticities between equipment capital and labor associated with routine and cognitive tasks did not change significantly with other specifications considered. Thus, my choice of functional form is based on the consistency of the model generated and data series of the manual labor share.

[28]This definition of elasticities are based on the assumption that all other factors are constant. When other factors change, elasticities of substitution might change as well. However, Polgreen and Silos (2009) report that none of the findings is significantly altered if Allen and Morishima elasticities of substitution are used instead.

(substantial improvement in technology) over the last decades, demand effect is expected to dominate, thereby increasing the task premium and wage bill ratio between non-routine and routine task occupations.

The representative firm maximizes its profits by choosing five factors of production $K_{str,t}$, $K_{eq,t}$, $h_{c,t}$, $h_{r,t}$ and $h_{m,t}$, while taking the efficiencies of three task groups $\varphi_{c,t}$, $\varphi_{r,t}$ and $\varphi_{m,t}$; and wage rates and rental rates as given. Using the final good and structural capital as the numeraire, and hence setting the price of final good as 1, the profit of the representative firm at time t is as follows:[29]

$$\Pi_t = Y_t - r_{str,t}K_{str,t} - r_{eq,t}K_{eq,t} - w_{c,t}h_{c,t} - w_{r,t}h_{r,t} - w_{m,t}h_{m,t} \tag{1.3}$$

where, $r_{str,t}$ and $r_{eq,t}$ are the rental rates of structural and equipment capital, respectively. Similarly, $w_{c,t}$, $w_{r,t}$ and $w_{m,t}$ denote the hourly wage rates of cognitive, routine, and manual task occupations at time t.

Two of the equations I will use in the estimation process are derived from the first order conditions of the firm's problem that can be found in equations 1.53-1.57 in Appendix B.[30] Those two equations are the task premiums between three task groups. Task premium between cognitive and routine occupations (equation 1.4) is obtained by dividing equation 1.53 by equation 1.54. Similarly, the second task premium I target is the relative wages of cognitive and manual tasks and it is calculated by dividing equation 1.53 by equation 1.55 (equation 1.5). Targeting these two automatically implies targeting the premium between routine and manual tasks as well, and thus, the third task premium is not among my targets. Finally, the third equation of the estimation is derived using equations 1.56 and 1.57 from the firm's problem and a no-arbitrage condition coming from the household problem as it

[29]We are assuming here that 1 unit of final good can be transformed into 1 unit of structural capital, while equipment capital is produced using a different technology that will be described soon. Validating this assumption, data reveals that price of final good and structural capital have a correlation of almost 1.

[30]For the sake of notational simplicity, I might not be using time subscript from now on. Yet, the reader should keep in mind that each equation is time specific.

will be described soon.

$$tp_{cr} = \frac{w_c}{w_r} = \frac{(1-\mu)\theta(1-\lambda)}{\mu}\left(\theta\left[\lambda K_{eq}^{\rho} + (1-\lambda)L_c^{\rho}\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^{\beta}\right)^{\frac{\sigma}{\beta}-1} \times \left[\lambda K_{eq}^{\rho} + (1-\lambda)L_c^{\rho}\right]^{\frac{\beta}{\rho}-1}\frac{L_c^{\rho}h_r}{L_r^{\sigma}h_c} \quad (1.4)$$

$$tp_{cm} = \frac{w_c}{w_m} = \frac{\theta(1-\lambda)}{1-\theta}\left[\lambda K_{eq}^{\rho} + (1-\lambda)L_c^{\rho}\right]^{\frac{\beta}{\rho}-1}\frac{L_c^{\rho}h_m}{L_m^{\beta}h_c} \quad (1.5)$$

Note that my estimation strategy differs from the works of Krusell et al. (2000) and Polgreen and Silos (2009) in the sense that I do not fit the labor share or wage-bill ratios, which are basically the relative labor shares of task groups. In contrast, I target the relative wages consistent with wage polarization and feed the hours of each type of labor, which are supposed to be consistent with job polarization. Then, the labor share is just plotted as an output of the model. One of the motivations of this paper is to investigate whether the decline of the labor share is consistent with job and wage polarizations and this strategy enables us to test this conjecture.

1.4.1.3 Equipment capital producing technology

Final output is used for three purposes: consumption C_t, investment in equipment capital $I_{eq,t}$ and investment in structural capital $I_{str,t}$:

$$Y_t = C_t + I_{eq,t} + I_{str,t} \quad (1.6)$$

Production technology of structural capital is quite standard: one unit of investment good is converted into one unit of structural capital. Hence, prices of both final good and structural capital are normalized as 1. On the other hand, equipment capital is produced by perfectly competitive firms, converting part of the final good that is invested in equipment capital into q_t units of equipment capital, where q_t is the relative productivity of equipment capital producing sector.

Perfect competition in this sector guarantees that:

$$p_{eq,t} = \frac{1}{q_t} \tag{1.7}$$

In our model, equipment capital biased technological advancements are formalized by increases in q_t. However, since q_t is hard to measure in data, following equation 1.7, I will use the decline in the relative price of equipment capital as the proxy of technological progress.

1.4.1.4 Household's problem

Even though, as common in the literature, I abstract from the households' labor supply decisions and take them as given for the representative firm in the estimation, households play a crucial role with their decisions on how to allocate the investment between two types of capital. The representative household faces the following budget constraint:

$$C_t + I_{str,t} + I_{eq,t} \leq W_t L_t + R_{str,t} K_{str,t} + R_{eq,t} K_{eq,t} \tag{1.8}$$

along with the laws of motion for two types of capital:

$$K_{str,t+1} = I_{str,t+1} - \delta_{str} K_{str,t} \tag{1.9}$$

$$K_{eq,t+1} = q_t I_{eq,t+1} - \delta_{eq} K_{eq,t} \tag{1.10}$$

where, δ_{str} and δ_{eq} are the depreciation rates of structural and equipment capital respectively, W_t is the wage per hour worked and $R_{str,t}$ and $R_{eq,t}$ are the gross returns of each type of capital.[31]

Household's utility maximization yields two Euler equations: one for each type of capital. Equilibrium requires that the expected rates of return on these two types of capital

[31] Note that we are assuming that households supply a certain amount of hours, which is then assigned into tasks by the representative firm. The wage rate W_t, then, can be considered as a weighted average of wage rates of each type of labor.

should be equalized. Otherwise, households would invest only in one type of capital. Thus, manipulating the two Euler equations, I obtain the third -and the last- equation that I use in the estimation process:

$$E\left(\frac{p_{eq,t+1}}{p_{eq,t}}\right) = \frac{1}{(1-\delta_{eq})}\left[MPK_{str,t+1} + (1-\delta_{str}) - \frac{MPK_{eq,t+1}}{p_{eq,t}}\right] \tag{1.11}$$

where E denotes the expected value and $MPK_{str,t+1}$ and $MPL_{eq,t+1}$ are marginal products of capital for structural and equipment capital. These are equivalent to $r_{str,t+1}$ and $r_{eq,t+1}$ coming from the first order conditions of the firm depicted in equations 1.56 and 1.57.

1.4.2 Estimation Strategy

The estimation strategy is in line with Krusell et al. (2000), while the methodology is mostly borrowed from Polgreen and Silos (2008). The partial equilibrium model, introduced in earlier sections, is reduced into a non-linear state space model with three observation and three state equations. The observation equations are equations 1.4 (task premium between cognitive and routine tasks), 1.5 (task premium between cognitive and manual tasks) and 1.11 (no-arbitrage condition in capital markets) summarized in the following form:

$$Z_t = f(X_t, \varphi_t, \varepsilon_t; \phi) \tag{1.12}$$

where, the function $f(.)$ contains the three non-linear observational equations, while $X_t = \{K_{str,t}, K_{eq,t}, h_{c,t}, h_{r,t}, h_{m,t}, p_{eq,t}\}$ is the set of observed covariates as described earlier. $\phi = \{\alpha, \sigma, \rho, \beta, \mu, \lambda, \theta, \varphi_{c,0}, \varphi_{r,0}, \varphi_{m,0}, \delta_s, \delta_e, \sigma^2_\varepsilon, \sigma^2_\eta\}$ is the set of parameters-most of which will be estimated while some of them are calibrated from the data. ε_t is the 3×1 vector of measurement error with a multivariate normal distribution with zero mean and variance $\Omega = \sigma^2_\varepsilon I_3$, where I_3 is 3×3 identity matrix. σ^2_ε will be estimated along with rest of the parameters. Finally, Z_t is a 3×1 vector of observations: two task premiums and the growth rate of the relative equipment capital price.

One source of estimation error stems from the relative price of equipment capital, which is related to the returns on both types of capital as summarized in equation 1.11. This error is accounted for in the measurement error vector ε_t. The second source of uncertainty is the three efficiency factors for each types of labor. Even though these factors are known to the firm, they are not observable to us from the data. Hence, we have to define a stochastic process for efficiency factors. Following the steps of Krusell et al. (2000), I rule out the trend variation in labor quality of each type and focus only on the effects of observable variables, such as capital deepening and labor supply on the income shares and the task premiums. The stochastic processes for three task groups compromise our state equations:

$$\log(\varphi_{j,t}) = \log(\varphi_{j,0}) + \eta_t \tag{1.13}$$

where, $\varphi_{j,0}$ is the vector of parameters specifying the average efficiencies of cognitive, routine, and manual labor and η_t is a 3×1 vector of shocks, which is assumed to have a multivariate normal distribution with zero mean and covariance matrix $\Sigma = \sigma_\eta^2 I_3$. σ_η^2 will also be an outcome of our estimation process.

Table 1.2 presents the list of parameters that needs to be estimated. Since μ, λ θ, $\varphi_{c,0}$, $\varphi_{r,0}$ and $\varphi_{m,0}$ are all scaling parameters, one of them is fixed as a normalization as Krusell et al. (2000) does: $\varphi_{c,0}$. Depreciation rates are both capital specific and I calibrate them using NIPA tables for capital stock and consumption. The resulting depreciation rates are 0.0275 for structural and 0.1460 for equipment capital. Since incorporating the manual labor into the model raised the number of parameters to be estimated, I preferred calibrating α using the EU-KLEMS capital and output files.[32] This suggests that $\alpha = 0.1058$, which is consistent with the finding of Krusell et al. (2000) as well.

1.4.3 Algorithm

I estimated the parameters of the production function using both two-stage simulated pseudo-maximum likelihood estimation (SMPLE) algorithm of Krusell et al. (2000), and the Bayesian

[32] Alternatively, I also estimated α along with rest of the parameters. However, this required targeting the labor share as well since the original targets does not have enough information to recover α. Estimating α with rest of the parameters did not alter the estimation results for other parameters.

Table 1.2: Parameters to be Estimated

$\frac{1}{1-\rho}$	Elasticity of subst. b/w L_c and K_{eq}
$\frac{1}{1-\sigma}$	Elasticity of subst. b/w L_r and composite of L_c, L_m and K_{eq}
$\frac{1}{1-\beta}$	Elasticity of subst. b/w L_m and composite of L_c and K_{eq}
μ	Share of l_r in CES b/w L_r and composite of L_c, L_m and K_{eq}
λ	Share of K_{eq} in CES b/w L_c and K_{eq}
$1-\theta$	Share of L_m in CES b/w L_m and composite of L_c and K_{eq}
$\varphi_{r,0}$	Average efficiency of L_r
$\varphi_{m,0}$	Average efficiency of L_m
σ_ε^2	Variance of the measurement errors
σ_η^2	Variance of the state equations errors

Estimation methodology of Polgreen and Silos (2008) and Polgreen and Silos (2009).[33] The estimation results are consistent between two methods. Therefore, the differences in the findings of this paper and the others mentioned above are data-driven, rather than methodological differences. This paper only describes and reports the results from the Bayesian Estimation methodology. A detailed description of SPMLE algorithm can be found in Krusell et al. (2000).

Different from Polgreen and Silos (2009), I follow an approach closer to Krusell et al. (2000) and use instrumental variables to allow for the possible dependence of hours worked on shocks. In this framework, cognitive, routine, and manual task hours are considered to be endogenous and hence regressed on current and lagged stocks of both types of capital, lagged relative equipment capital price, a time trend and the lagged value of OECD's leading business cycle indicator. The fitted values are later used in the methodology of Polgreen

[33] The steps described here are heavily based on an earlier version of Polgreen and Silos (2008) and described in detail in Polgreen and Silos (2005).

and Silos (2009). That is why I name the methodology I use here as two-stage Bayesian Estimation.[34]

As listed in Polgreen and Silos (2009), there are several advantages of using Bayesian inference techniques, especially when there is high-dimensionality problem and it is possible to partition the set of parameters to be estimated. The method used is based on the explicit assumption of measurement error and it uses a Metropolis Hastings-Algorithm, which is a Markov Chain Monte Carlo (MH-MCMC) method of obtaining a sequence of random samples from a probability distribution. Here, a special sampling method is used- namely, Gibbs Sampling, which involves choosing different samples for different dimensions, rather sampling for the whole dimension of the study. Gibbs sampling is especially possible when some of the random variables can be conditioned on some of the others. Considering that we have a large set of parameters to estimate but relatively low number of observations, Gibbs sampling makes the process more efficient by breaking the complex high dimensional problem into simpler low dimensional ones.

Let $\phi = \{\sigma, \rho, \beta, \mu, \lambda, \theta, \varphi_{r,0}, \varphi_{m,0}, \sigma_\varepsilon, \sigma_\eta\}$ be the set of parameters to be estimated. The goal is to characterize the distribution of the parameter set conditional on the covariates and the endogenous variables on the left hand side of the observational equations. I start with an initial guess of probability distribution of parameters, which is called as prior distribution: $p(\phi)$. Using Bayes' theorem, we know that:

$$p(\phi|Z, X) \propto p(\phi)L(Z|\phi, X)$$

where, X is the set of covariates as described earlier, Z is the vector of endogenous variables, $p(\phi|Z, X)$ is the posterior distribution and $L(Z|\phi, X)$ is the likelihood function. Our goal

[34]Apart from this, I deviate from Polgreen and Silos (2009) in two dimensions. First, the production function used is different as it has three types of labor, rather than two. Second, I incorporate total factor productivity into the estimation process as well. They, however, ignore total factor productivity and thus have to restrict the parameter governing the compensation share of structural capital around the level found by Krusell et al. (2000).

is to characterize $p(\phi|Z, X)$ by using the proportionality property above and random sampling. The parameter set ϕ is partitioned into 3 blocks: $\{\sigma, \rho, \beta, \mu, \lambda, \theta\}$, $\{\Omega\}$, $\{\varphi_{r,0}, \varphi_{m,0}, \Sigma\}$ (conditioning on ϕ_{-i}).

The estimation is done in three steps and at each step we apply to a Metropolis Hasting MCMC algorithm. In step 1, the unobserved state (Geweke-Tanizaki method) is sampled. We take the drawn parameters and an initial state space $\{\{\varphi_{i,t}^{k-1}\}_{t=1}^{T}\} \quad \forall i \in \{c, r, m\}$ and update the state space applying to a MH-MCMC step. Step 2 involves sampling the parameters of the measurement equations: first the parameters of the production function and then updating the matrix of measurement errors (Ω) taking the parameters as given. Finally, in step 3, the parameters of transition equations are sampled; first the efficiency parameters and then variances of shock processes.

The priors chosen are close to the ones used by Polgreen and Silos (2009) and presented in Table 1.3. All the findings are strongly robust to the choice of priors as the methodology does not heavily depend on neither the priors nor the initial starting points. Furthermore, as I iterate the process for $1,000,000$ times and burn the first half of the draw before calculating the moments, the effects of the initial choice of parameter means vanish. Finally, I aimed at an acceptance rate between 20% to 40% for each block of the estimation.

1.4.4 Estimation Results

1.4.4.1 Model fit and predictions

One of the goals of the empirical part is to estimate the production function that best describes the job and wage polarizations experienced over the last few decades and see whether the decline in the labor share is consistent with these phenomena. Therefore, I targeted three series from the data: two task premiums and a no-arbitrage condition between the expected returns on two types of capital. Labor share, on the other hand, is the outcome of the model when it is fed with the observables. Panels (a) and (b) of Figure 1.6 show the data and model fit for the task premium between cognitive and routine, and cognitive and

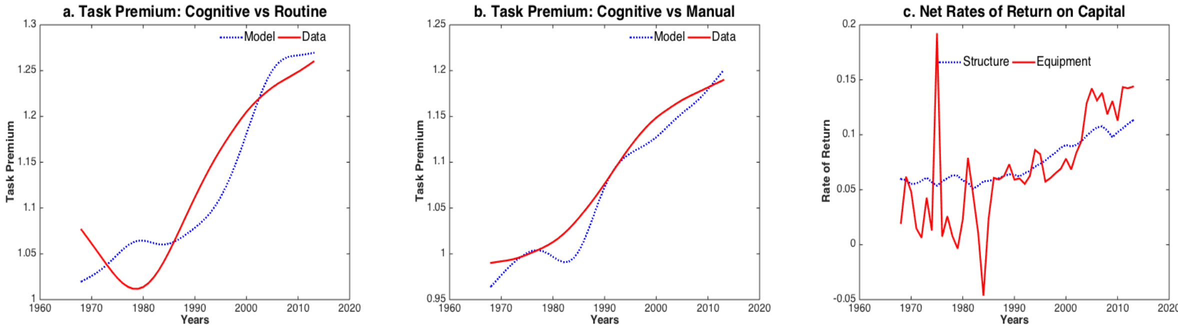
Table 1.3: Priors

Parameter	**Distr.**	**Mean**	**Std.**	**Range**
σ	Normal	0.5	0.25	$[-2, 1]$
ρ	Normal	-0.5	0.25	$[-2, 1]$
β	Normal	-0.5	0.25	$[-2, 1]$
μ	Normal	0.5	0.2	$[0, 1]$
λ	Normal	0.5	0.2	$[0, 1]$
θ	Normal	0.5	0.2	$[0, 1]$
$\varphi_{r,0}$	Normal	0	0.25	$(-\infty,\infty)$
$\varphi_{m,0}$	Normal	-2	0.25	$(-\infty,\infty)$
σ_e^2	Gamma	0.3	0.01	$(0,\infty)$
σ_η^2	Gamma	0.4	0.01	$(0,\infty)$

manual tasks, respectively. To remove noise in data, I present the series in trends since the focus of this paper is long term study of the labor share. The dotted blue lines showing model fit in panels (a) and (b) are plotted with the assumption of zero shocks to the efficiencies and hence, they show the ability of the model and observable covariates such as capital and hours series to account for the changes in data. As panel (a) implies, the model can account for most of the rise in the task premium between cognitive and routine task occupations since 1980s but fails to fully capture the fall prior to that year. Panel (c) on the other hand, shows the net rates of returns on two types of capital, which is obtained by rearranging the no-arbitrage condition.

Figure 1.7 plots the model's predictions in terms of disaggregated and aggregate labor shares. As panels (a) and (b) demonstrate, the model can fully predict the trend rise in cognitive labor share and the decline in routine labor share. However, the model overshoots the rise in manual labor share as it predicts around 15% rise since 1990, while the actual

Figure 1.6: Model Targets: Data vs Model



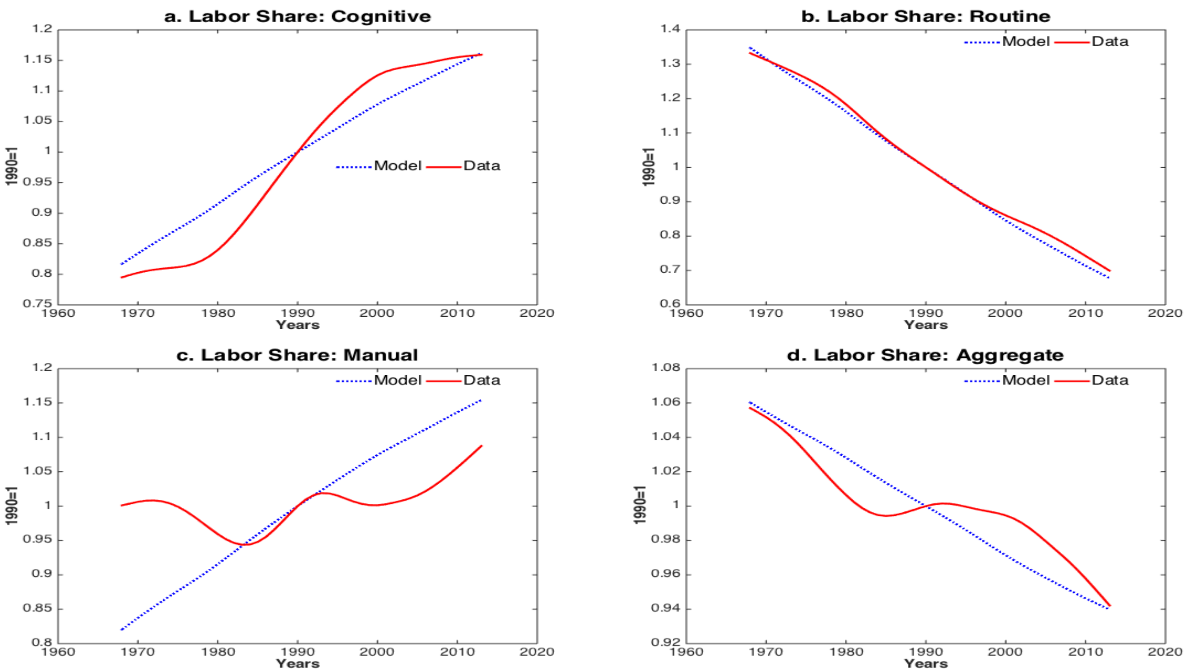
Note: Panels (a) and (b) are HP-trends. Panel (c) shows the expected rates of return on two types of capital in model.

increase is below 10% in the same period. Prior to 1990 on the other hand, the share of this group in total income remained roughly constant while the model predicts 25% rise. This is not surprising in the sense that the complementarity between cognitive and manual tasks is a relatively new phenomenon. Furthermore, in the job polarization literature, manual task occupations are usually not included as one of the factors of the production of the final good. However, the share of this group in total wage bill and hours is very small. Besides, the success of our model to capture the trend decline in the labor share stems from task-based definition, rather than inclusion of manual tasks separately from cognitive non-routine tasks.[35] Therefore, I preferred keeping it as a part of the final good production for computational purposes. However, I will define a second sector employing only manual task labor in the general equilibrium version of the model.

Panel (d) of Figure 1.7 shows that a model describing the job and wage polarizations can fully account for the trend decline in the aggregate labor share. At this point, the reader might wonder whether the estimation strategy automatically implies targeting the

[35]The fit of the aggregate labor share significantly improves when we switch from the education-based skill classification to the task-based classification. On the other hand, when I estimate the model by aggregating cognitive and manual tasks as "non-routine", the fit of the aggregate labor share is not noticeably altered.

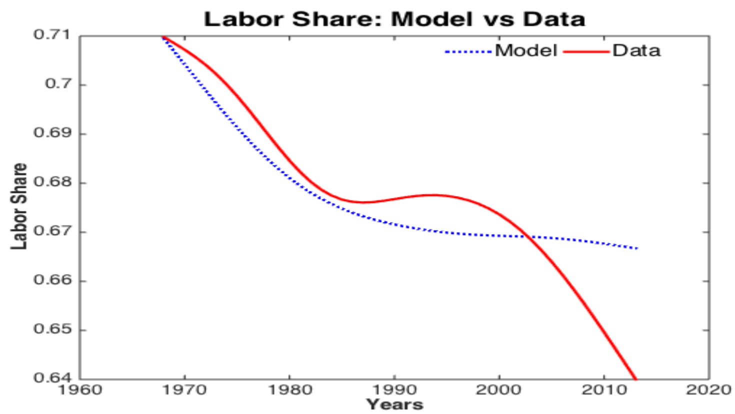
Figure 1.7: Labor Shares: Data vs Model



Note: The series are HP-trends.

labor share or not. In the end, we are targeting relative prices of types of labor and feeding their quantities. Can this guarantee that the labor share trend will be captured in any case? As Figure 1.8 depicts, the answer to this question turns out to be no. This figure shows the model-generated labor share when I estimate the model with the same strategy but define the skill on the basis of having a college degree or not. As in our baseline estimation, I targeted the skill premium and the regular no-arbitrage condition, thereby making the labor share an outcome of the model. Figure 1.8 shows that the model is unable to foresee the decline in the aggregate labor share in the last decade. During the entire period, the model predicted only around 60% decline in the labor share. This proves that switching to the task-based skill definition significantly improves our understanding of the decline of the labor share.

Figure 1.8: Model's Prediction with Education-Based Skill Classification



Note: The series are HP-trends.
The dotted blue line shows the fit of the model when the labor is split as skilled and unskilled on the basis of years of education.

1.4.4.2 Parameter estimates

The key parameters of interest are three elasticities of substitution that were discussed earlier. The estimation results for these parameters are presented in Table 1.4. The elasticity of substitution between equipment capital and labor devoted to routine tasks is measured as 2.40, while equipment capital and labor employed in non-routine occupations are found to be neither substitutes nor complements.[36] Finally, as it can be seen in last column of Table 1.4, there is neither strong complementarity nor substitutability between manual service tasks and the composite of equipment capital and cognitive tasks. This is consistent with the common view in the job polarization literature.

Significance tests conducted at 95% confidence level give p-values higher than 0.05 for

[36]Even though not directly comparable due to different classifications of labor, these elasticities are stronger than the the commonly used measures in the capital-skill complementarity literature. Krusell et al. (2000) report the elasticity of substitution between equipment capital and unskilled labor, which is most closely corresponds to our routine labor, as 1.67. Also, they estimate a strong complementarity between equipment capital and skilled labor, which can be considered as our cognitive labor. The elasticity of substitution between these two factors are measured as 0.67

Table 1.4: Estimation Results

	σ	ρ	β
Mean	0.5833	0.0240	0.0420
Mode	0.5930	-0.0044	0.0462
Standard Deviation	0.0160	0.0198	0.0252
Elasticity	2.40	1.02	1.04

the parameters ρ and β.[37] In other words, the elasticities of substitution between equipment capital and cognitive task, and between manual task and composite of equipment capital and cognitive task are not significantly different from 1. This implies that we can model job/wage polarization and the labor share with a functional form of production that has a Cobb-Douglas relationship between equipment capital, cognitive task and manual task. In more aggregate terms, I document that the production function is Cobb-Douglas between equipment capital and labor associated with non-routine task occupations.

1.4.4.3 Implications

The partially Cobb-Douglas production function has important implications. First of all, it shows that the Neoclassical view of constancy of the labor share is still valid, albeit at a smaller scale. Any part of the income that is lost by labor employed in routine task occupations is proportionately captured by equipment capital and labor devoted to non-routine tasks. This implies that the economy will converge to another steady state with a constant but lower labor share once this transformation is completed. Second, as it will be formally proven in next subsection, with this Cobb-Douglas structure, the changes in the labor share can be pinned down only to the changes in the composition of the wage bill. To

[37] p-value reported for ρ is 0.2265 and for β is 0.0952. Here, the null hypotheses are ρ and β are separately not different from zero.

be more specific, the decline in the labor share can be explained and modeled by capital-task complementarity that will distort the wage-bill ratio between non-routine and routine tasks in favor of the non-routine labor following technological advances. In the upcoming sections, I will introduce a simple general equilibrium model following from this finding and show that equipment-specific technological progress prices and capital-task complementarity alone can account for most of the decline of the labor share. Finally, using Cobb-Douglas specification significantly reduces the burden of the estimation as we now have two less parameters to estimate.

Since the estimation of the general functional form indicate a Cobb-Douglas specification instead of inner CES aggregators, we can use the following production function:

$$Y = AK_{str}^{\alpha}\left(\mu L_r^{\sigma} + (1-\mu)\left[K_{eq}^{\gamma} L_c^{\delta} L_m^{1-\gamma-\delta}\right]^{\sigma}\right)^{\frac{1-\alpha}{\sigma}} \quad (1.14)$$

When I estimate the model using the production function specification in equation 1.14, neither the model fit, nor the prediction of the model in terms of the labor shares is visibly altered. Figure 1.18 replicates Figures 1.6 and 1.7 for the Cobb-Douglas version of the model and the reader can verify that the model fit does not worsen, if not improve.

Table 1.5 reports the estimation outcome for the key parameters. The elasticity of substitution between routine task and the composite of equipment capital and non-routine tasks is 2.33, which is close to the one obtained for the general functional form. As reported in the last column, 35% of the total income that is left after the compensations of structural capital and the routine tasks are paid goes to equipment capital, while the remaining 65% goes to labor employed in non-routine task occupations. Hence, the 65%-35% balance between labor and capital in Neoclassical theory turns out to be still valid in a smaller scale than the aggregate economy.

Table 1.5: Estimation Results for the Cobb-Douglas Specification

	σ	δ	γ
Mean	0.5708	0.5566	0.3528
Mode	0.5610	0.5530	0.3567
Standard Deviation	0.0057	0.0198	0.0066
Elasticity	2.33	-	-

1.4.4.4 Labor share in the model

The production function in equation 1.14 yields the following labor share equation:

$$LS_t = (1-\alpha)\frac{\mu L_{r,t}^{\sigma} + (1-\mu)(1-\gamma)K_{eq,t}^{\sigma\gamma}L_{c,t}^{\sigma\delta}L_{m,t}^{\sigma(1-\delta-\gamma)}}{\left(\mu L_{r,t}^{\sigma} + (1-\mu)\left[K_{eq,t}^{\gamma}L_{c,t}^{\delta}L_{m,t}^{1-\delta-\gamma}\right]^{\sigma}\right)} \tag{1.15}$$

When this equation is rearranged, details of which can be found in equations 1.63-1.70 in Appendix 1.9.2, I obtain the following relationship between the labor share and the wage-bill ratio between non-routine and routine tasks.

$$LS_t = (1-\alpha)\frac{1 + wbr_t}{1 + \frac{wbr_t}{1-\gamma}} \tag{1.16}$$

In growth terms:[38]

$$\widehat{LS}_t = -\widehat{wbr}_t\left[\frac{\gamma}{wbr_t + (2-\gamma) + \frac{(1-\gamma)}{wbr_t}}\right] \tag{1.17}$$

where, the growth rate of the wage-bill ratio between non-routine and routine tasks is given as:

$$\widehat{wbr}_t = \sigma\left[\delta\widehat{L}_{ct} + \gamma\widehat{K}_{eq_t} + (1-\delta-\gamma)\widehat{L}_{mt} - \widehat{L}_{rt}\right] \tag{1.18}$$

Equation 1.17 reduces the growth rate of the labor share down only to negative of the growth rate of wage-bill ratio and a key parameter: γ, which is the weight of equipment capital in Cobb-Douglas segment of the production function. The wage-bill ratio, on the

[38]Steps of converting equation 1.16 into growth terms are presented in equations 1.71-1.77

other hand, rises faster if (i) the possibilities to switch from routine task to non-routine tasks and equipment capital are higher and (ii) the cost function is more sensitive to the changes in equipment capital prices. The former condition corresponds to a larger elasticity of substitution between routine task and composite output of equipment capital and non-routine tasks, while the latter corresponds to a larger weight of equipment capital (γ) in Cobb-Douglas specification.[39]

Equation 1.17 shows that anything that will raise the wage-bill ratio in favor of non-routine labor will cause a decline in the labor share. Thus, in an environment where price of equipment capital declines rapidly and hence stock of equipment capital grows, capital-task complementarity is sufficient to distort the wage-bill ratio in favor the labor working in non-routine task occupations and hence to cause a decline in the labor share. Nonetheless, the effect of the rise in the wage-bill ratio on the labor share decreases over time even if the wage-bill ratio continues to grow infinitely. This can be seen from the second term in equation 1.17: $D_t = \frac{\gamma}{wbr_t + (2-\gamma) + \frac{(1-\gamma)}{wbr_t}}$. The term D_t first rises in wbr_t and then starts falling as wbr_t passes a certain threshold as shown in Figure 1.19. This strengthens our conjecture that the US economy is currently at early stages of a long-term transition period that is likely to cool down in medium term even if the composition of the wage bill continues to change at its current pace.

1.4.4.5 Testing the estimation outcome using the aggregate and sectoral data

If the functional form estimated is correct, we should be able to replicate the decline of the labor share by feeding equation 1.17 with the wage-bill ratio series calculated from the CPS data. Figure 1.9 plots the model fit obtained from this exercise. It is clear from the figure

[39]Note that this condition is also equivalent to having a larger capital-task complementarity, which is measured by σ in our case since the parameter governing the elasticity of substitution between non-routine tasks and equipment capital is documented to be zero. Hence, $\sigma - 0 = \sigma$ is at the same time our capital-task complementarity measure.

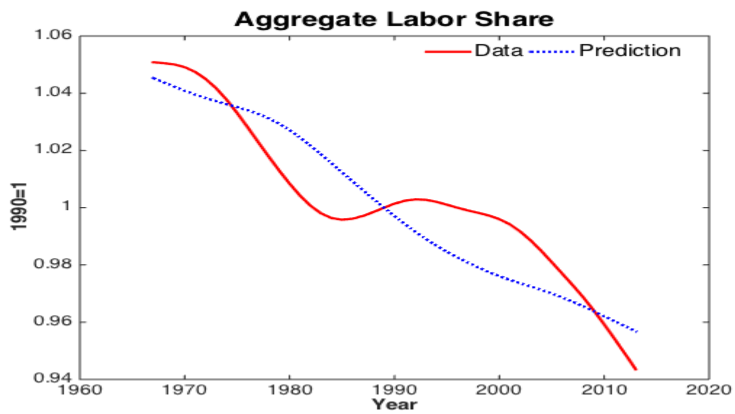
that the wage-bill ratio series can account for almost all of the trend decline of the labor share.

A similar exercise is repeated for some selected sectors. To do so, I first calibrate γs for each sector.[40] Then, I feed equation 1.17 with the sectoral wage-bill ratios. As panels (a) and (b) of Figure 1.20 show, the wage-bill ratio does remarkably well in replicating the decline in labor shares in some sectors such as Food, Tobacco and Beverages, and Finance and Insurance. However, as panels (c) and (d) depict, equation 1.17 fails to fully explain why the labor share rises in some of the sectors. Yet, it does not predict a fall in these sectors either. This failure most probably stems from ruling out other sector-specific factors such as an increase in relative demand for those sectors or heterogeneity in sector-specific technological progresses. Therefore, the model's predictions of the labor share should be considered as a lower bound of our ability to explain the labor share trends by equipment-specific technological change and capital-task complementarity.

Being able to replicate the labor share trend based only on the wage-bill ratio series and a single parameter significantly reduces the burden of the analysis. To be more specific, we do not need to make assumptions about a whole set of capital stocks and prices and labor hour series if we wanted to predict the future path of the labor share. For instance, if we assume that the wage-bill ratio continues to grow at its current average rate of 2% per year, equation 1.17 tells us that the labor share should stabilize around 55%. This also simplifies the general equilibrium model that I will use to quantify the decline of the labor

[40]To calibrate sector specific γs, I first calculated the wage-bill of labor employed in non-routine task occupations from the CPS data. Then I used the ratio of this to total wage bill as the weight of this group in the aggregate labor share. Multiplying this weight by the labor share of this sector in EU-KLEMS data set gave me income share of labor devoted to non-routine tasks in that sector. The share of equipment capital is also calculated from the EU-KLEMS data set. γ is then obtained as the ratio of the equipment capital compensation share to the sum of the compensation shares of equipment capital and labor associated with non-routine tasks.

Figure 1.9: Labor Share Fit by Wage-Bill Ratio Series Alone



The series are HP-trends.

The dotted blue line is generated by feeding equation 1.17 with the wage-bill ratio series calculated from the CPS data and using the parameter $\gamma = 0.3528$.

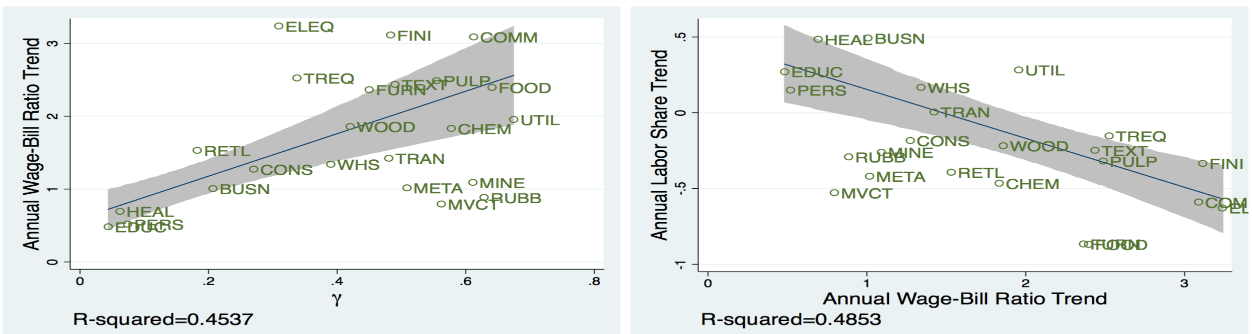
share that can be attributed to equipment-specific technological progress and capital-task complementarity. As long as we have the correct elasticities of substitution between factors of production and a correct weight of equipment capital in Cobb-Douglas specification; the decline in relative equipment capital price will be sufficient to raise the wage-bill ratio in favor of labor working in non-routine task occupations. This, in turn, is expected to generate a trend decline in the labor share at a magnitude similar to the data if the model parameters are well identified.

Before proceeding to the general equilibrium model, I test the key mechanism implied by the estimation using the sectoral data. Left panel of Figure 1.10 shows that for a given level of elasticity of substitution between routine task and composite output of equipment capital and non-routine tasks, in sectors for which the weight of equipment capital compensation in Cobb-Douglas specification is larger, the rise in the wage-bill ratio is larger as well. The weighted coefficient of correlation between the annual trend change of the wage-bill ratio and the parameter γ is 0.67 and significant with a p-value of almost 0.[41] Right panel of Figure 1.10

[41] When producing the figure and correlation coefficient, I excluded four outlier sectors: Mining, Coke and Refined Petroleum, Machinery Equipment, and Hotels and Restaurants. Reader is invited to see Table 1.9

confirms the remaining part of the mechanism: in sectors where the wage-bill ratio rose more, the trend decline of the labor share was larger as well. The weighted correlation coefficient in this case is -0.70 and again significant. To sum up, considering that we ruled out possible differences in elasticities of substitution across sectors, the estimated aggregate production function and the implied key channel driving the labor share trend does remarkably well in capturing the sectoral level experiences as well.

Figure 1.10: Key Channel Tested at the Sectoral Level



Note: Trend coefficients are obtained from regressions of log series on a constant and a time variable.

1.5 General Equilibrium Model

The estimation part has provided us with two important ingredients for modeling the decline of the labor share. First, it gave us the elasticity of substitution measures that are consistent with job and wage polarizations, as well as the decline in the labor share. Second, and more importantly, it revealed that we can model the labor share decline by a rise in the wage-bill ratio, which is triggered by technological advances and capital-task complementarity. Up to now, all the variables of the model, including the wage-bill ratio, were exogenous in

for the abbreviations. Finally, average value added shares of the sectors are used as weights in the regression and the scatter plot.

our analysis. From now on, I will only keep technological change as exogenous and all the remaining variables will be determined endogenously within a dynamic general equilibrium framework. This way, we can quantify part of the labor share trend that we can explain by the decline in relative equipment capital prices only. This model can also be used for conducting counterfactual exercises, labor share projections and policy analysis.

1.5.1 Model Environment

The household sector consists of two types of agents: skilled and unskilled. The representative household of each type has a continuum measure of unit 1 individuals differing in their routine task efficiencies. The representative households supply their labor inelastically and, taking the wages as given, assign their members to the occupations. Members of the skilled household can work in either cognitive or routine task occupations, while the unskilled household makes a choice between routine and manual task occupations. Cognitive and routine hours in efficiency are combined with both structural and equipment capital to produce the final good that is consumed and invested. In addition, there also exists a sector producing manual services by employing only labor doing manual task.[42] Finally, technological progress enters the model exogenously in the form of a rise in the productivity of equipment capital-specific production.

1.5.2 Households' Problem

There is a measure of S skilled and a measure of U unskilled households in the economy. Both types of agents have similar problems in the sense that they assign their members into occupations and save an asset that is used in purchasing both types of capital. However, each type of agent differs in a couple of dimensions. First, members of the skilled household do not have access to the manual labor market, while the unskilled agents cannot be employed

[42]The manual services in the model represent the personal services such as child care, cleaning and home health care.

in cognitive task occupations.[43] On the other hand, both types can work in routine task occupations. Secondly, the manual services are assumed to be consumed only by the skilled agents. This assumption is consistent with the proposed relationship between cognitive task labor and manual services in the job polarization literature. Yet, this is a trivial assumption and does not affect the quantitative findings of the paper.

1.5.2.1 Problem of the skilled agent

The skilled household has members with the vector of efficiencies $(\zeta, \tau_i, 0)$ for cognitive, routine, and manual task occupations respectively. In other words, skilled individuals have access to two labor markets. If they work in cognitive task occupations, their efficiency is ζ and thus, they receive an hourly wage rate of $\zeta w_{c,t}$, where $w_{c,t}$ is the wage rate for cognitive task occupations. Alternatively, they can prefer working in routine task occupations. Their efficiencies in routine task occupations are ranked by τ_i, which is assumed to be distributed uniformly between 0 and 1: $\tau_i \sim U[0,1]$. These identifiers are translated into routine task efficiencies through the function $h(\tau_i)$.[44] Thus, the skilled individuals working in routine task occupations receive efficiency wages equivalent to $h(\tau_i)w_{r,t}$, where $w_{r,t}$ is the wage rate for these occupations.[45] Following Beaudry et al. (2013), I choose $h(\tau_i) = \tau_i^{-\frac{1}{2}}$ as the functional form of routine task efficiency.

The skilled household consumes a composite of final good and manual services; save assets

[43] Even if the skilled agents were allowed to work in manual task occupations, they wouldn't prefer doing so unless manual sector wages are too high. Thus, the set up is simplified by ruling out the manual employment of the members of the skilled household.

[44] Following Beaudry et al. (2013), I rank the efficiencies in descending order: $h(\tau_i') < 0$.

[45] Instead of allowing the members of the skilled household differ in their cognitive task efficiencies, I preferred the current set up for modeling purposes. Thus, having a high routine task efficiency can be considered as having comparative advantage in routine tasks. Therefore, from a reverse perspective, these members of the skilled group can be thought of as having comparative disadvantage in occupations requiring cognitive skills.

and chooses a cutoff $\bar{\tau}_t$ that determines the allocation of its members between occupations. The household's inter-temporal problem is:

$$\max_{c_{s,g,t},c_{s,m,t},a_{s,t+1},\bar{\tau}_t} E\left[\sum_{t=0}^{\infty}\Gamma^t log(c_{s,t})\right]$$

subject to:

$$c_{s,g,t} + p_{m,t}c_{s,m,t} + \gamma_z a_{s,t+1} \leq w_{c,t}\int_{\bar{\tau}_t}^{1}\zeta d\tau + w_{r,t}\int_{0}^{\bar{\tau}_t} h(\tau_i)d\tau + R_t a_{s,t} \tag{1.19}$$

Here, $c_{s,g,t}$ and $c_{s,m,t}$ are the skilled household's consumption of final good and manual services, respectively. $a_{s,t+1}$ is the household's assets at time $t+1$, while R_t is the gross return on the asset between periods t and $t+1$. γ_z, on the other hand, is a common growth factor, used in de-trending the variables and Γ is the discount factor. Finally, $c_{s,t}$ is the composite consumption of the skilled household such that:

$$c_{s,t} = \left(\chi c_{s,g,t}^{\kappa} + (1-\chi)c_{s,m,t}^{\kappa}\right)^{\frac{1}{\kappa}} \tag{1.20}$$

where, the demand elasticity of substitution between final good and manual services is $\frac{1}{1-\kappa}$.

Utility maximization requires that the marginal utilities per dollar should be equalized between the final good and manual services consumptions:

$$p_{m,t} = \frac{1-\chi}{\chi}\left(\frac{c_{s,g,t}}{c_{s,m,t}}\right)^{1-\kappa} \tag{1.21}$$

First order condition with respect to $\bar{\tau}_t$ gives us the rule for cutoff efficiency rank. Equation 1.22 shows that the member of the household with efficiency rank $\bar{\tau}_t$ will be indifferent between working in cognitive and routine task occupations. The members with efficiency rank above $\bar{\tau}_t$, on the other hand will supply their labor endowment to occupations associated with cognitive tasks. When the advances in technology raises the relative wage of cognitive task occupations, cutoff efficiency rank will fall and hence more skilled labor will be employed in these occupations.

$$\frac{w_{c,t}}{w_{r,t}} = \frac{\bar{\tau}_t^{-\frac{1}{2}}}{\zeta} \tag{1.22}$$

Finally, we have the usual Euler equation that makes the skilled household indifferent between consuming one more unit today and saving that one unit and consuming it in the next period:

$$\frac{c_{s,g,t}^{\kappa-1}}{c_{s,t}^{\kappa}}\gamma_z = \Gamma\frac{c_{s,g,t+1}^{\kappa-1}}{c_{s,t+1}^{\kappa}}R_{t+1} \tag{1.23}$$

1.5.2.2 Problem of the unskilled agent

The problem of the unskilled household is similar to the problem of the skilled household. The unskilled household has members with the vector of efficiencies $(0, \psi_i, 1)$ for cognitive, routine and manual task occupations, respectively. Thus, unlike the skilled agent, the unskilled does not have access to the labor market for cognitive occupations. However, it competes with the skilled agents for the routine task occupations. The members of the household are uniformly ranked between 0 and 1. Their rank, ψ_i, determines their efficiency in routine task occupations. Similar to the skilled agents, these identifiers are translated into routine task efficiencies through the function $g(\psi_i)$. As before, I assume that the efficiency is decreasing in ψ_i, meaning that $g(\psi_i') < 0$. However, it is assumed, on average, that the routine task efficiency of the unskilled labor is lower than that of skilled labor. In particular, I specify that for each rank level $\psi_i = \tau_i$, $g(\psi_i) = bh(\tau_i)$ where $0 \leq b \leq 1$. Thus, the unskilled individuals doing routine tasks receive $g(\psi_i)w_{r,t}$ worth of efficiency wage. The members of the unskilled household also have the option of supplying their labor endowments to manual service production, where the wage rate is $w_{m,t}$. Comparing these two wage rates in efficiency units, the household chooses an efficiency rank cutoff that determines the fraction of its members assigned to routine and manual task occupations.

The unskilled household consumes only the final good and similar to the skilled agent, it saves an asset and chooses a cutoff $\bar{\psi}_t$ that determines the allocation of its individuals between tasks. The household's inter-temporal problem is:

$$\max_{c_{u,g,t}, a_{u,t+1}, \bar{\psi}_t} E\left[\sum_{t=0}^{\infty}\Gamma^t log(c_{u,g,t})\right]$$

subject to:

$$c_{u,g,t} + \gamma_z a_{u,t+1} \leq w_{r,t} \int_0^{\bar{\psi}_t} g(\psi_i) d\psi + w_{m,t} \int_{\bar{\psi}_t}^1 1 d\psi + R_t a_{u,t} \tag{1.24}$$

where, $c_{u,g,t}$ is the unskilled household's consumption of final good, $a_{u,t+1}$ is its asset holdings at the end of period t and $\bar{\psi}_t$ is the efficiency rank cutoff that determines the allocation of members of the household across occupations. This cutoff is determined by the first order condition with respect to $\bar{\psi}_t$. When there is technological advancement, the demand for cognitive tasks is expected to rise. This, in turn, will raise the total income of the skilled group. Since they are the sole demanders of manual services, the demand and relative price of these services will rise. Hence, wage paid to manual task occupation will rise relative to the occupations associated with routine tasks and as equation 1.25 shows, this will raise the cutoff, leaving less unskilled workers in routine task occupations.

$$\frac{w_{m,t}}{w_{r,t}} = b\bar{\psi}_t^{-\frac{1}{2}} \tag{1.25}$$

Finally, we have our usual Euler equation coming from the agent's intertemporal saving decisions:

$$\frac{1}{c_{u,g,t}} \gamma_z = \Gamma \frac{1}{c_{u,g,t+1}} R_{t+1} \tag{1.26}$$

1.5.3 Final Good Production

The representative firm produces the final good that is either consumed or invested in either structural or equipment capital. The final good Y_g is produced using four factors of production: structural capital (K_{str}), equipment capital (K_{eq}), cognitive (L_c), and routine task (L_r) hours in efficiency units. In consistent with the estimation outcome, there is a Cobb-Douglas relationship between equipment capital and cognitive task, while there is non-unitary elasticity of substitution between composite of these two factors and routine task. A_t in equation 1.27 is the total factor productivity (tfp) term, for which the stochastic process is defined. This tfp process will be fed with the shocks, which I obtained from the estimation process, when solving for the general equilibrium model under perfect foresight.

$$Y_{g,t} = A_t K_{str,t}^{\alpha} \left(\mu L_{r,t}^{\sigma} + (1-\mu) L_{c,t}^{(1-\gamma)\sigma} K_{eq,t}^{\gamma\sigma} \right)^{\frac{1-\alpha}{\sigma}} \tag{1.27}$$

$$\ln A_t = \rho_A \ln A_{t-1} + \sigma_{A,t}$$

The final good is chosen as the numeraire and thus its price is set as 1. The representative firm takes the wages and rental rates of capitals as given and maximizes its profits by choosing four factors of production. The problem of the firm at time t is described as:

$$\max_{K_{str,t},K_{eq,t},L_{c,t},L_{r,t}} Y_{g,t} - w_{c,t}L_{c,t} - w_{r,t}L_{r,t} - r_{str,t}K_{str,t} - r_{eq,t}K_{eq,t}$$

The firm's optimal decision rules are given by the following first order conditions:

$$w_{c,t} = (1-\alpha)(1-\mu)(1-\gamma)\frac{Y_{g,t}}{\mu L_{r,t}^{\sigma} + (1-\mu)L_{c,t}^{(1-\gamma)\sigma}K_{eq,t}^{\gamma\sigma}}K_{e,t}^{\gamma\sigma}L_{c,t}^{(1-\gamma)\sigma-1} \tag{1.28}$$

$$w_{r,t} = (1-\alpha)\mu\frac{Y_{g,t}}{\mu L_{r,t}^{\sigma} + (1-\mu)L_{c,t}^{(1-\gamma)\sigma}K_{eq,t}^{\gamma\sigma}}L_{r,t}^{\sigma-1} \tag{1.29}$$

$$r_{eq,t} = (1-\alpha)(1-\mu)\gamma\frac{Y_{g,t}}{\mu L_{r,t}^{\sigma} + (1-\mu)L_{c,t}^{(1-\gamma)\sigma}K_{eq,t}^{\gamma\sigma}}K_{eq,t}^{\gamma\sigma-1}L_{c,t}^{(1-\gamma)\sigma} \tag{1.30}$$

$$r_{str,t} = \alpha\frac{Y_{g,t}}{K_{str,t}} \tag{1.31}$$

1.5.4 Personal (Manual) Services Production

The manual services sector represents the home production. This sector is essential in the sense that it helps the model to generate a decline in labor devoted to routine tasks in the response to declining demand for this type of labor following the fall in equipment capital prices. In the job polarization literature, the manual task occupations are neither complements nor substitutes to equipment capital. However, equipment capital and manual task occupations are indirectly linked through the consumption behavior of labor employed in cognitive task occupations. As demand for these high-skill types of task rises, their income rises as well. This, in turn, increases the demand for manual services by labor employed in cognitive task occupations. Therefore, the share of labor devoted to manual tasks in total income and hours shows a modest rise.

Consistent with the job polarization literature, including Autor and Dorn (2013), the production function for the manual services is assumed to be linear. To be more specific, one unit of manual hours produces 1 unit of manual services.

$$Y_{m,t} = L_m \tag{1.32}$$

Letting p_m denote the price of one unit of manual service and w_m the hourly wage rate in this market, the profit maximization under perfect competition yields:

$$p_m = w_m \tag{1.33}$$

1.5.5 Technological Progress

Final good is either consumed or invested in structural or equipment capital. One unit of investment in structural capital is converted into one unit of this type of capital. On the other hand, investment in equipment capital is scaled by a factor q_t before being added to equipment capital stock. q_t here represents the equipment-specific technological progress and will be assumed to be exogenous in the model. As it had already been discussed in the estimation part, perfect competition drives the relative price of equipment capital to:

$$p_{eq,t} = \frac{1}{q_t} \tag{1.34}$$

1.5.6 Equilibrium

For a given level of equipment-specific technology q_t, an equilibrium for our model economy is a collection of time paths of prices $\{w_{c,t}, w_{r,t}, w_{m,t}, r_{s,t},\ r_{e,t}, R_t, p_{m,t}, p_{eq,t}\}$, capital stocks and assets: $\{K_{str,t}, K_{eq,t}, a_{s,t}, a_{u,t}\}$, quantities of consumption and output: $\{Y_{g,t}, Y_{m,t}, c_{s,t}, c_{s,g,t}, c_{s,m,t}, c_{u,g,t}\}$, labor hours in efficiency units: $\{L_{c,t}, L_{r,t}, L_{m,t}\}$, and efficiency rank cutoffs: $\{\bar{\tau}_t, \bar{\psi}_t\}$ such that: (1) households maximize their discounted utilities subject to their budget constraints, (2) both the final good producers and manual service producers maximize their profits, and:

Labor markets clear:

$$L_{c,t} = \int_{\bar{\tau}_t}^{1} \zeta d\tau S = (1 - \bar{\tau}_t)\zeta S \tag{1.35}$$

$$L_{r,t} = \int_0^{\bar{\tau}_t} \tau_i^{-1/2} d\tau S + b \int_0^{\bar{\psi}_t} \psi_i^{-1/2} d\psi U = 2\bar{\tau}_t^{\frac{1}{2}} S + 2b\bar{\psi}_t^{\frac{1}{2}} U \tag{1.36}$$

$$L_{m,t} = \int_{\bar{\psi}_t}^1 1 d\psi U = (1 - \bar{\psi}_t)U \tag{1.37}$$

Capital and asset markets clear:

$$a_{s,t}S + a_{u,t}U = K_{str,t} + p_t K_{eq,t} \tag{1.38}$$

$$\frac{p_{eq,t+1}}{p_{eq,t}} = \frac{1}{1-\delta_{eq}} \left[r_{str,t+1} + (1-\delta_{str}) - \frac{r_{eq,t+1}}{p_{eq,t}} \right] \tag{1.39}$$

$$R_t = 1 - \delta_{str} + r_{str,t} \tag{1.40}$$

Manual service market clears:

$$c_{s,m,t}S = Y_{m,t} \tag{1.41}$$

Households invest in one type of asset, which is then purchased by a zero-profit intermediary and converted into two types of capital. Thus, market clearing requires that total amount of savings should be equal to the total value of the capital (equation 1.38). The intermediary's investment decision will be such that the expected return on two types of capital should be equal (equation 1.39). Otherwise, there would be investment in only one type of capital in the model economy. Finally, gross returns on the asset and each type of capital should be equalized as well (equation 1.40).

In summary, there are 23 unknowns in our model $\{w_{c,t}, w_{r,t}, w_{m,t}, r_{s,t}, r_{e,t}, R_t, p_{m,t}, p_{eq,t}, K_{str,t}, K_{eq,t}, a_{s,t}, a_{u,t}, Y_{g,t}, Y_{m,t}, c_{s,t}, c_{s,g,t}, c_{s,m,t}, c_{u,g,t}, L_{c,t}, L_{r,t}, L_{m,t}, \bar{\tau}_t, \bar{\psi}_t\}$ and all 23 equations between 1.19 and 1.41 solve for these unknowns.

1.6 Quantitative Analysis

In this section, the general equilibrium model introduced above is used to quantify the contribution of the equipment-specific technological progress to the trend decline in the labor share. First, I discuss the parameterization of the model. Later, I briefly present the solution method. Finally, model's findings are reported.

1.6.1 Parameterization

The model parameters are set in three main blocks: estimation, regression, and calibration. Below, I describe each of these in detail. The reader can skip to Table 1.10 in Appendix 1.9.1 that lists all the parameters of the model and the sources of parameterization.

1.6.1.1 Estimation

The first set of parameters are already available from the estimation part in Section 4. In particular, $\sigma = 0.5708$, which is the parameter that governs the elasticity of substitution between labor employed in routine task occupations and the composite output of equipment capital and non-routine tasks. This implies an elasticity of substitution of 2.33. Furthermore, the choice of production function in equation 1.27 is based on the estimation result that equipment capital and cognitive tasks are neither complements, nor substitutes. Finally, I borrow the parameter γ, which is the share of equipment capital in partial Cobb-Douglas specification between equipment capital and cognitive task, from Table 1.5.[46]

1.6.1.2 Regression

There are two parameters in the CES consumption aggregator in equation 1.20: κ is the parameter that shapes the elasticity of substitution between consumption of final good and manual services. The other parameter, χ, is the share of final good in aggregate consumption of the skilled agent. To recover these two parameters, I used the first order conditions of the skilled household with respect to each types of consumption:

$$p_{m,t} = \frac{1-\chi}{\chi}\left(\frac{c_{s,g,t}}{c_{s,s,t}}\right)^{1-\kappa}$$

[46]However, here an adjustment is needed since the production function for the final good in general equilibrium model does not encompass manual tasks. Thus, I distribute the share of labor employed in manual task occupations reported in Table 1.5 proportionally to equipment capital and labor devoted to cognitive task occupations. This gives us $\gamma = 0.3879$.

Then, I took the logarithm of this equation and ran a simple regression:

$$\ln p_{m,t} = \ln \frac{1-\chi}{\chi} + (1-\kappa) \ln \left(\frac{c_{s,g,t}}{c_{s,s,t}} \right) + u_t$$

In this regression, I used personal consumption of goods and services (other than 'other services') from NIPA Table 2.3.6 as consumption of final good in our model: $c_{s,g,t}$; and personal consumption expenditures on other services as manual services: $c_{s,m,t}$. The price series, on the other hand, are taken from NIPA Table 2.3.4 for the period 1967-2013. This regression gives us $\chi = 0.9410$ and $\kappa = -0.1547$. This level of κ corresponds to an elasticity of substitution between final good and manual services equal to 0.87, which implies complementarity between these two consumption items.

1.6.1.3 Calibration

Data: Some parameters are taken directly from the data. To begin with, the depreciation rates for each type of capital are easily recoverable from NIPA Fixed Assets tables. For the entire period 1967-2013, I divided the consumption of capital series from Table 2.4 by the capital stock series from Table 2.1. The average depreciation rates found are $\delta_s = 0.0275$ for structural capital and $\delta_e = 0.1460$ for equipment capital. Furthermore, the discount rate Γ is taken as 0.96 to match around annual 4% interest rate in equilibrium. The measure of the unskilled agents is normalized as 1. Then I calculated the average share of the hours by college and above educated labor in total hours from the CPS data set for the period 1967-2013. This gave $S = 0.361$. Finally, γ_z, the common growth factor, is set equal to the growth rate of the total factor productivity obtained as a residual from the estimation in Section 1.4.

Targeting initial values: There remain four parameters to calibrate: μ is the share of routine task occupations in CES between routine task occupations and the composite of equipment capital and cognitive task occupations as in production function in equation 1.27; b is the scale parameter between the routine task efficiencies of the skilled and the unskilled agents; ζ is the cognitive task efficiency of the skilled households and, $p_{eq,0}$ is the initial

Table 1.6: Targets and Other Selected Moments for 1966

	Data	Model		Data	Model
Targeted			Not Targeted		
wbr_{cr}	0.58	0.58	LS_{agg}	0.70	0.73
tp_{cr}	1.46	1.46	LS_{cog}	0.24	0.26
tp_{mr}	0.70	0.70	LS_{rtn}	0.41	0.45
$\frac{K_{eq}}{K_{str}}$	0.78	0.78	LS_{man}	0.05	0.03
			wbr_{mr}	0.11	0.10

relative price of equipment capital. To set these parameters, I took year 1966 as the initial steady state and targeted levels of some of the key variables in that year. To be more specific, I targeted the wage-bill ratio between cognitive and routine tasks in 1966 to recover μ. To obtain two efficiency parameters, I targeted the task premiums. Finally, the ratio of the real equipment capital stock to the real structural capital stock gives us $p_{eq,0}$. These targets are shown in the left two columns of Table 1.6. The right two columns, on the other hand, show data and model levels of other selected variables for the initial year.

These targets give us $\mu = 0.4160$, $\zeta = 1.8681$, $b = 0.6493$ and $p_{eq,0} = 0.8302$.

1.6.2 Perfect Foresight Solution

It is well known in the literature that my model, like any other model with capital-augmenting technological growth, does not have balanced growth path properties. Therefore, I rule out the growth in equipment-specific technology and define a random walk process for it, thereby making every technology shock persistent. Hence, following each shock to the equipment-specific technology, the economy moves towards a potentially new steady state.

I solve the model under perfect foresight assumption. In other words, I assume that at the beginning of the first period, the agents are fully aware of future paths of q_t and shocks to the total factor productivity. This solution method requires imposing initial and terminal conditions and solving the path from one to the other. To do so, I assumed that the relative equipment capital price was constant up to year 1967 at its price in this year. Then, the year 1966 is imposed as the initial steady state. Later, agents are assumed to learn the future path of both technology and total factor productivity shocks beginning from 1967. In the baseline scenario, I assume that equipment capital-specific technology stays constant at its 2013 level and the economy reaches its new steady state at this level of technology T periods later. Then, I solved $23 \times (T + 47)$ equations simultaneously. I tried various Ts ranging from 50 to 500 periods to check if the choice of the terminal year affects the results. Fortunately, there was no noticeable differences in results for different choices of Ts in this range.

1.6.3 Quantitative Findings

The paths of the key variables under perfect foresight solution are presented in Figure 1.11. The three figures in the top row show the labor share trends for three task groups. Both panels (a) and (b) show that the task-based explanation for the trend decline in the labor share is quite successful for labor employed in cognitive and routine task occupations for the period after 1990. However, in the first half the period of study, the model can account for only around 40% of the trend changes in these labor shares. Furthermore, even though the model is unable to capture the large cycles observed in data, it successfully captures the total rise in the income share of labor associated with manual tasks as depicted in panel (c) of the Figure 1.11.

Consistent with the task-level labor shares, the model's success in predicting the aggregate labor share is different in the first and second halves of our period of study. As panel (d) of Figure 1.11 shows, 87% of the labor share trend after 1990 can be explained by the advances in equipment-specific technology. Up to year 1990, on the other hand, we can attribute only 45% of the decline to this channel. Overall, for the entire period 1967-2013, we can account for 72.2% of the trend decline in the labor share by equipment-specific technological progress and capital-task complementarity.

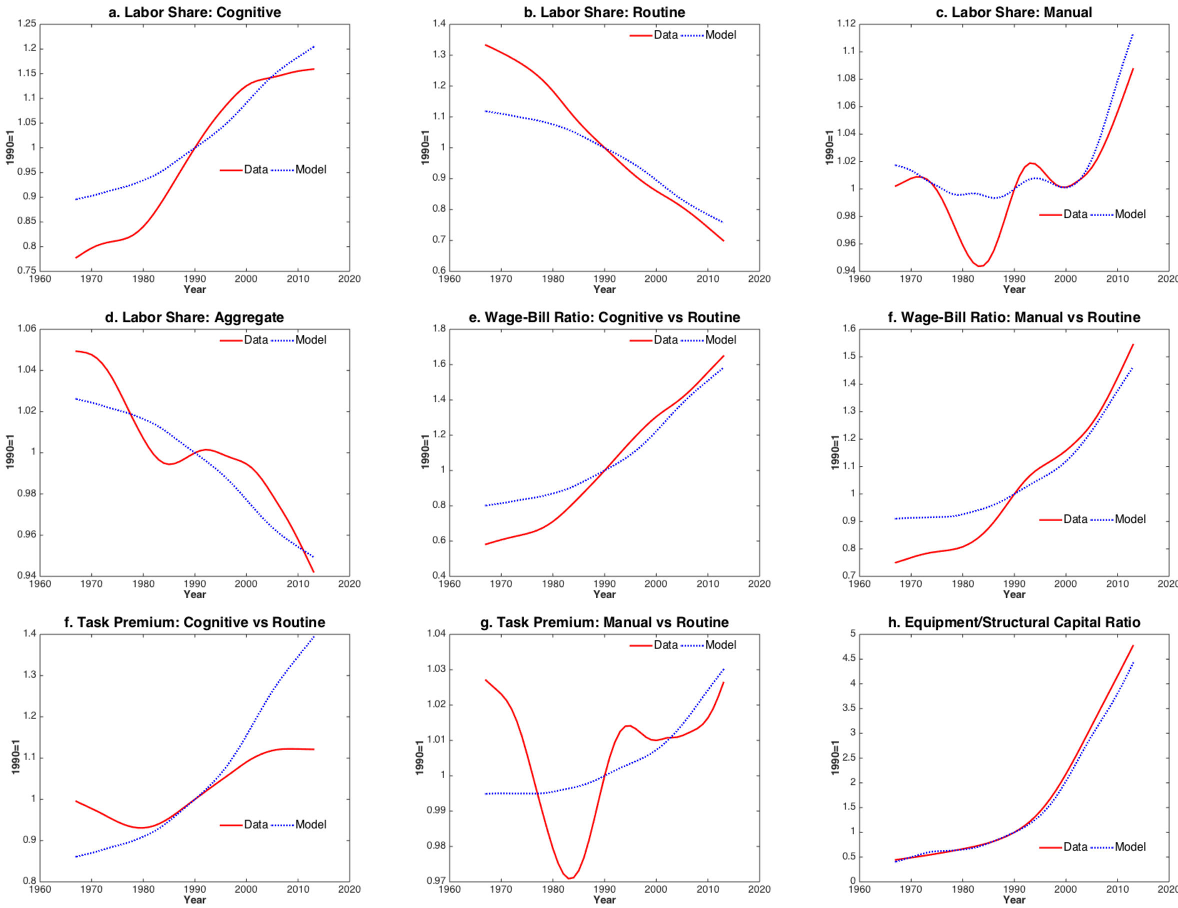
The model's performance in predicting the paths of the wage-bill ratios between various tasks groups is similar to the labor shares (panels (e) and (f) of Figure 1.11). This is not a surprising outcome as the advances in technology affect the the labor share through changes in wage-bill ratio in my model. However, the model foresees substantially larger growth in task premiums -especially between cognitive and routine tasks- than what we observe in data. This is due to the assumption of exogenous and fixed measures of skill groups. My model does not allow for skill accumulation and hence, the measures of the skilled and the unskilled agents are fixed at some pre-given levels. Normally, when there is technological progress and capital-task complementarity and thus the demand for cognitive tasks rises, we would expect to see both a rise in relative wage and also over time rise in total supply of skilled agents, who are the sole suppliers of the cognitive hours. However, since the skill supply channel is shut off in our model, the rise in the wage-bill ratio mostly stems from the rise in the task premium, rather than a combination of relative hours and wages. My future plan is to incorporate a simple educational choice, like in Chapter 3 of this dissertation, into the baseline model here to eliminate the overshooting of the task premium.

1.6.3.1 Counterfactual: effect of the technological boom on labor share trend

The model's inability to fully account for the decline in the labor share for the pre-1990 period is consistent with the data. As I had discussed earlier, between-sector component was the dominant factor in this period and my model does not allow structural shifts. On the other hand, most of the decline in the labor share is due to the within sectoral changes for the post-1990 period. As a matter of fact, during the eight years between 1996 and 2003, the growth rate of technological progress has doubled (Table 1.7). This technological boom has been followed by an acceleration of the decline in the labor share. Since this is consistent with the proposed channel in my model, its performance in explaining the labor share trend is substantially stronger for this period.

The model enables us to quantify the contribution of this technological boom alone on the labor share trend. To do so, as depicted in panel (a) of Figure 1.12, for the 1996-2003

Figure 1.11: Prefect Foresight Solution: Data vs Model



Note: The series are HP-trends.

period, I fixed the growth rate of the relative equipment capital price at its average level. Panel (b) of Figure 1.12 shows that labor share would have been around 2 points higher today if we had not had the technological boom of 1996-2003. This corresponds to about 22% of the decline in the labor share.

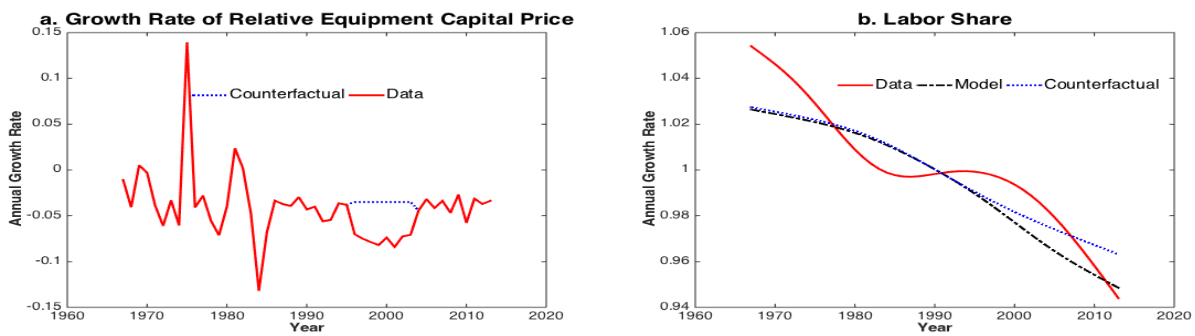
1.6.3.2 Projection of the labor share

My model has a unique prediction for the future path of the labor share. The studies relating the decline in the labor share to the substitutability between aggregate capital and labor,

Table 1.7: Annual Growth Rate of Relative Equipment Capital Prices

Period	**Growth Rate**
1967-1995	$-.0342$
1996-2003	$-.0759$
2004-2013	$-.0378$
1967-2013	$-.0424$

Figure 1.12: Counterfactual: Effect of the Technological Boom on the Labor Share

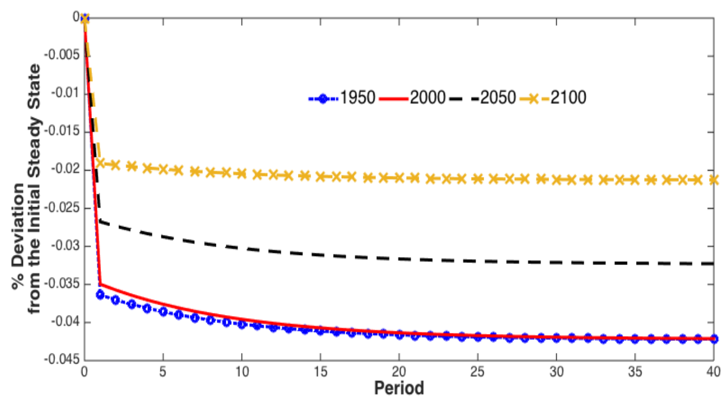


Note: The labor share series in panel (b) are HP-trends.

such as Karabarbounis and Neiman (2014b), imply that the labor share should converge to 0 over time if technological progress continues at its ongoing pace. However, this paper documents that there is a specific group of labor that is losing due to technological progress and a constant share of their losses is captured by the other group of labor. Thus, the explanation proposed in this paper foresees a stabilization of the labor share in the long run as the economy completes its transition to a new steady state with a very low share of the labor employed in occupations associated with routine tasks.

To visualize this convergence to a new economy with lower but stable labor share, I analyzed how the labor share would respond to a 1% positive shock to equipment-specific technology at various stages of technological progress. To do so, I imposed a level of technology for each year after 2013 based on the assumption that the relative equipment capital price would continue to decline at its current average annual rate of 4.24% for another 200 years. Then, I independently gave a 1% technological shock at each level and plotted the impulse responses of the labor share to these shocks at various years.[47] Each line in Figure 1.13 corresponds to the response of the labor share to a 1% technological shock at the level of equipment-specific technology in the specified year. As the figure depicts, the impact of technological progress on the labor share gradually fades even if technological progress maintains its strength.

Figure 1.13: Impulse Response of the Labor Share to a 1% Technological Shock

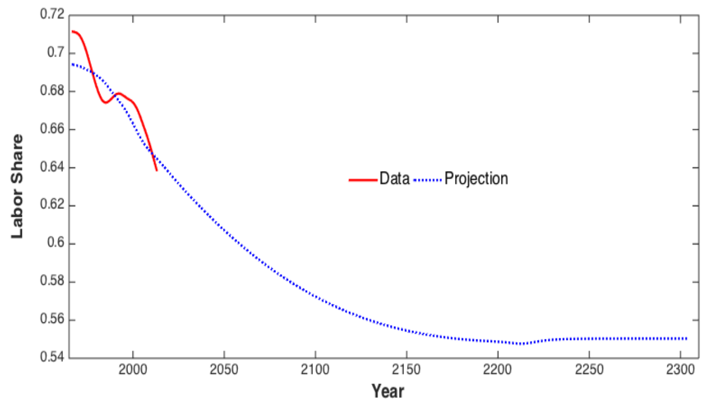


To project the lower bound for the US labor share, I used the imposed future path for the relative equipment capital price and solved the model under perfect foresight assumption. Even under this extreme case, the model predicts that the labor share will stabilize around 55% in the long run as Figure 1.14 shows. Considering that technological progress might slowdown or the substitutability of capital and types of labor might change over time, this number should be interpreted as a lower bound for the labor share. In summary, even though

[47]To solve for the stochastic version of the model, I defined a random-walk process for the equipment-specific technology. Thus, each shock to the technology is permanent and the economy slowly moves to a new steady state after the shock. I should clarify at this point that each shock is given separately for each year under the assumption that the economy is at the steady state before the shock.

my paper does not predict a reversal of the trend decline in the labor share, the message of the paper is optimistic in the sense that the constancy of the labor share is expected to be reconstructed once the adjustment process is complete.

Figure 1.14: Projection of the Labor Share



Note: The series are HP-trends.

1.6.3.3 Estimating the aggregate elasticity of substitution

As I discussed earlier, there is a debate over the elasticity of substitution between aggregate capital and labor. While most of the literature provides estimates ranging between 0.5 and 0.8 (see Leon-Ledesma et al. (2010) for a review of the estimates), a few recent studies such as Karabarbounis and Neiman (2014a), Karabarbounis and Neiman (2014b) and Piketty and Zucman (2014) reported estimates between 1.25 and 1.40. These conflicting findings are mainly due to the differences in methodologies and data sets and each view has some inconsistent implications about the labor market trends. I believe that the studies attributing the decline in the labor share to falling relative price of capital come with upward biased estimates of the aggregate elasticity since coexistence of those two would require substitutability between capital and labor.

In this paper, I showed that what matters for explaining the labor share trend are the elasticities at a more disaggregated level. However, I can also contribute to the discussion over the aggregate elasticity of substitution between capital and labor from a different approach. To be more specific, I simulate my model and obtain the efficient total labor hours, aggregate capital and wage and rental rate series. Then, I use these simulated series in a standard regression to estimate the aggregate elasticity measure implied by my model.

$$\log \frac{K_t}{L_t} = c + \epsilon_{agg} \log \frac{w_t}{r_t} + v_t \tag{1.42}$$

where, K is aggregate capital stock, L is aggregate labor hours in efficiency units, w is the wage rate and r is the rental rate. Furthermore, ϵ_{agg} is the elasticity of substitution between aggregate capital and labor.

Equation 1.42 gives us a measure of the aggregate elasticity of 1.06. Even though this estimate is on the side of studies documenting substitutability between aggregate capital and labor, it lies somewhere in the middle of two opposite views. Nevertheless, unlike the existing estimates, this measure is consistent with both the decline in the labor share and other labor market trends such as job and wage polarizations.

1.7 Explaining the Trend Differences Across Sectors

As discussed earlier, there has been substantial heterogeneity in the labor share trends across sectors (Figure 1.4). Most of the goods sectors, including the manufacturing industries, have experienced large trend decline in the labor share, while service sectors have shown a limited decline, if not a rise. How consistent is the sectoral experience with our technological process and capital-task complementarity story? In the end, all the sectors have faced same equipment-specific technological progress. Likewise, task premiums between various tasks have been rising at similar magnitudes in each sector. If sectors were to operate under same technology, we would expect the labor shares to exhibit similar trends across sectors as well.

In Chapter 2 of this dissertation, I showed that if we allow the elasticities of substitution, and hence the degrees of capital-task complementarity, to differ across sectors, we can account for trend differences in the labor shares across sectors. Similarly, in their recent paper, Alvarez-Cuadrado et al. (2015) claim that differences in the degree of capital-labor substitutability across sectors can explain the decline in the sectoral and aggregate labor shares. However, a three-sector extension of our model shows that we can replicate the sectoral differences in the labor share trends even when the elasticities between equipment capital and various types of labor were the same across sectors. In other words, our key channel working through the rise in the wage-bill ratio is consistent with the sectoral experiences as well and this consistency does not rely on heterogeneity in the capital-task complementarities. The only factor that causes sectors to react differently to technological change is the share of equipment capital in partial Cobb-Douglas specification. When the extended model is calibrated to the US data, I show that in sectors where the share of equipment capital is larger (such as manufacturing), the advances in technology causes a larger rise in equipment capital per efficiency hour and in the wage-bill ratio between labor devoted to cognitive and routine tasks, thereby leading to a larger fall in the labor share.

1.7.1 Model

The problem of the households is the same as in the baseline model and thus is not presented again. Furthermore, the manual service sector is kept as before as well. The key difference between baseline model and the extended model in this section is the introduction of two intermediate outputs that are aggregated into our final good used in consumption and investment. The production functions for these intermediate sectors are similar except for three parameters that will be calibrated in next subsection.

1.7.1.1 Intermediate sectors

Each intermediate sector $i \in \{1, 2\}$ has the following production function:

$$Y_{g,i,t} = A_t K_{str,i,t}^{\alpha_i} \left(\mu_i L_{r,i,t}^{\sigma} + (1 - \mu_i) L_{c,i,t}^{(1-\gamma_i)\sigma} K_{eq,i,t}^{\gamma_i \sigma} \right)^{\frac{1-\alpha_i}{\sigma}} \tag{1.43}$$

Equation 1.43 implies that two intermediate sectors face the same total factor productivity shocks (A_t). Furthermore, the elasticity of substitution between routine task occupations and the composite output of equipment capital and non-routine task occupations ($\frac{1}{1-\sigma}$) is the same in both sectors as well. Moreover, I assume that neither capital, nor labor is sector-specific. Thus, the wages and rental rates are equalized across sectors.

Nevertheless, sectors differ in three parameters: μ_i, which governs the compensation shares of factors; α_i, which determines the compensation share of structural capital; and, γ_i, which is the share of equipment capital in partial Cobb-Douglas specification. However, as summarized in equations 1.17 and 1.18, the first two of these parameters do not play any role in the changes of the labor share. On the other hand, γ_i is the key parameter in shaping the reaction of the wage-bill ratio and the labor share since it shows how sensitive the cost function is to changes in the price of equipment capital. In addition, it also determines how a given change in the wage-bill ratio is translated into changes in the labor share.

Letting $p_{i,t}$ be the price of intermediate output i, the representative firm in sector i takes the wage rates and rental rates as given and solves the following profit maximization problem:

$$\max_{K_{str,i,t},K_{eq,i,t},L_{c,i,t},L_{r,t}} p_{i,t}Y_{g,i,t} - w_{c,t}L_{c,i,t} - w_{r,t}L_{r,i,t} - r_{str,t}K_{str,i,t} - r_{eq,t}K_{eq,i,t}$$

The first order conditions of the firm's problem are:

$$\frac{w_{c,t}}{p_{i,t}} = (1-\alpha_i)(1-\mu_i)(1-\gamma_i)\frac{Y_{g,i,t}}{\mu_i L^{\sigma}_{r,i,t} + (1-\mu_i)L^{(1-\gamma_i)\sigma}_{c,i,t}K^{\gamma_i\sigma}_{eq,i,t}}L^{(1-\gamma_i)\sigma-1}_{c,i,t} \tag{1.44}$$

$$\frac{w_{r,t}}{p_{i,t}} = (1-\alpha_i)\mu_2\frac{Y_{g,i,t}}{\mu_i L^{\sigma}_{r,i,t} + (1-\mu_i)L^{(1-\gamma_i)\sigma}_{c,i,t}K^{\gamma_i\sigma}_{eq,i,t}}L^{\sigma-1}_{r,i,t} \tag{1.45}$$

$$\frac{r_{eq,t}}{p_{i,t}} = (1-\alpha_i)(1-\mu_i)\gamma_i\frac{Y_{g,i,t}}{\mu_i L^{\sigma}_{r,i,t} + (1-\mu_i)L^{(1-\gamma_i)\sigma}_{c,i,t}K^{\gamma_i\sigma}_{eq,i,t}}K^{\gamma_i\sigma-1}_{eq,i,t} \tag{1.46}$$

$$\frac{r_{str,t}}{p_{i,t}} = \alpha_i\frac{Y_{g,i,t}}{K_{str,i,t}} \tag{1.47}$$

1.7.1.2 Final good aggregator

Two intermediate outputs are aggregated into the final good that is used for consumption and investment by perfectly competitive intermediaries using the following CES aggregator:

$$Y_{g,t} = \left(\xi Y^{\nu}_{g,1,t} + (1-\xi)Y^{\nu}_{g,2,t}\right)^{\frac{1}{\nu}} \tag{1.48}$$

The final good aggregating intermediaries take the prices of the intermediates as given. As before, the final good is the numeraire in the model and hence its price is set as 1. Thus, the problem of the representative final good aggregating intermediary is as follows:

$$\max_{Y_{g,1,t},Y_{g,2,t}} Y_{g,t} - p_{1,t}Y_{g,1,t} - p_{2,t}Y_{g,2,t}$$

The firm's problem gives the following relationship between prices and quantities of two intermediates:

$$\frac{p_{1,t}}{p_{2,t}} = \frac{\xi}{1-\xi}\left(\frac{Y_{g,1,t}}{Y_{g,2,t}}\right)^{\nu-1} \tag{1.49}$$

1.7.1.3 Equilibrium

Our equilibrium definition is the same as before. Here, I present only the market clearing conditions that are different from the ones in our baseline model. First of all, we assumed that capital is perfectly mobile across sectors. Hence, the asset market clearing condition now becomes:

$$a_{s,t} + a_{u,t} = K_{str,1,t} + K_{str,2,t} + p_t\left(K_{eq,1,t} + K_{eq,2,t}\right) \tag{1.50}$$

Two of the labor market clearing conditions now also have to reflect the mobility of labor across two intermediate sectors:

$$L_{c,1,t} + L_{c,2,t} = (1-\bar{\tau}_t)\zeta S \tag{1.51}$$

$$L_{r,1,t} + L_{r,2,t} = 2\bar{\tau}_t^{\frac{1}{2}}S + 2b\bar{\psi}_t^{-\frac{1}{2}}U \tag{1.52}$$

1.7.2 Parameterization

I keep the parameters of the baseline model the same for the extended version. Those parameter values can be found in the first block of Table 1.10. This leaves eight parameters specific to three-sectors version to calibrate. Six of those are sector specific parameters governing the compensation shares of factors: $\alpha_1, \alpha_2, \mu_1, \mu_2, \gamma_1$ and γ_2. The other two parameters come from the CES aggregator in equation 1.48: $\frac{1}{1-\nu}$ is the elasticity of substitution between two intermediates and ξ shapes the shares of the intermediate sectors in aggregation. The calibration of each parameter is described below in detail and the second block of Table 1.10 reports the calibrated values.

First of all, the two sectors chosen for parameterization are goods sectors including manufacturing and, service sectors excluding personal services. The goods sector (sector 1) experienced, on average, 0.6% annual decline in the labor share, while in the service sector (sector 2), the labor share has risen by 0.12% each year for the years between 1977-2007.[48][49] To obtain α_1 and α_2, I used the capital and output files of EU-KLEMS for the years between 1977 and 2007 and divided the compensation of the non-residential structural capital by the value added. Then I took the average as the compensation share of the structural capital in that sector. This gave $\alpha_1 = 0.1355$ and $\alpha_2 = 0.0921$. Similarly, to derive γ_1 and γ_2, I took the equipment capital compensation shares from EU-KLEMS capital file and calculated the weight of the income of the labor associated with cognitive tasks in aggregate labor share from the CPS data. Multiplying this weight by the labor share in EU-KLEMS file gave me the cognitive labor share. Then, γ_is are found by dividing the equipment capital compensation share by the total of the compensation shares of equipment capital and labor employed in cognitive task occupations. The obtained parameters are: $\gamma_1 = 0.5043$ for the goods sector and $\gamma_2 = 0.2653$ for the service sectors. In other words, equipment capital has a substantially larger share in production relative to cognitive tasks in the goods sector.

Similar to the parameters of the consumption aggregator, I used a simple regression for parameterizing the final good aggregator in equation 1.48 as well. To begin, I took the logarithm of both sides of equation 1.49, which yields:

$$\ln \frac{p_{1,t}}{p_{2,t}} = \ln \frac{\xi}{1-\xi} + (\nu - 1) \ln \left(\frac{Y_{g,1,t}}{Y_{g,2,t}} \right)$$

Using NIPA tables 1.5.5 for quantity and 1.6.4 for prices for the period 1967-2013, the

[48]If we exclude public services such as education and health, then service sector exhibits a small trend decline as well.

[49]The choice of period for parameterizing the sectors is constrained by the availability of detailed capital compensation data by sectors in EU-KLEMS files.

Table 1.8: Targets and Other Selected Moments for 1966

Targeted			Not Targeted		
	Data	**Model**		**Data**	**Model**
$wbr_{cr,sec1}$	0.29	0.29	LS_{agg}	0.70	0.75
$wbr_{cr,sec1}$	1.02	1.02	LS_{sec1}		0.70
			LS_{sec2}		0.77
			tp_{cr}	1.46	1.62
			tp_{mr}	0.70	0.70
			wbr_{mr}	0.11	0.06
			$\frac{K_{eq}}{K_{str}}$	0.78	0.66

estimated regression is:

$$\ln \frac{p_{1,t}}{p_{2,t}} = -.5204601 - 1.161871 \ln \left(\frac{Y_{g,1,t}}{Y_{g,2,t}} \right)$$

This regression gives us: $\xi = 0.3728$ and $\nu = -0.1619$. This level of ν implies complementarity between goods and services.

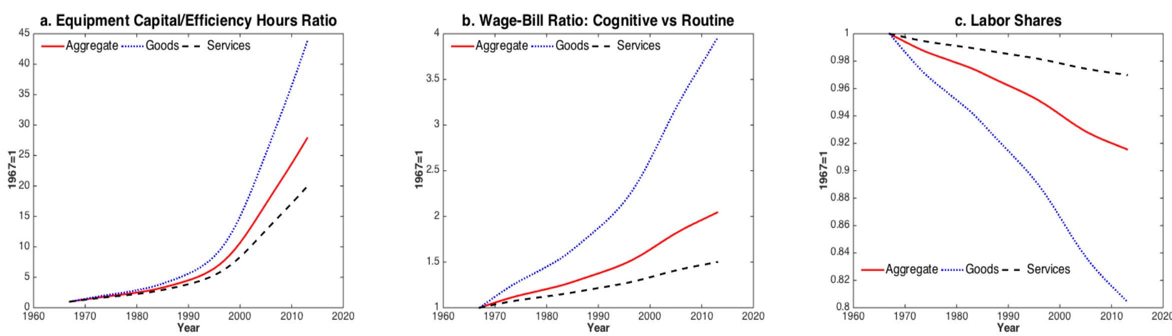
Finally, there are two weight parameters to be calibrated: μ_1 and μ_2, which are the share of routine task associated occupations in the outer CES production function. These parameters only affect the level of the wage-bill ratio and have no role in changes of the labor share. As in the baseline model, I assume that the year 1966 was the initial steady state and choose μ_1 and μ_2 to match the wage-bill ratios of each sector in 1966. The targeted and non-targeted starting points are reported in Table 1.8. The calibrated parameters are $\mu_1 = 0.4039$ and $\mu_2 = 0.3276$.

1.7.3 Perfect Foresight Solution

The model is solved under perfect foresight in the same way the baseline model is solved. As before, agents know the future paths of the relative equipment capital price and the total factor productivity. The year 1966 is taken as the initial steady state and capital prices are assumed to stay at their 2013 level after this year. Later, the economy is assumed to reach to a terminal equilibrium point in T years. Using the value of assets at the initial year and consumptions $T + 47$ years later, I simultaneously solve the paths of every variable between two steady states.

Two sectors face the same price and total factor productivity shocks. Furthermore, since both labor and capital are perfectly mobile across sectors, the relative task and capital prices are the same for each sector as well. Sectors only differ in their initial levels of the wage-bill ratios and the parameters governing the compensation shares of factors. As discussed before, the parameter γ_i, which is the share of equipment capital in partial Cobb-Douglas between equipment capital and cognitive tasks, is the key parameter affecting the changes in the wage-bill ratio and the labor share.

Figure 1.15: Extended Model's Solution Under Perfect Foresight



Note: Series are HP-trends.

Panel (a) of Figure 1.15 shows equipment capital stock per efficient hour at the aggregate and sectoral levels. The large increases in this variable is comparable to the rise observed in the data.[50] Since equipment capital per efficient hour rises faster in the goods sector and

[50]For instance, equipment capital per efficient hour at the aggregate level has risen 26 times in data and 28 times in the model.

there is capital-task complementarity, the wage-bill ratio between cognitive and routine tasks also increases significantly more in this sector as shown in panel (b). This is translated into around 20% decline in the labor share of this sector as depicted in panel (c) of Figure 1.15. On the other hand, both the rise in the wage-bill ratio and the fall in the labor share remains limited in the service sector.

Even though equipment capital per efficient hours and the labor share series generated by the model are in line with the data, the model significantly overshoots the rise in the wage-bill ratio of the goods sector. To be more specific, the rise in the wage-bill ratio in goods sector is 300% in the model, whereas it is only around 150% in the data. However, this does not invalidate our explanation for the decline in the labor share through the changes in the task composition of the wage bills. Despite quantitatively overshooting the wage-bill ratios, the model qualitatively captures two facts derived from the data: (i) the larger the share of equipment capital in Cobb-Douglas specification, the larger the rise in the wage-bill ratio and, (ii) the larger the rise in the wage-bill ratio, the larger the fall in the labor share. These facts were presented earlier in panels (a) and (b) of Figure 1.10, respectively.

To summarize, the model is quite successful in capturing the cross-sectional differences in the labor share in response to advances in technology. At this point, one can wonder whether this is the result of differences in initial employment of labor devoted to routine task occupations or weights of equipment capital in Cobb-Douglas specification. To answer this question, I set the initial wage-bill ratios close to each other by setting $\mu_1 = \mu_2$. The resulting transition paths of the wage-bill ratios and labor shares were similar to those in Figure 1.15. A reverse exercise setting $\gamma_1 = \gamma_2$, on the other hand, eliminates the sectoral differences generated by the model. Thus, the sectoral differences in terms of the labor share trends are solely driven by the differences in shares of equipment capital in the Cobb-Douglas relationship between equipment capital and cognitive tasks.

1.8 Conclusion

This paper assessed the relationship between technological progress and the decline of the aggregate and sectoral labor shares in the US over the last few decades through the lenses of capital-task complementarity and job polarization. Consistent with this, labor is disaggregated into three groups classified by the particular tasks associated with their occupations: cognitive, routine, and manual. The estimation analysis revealed that it is not labor per se that is being substituted away. Rather, the substitution had been solely away from routine tasks to both equipment capital and non-routine tasks, and the income loss of this group accounts for the entire decline of the labor share during the 1967-2013 period.

The key insight of this paper is that changes in occupational composition of the labor force have played the key role in shaping the response of the labor share to technological progress. This has several differing implications compared to the existing studies that attribute the decline of the labor share to substitutability between aggregate capital and labor. First, decline of the labor share can be considered as a natural outcome of a transition process of the US economy to a new steady state with a very low level employment share of routine task labor. Both the estimation analysis and the dynamic general equilibrium model predict that the decline of the labor share should come to a halt in the long run and reach to a lower bound even if equipment-specific technological progress continues at its current pace. Secondly, potential policy implications differ from rest of the literature as well. To be more specific, rather than taxing capital, as suggested by Piketty (2014), policies to train routine task labor to acquire skills compatible with non-routine cognitive tasks would be more effective in alleviating inequalities.

In the second half of the paper, a dynamic general equilibrium job polarization model is solved to quantify the contribution of this capital-task channel to the trend fall in the labor shares. The model reveals that fall in relative equipment capital prices alone can account for around 72% of the decline of the labor share during the entire period of study (1967-2013). Furthermore, the model shows that the initial response of the labor share to permanent technological shocks gradually declines over time as the economy moves closer to its new steady state. Finally, the model allows us to project the lower limit of the labor share in the US, which is found to be slightly above 55%.

The task based explanation provided by the aggregate analysis is tested at the sectoral level as well. Both empirical analysis and a three sector extension of the baseline model reveal that sectoral experiences are consistent with the aggregate story. Even when the elasticities of substitution between factors are the same across sectors, they can experience substantially differing labor share trends if the weights of equipment capital in production differ across them. To be more specific, in sectors where equipment capital has a larger weight in the partial Cobb-Douglas specification, equipment capital per efficiency hour rises faster. This comes with a stronger demand for cognitive tasks and hence, the task composition of the wage bill experiences a larger shift, thereby creating a larger trend decline in the labor share.

Finally, this paper also claims that the theory based on capital-task interactions improves our understanding of the decline in the labor share compared to the capital-skill complementarity theory. The existing measures of elasticities between equipment capital and skilled and unskilled labor predict a counterfactual rise in the labor share since 1990s, while capturing the course of the skill premium in a manner consistent with data. Re-estimating those elasticities using extended data set reveals that the complementarity between equipment capital and skilled labor has been weaker in last two decades. This curbs the rise in the labor share to a great extent at the expense of worsening of the fit of the skill premium. Even in this case, the explained part of the labor share declines by around 40%, thereby making changes in task composition of the labor force a more promising explanation relative to changes in skill composition in modeling the decline of the labor share.

Since my model is successful in replicating the experience of the US economy in terms of the labor share, it is promising for conducting interesting policy analysis such as measuring the potential impacts of a policy that subsidizes labor for skill upgrading. To this end, my first future plan is to make the skill supply in the model economy endogenous. One way to make this possible is to introduce idiosyncratic shocks to labor productivities and an exogenous death probability. Once a new comer inherits the assets of the dead agents, he/she makes a decision over obtaining a college degree or not based on the cost of education and the level of assets inherited. As the rewards for the skill increases over time due to equipment-specific technological progress, the relative skilled labor supply would rise as well. This set up will enable us to relax the constant skill supply assumption of my model and thus can evaluate the impact of skill accumulation on the labor share and task premiums. More importantly, such a model will allow us to conduct more realistic experiments to assess the welfare implications of labor market policies.

Two other possible questions can be addressed by extending the model presented in this paper. First, currently my model captures only the decline in the labor share that is due to the within sector changes, while ignoring the between sector effects. In future, by introducing heterogeneities in sector-specific demand shocks and/or technologies, I am planning to study the impact of sectoral shifts as well to improve our understanding of the labor share. Another interesting extension would be treating the cognitive tasks as a stock rather than a flow as in Beaudry et al. (2013). This way, the model can capture the recent slowdown in demand for cognitive non-routine tasks. I believe that this set up has the potential of providing a more accurate explanation for the most recent acceleration of the decline in the labor share during the last decade. Finally, I plan using data from other countries with the model parameters estimated for the US economy to test the consistency of the findings of this paper in other countries.

1.9 Appendices

1.9.1 Additional Tables and Figures

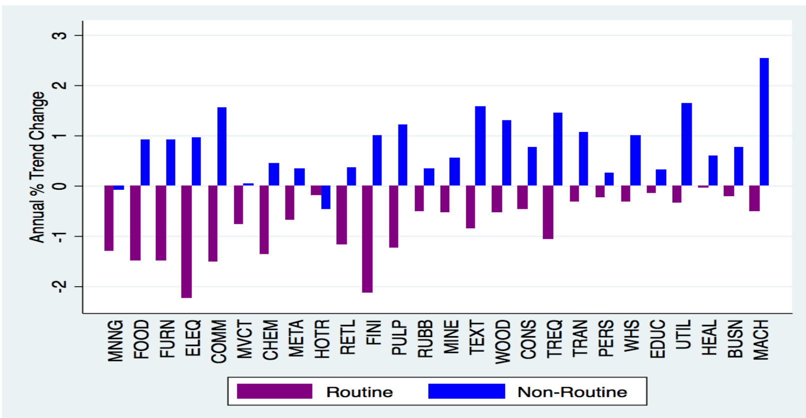
Table 1.9: Abbreviations of the Sectors

Abbreviation	Sector	Abbreviation	Sector
AGRI	Agriculture, Hunting and Fishery	MINE	Non-Metallic Products
BUSN	Real Estate and Business	MING	Mining and Quarrying
CHEM	Chemicals and Chemical Products	MVCT	Motor Vehicles Trade
COMM	Post and Telecommunication	PERS	Other Personal Services
CONS	Construction	PETR	Coke and Refined Petroleum
EDUC	Educational Services	PULP	Pulp, Paper and Printing
ELEQ	Electrical and Optical Equipment	RETT	Retail Trade and Repair
FINI	Financial Intermediation	RUBB	Rubber and Plastic Products
FOOD	Food, Tobacco and Beverage	TEXT	Textile, Leather and Footwear
FURN	Furniture and Recycling	TRAN	Transportation and Storage
HEAL	Health Services	TREQ	Transport Equipment
HOTR	Hotels and Restaurants	UTIL	Utilities
MACH	Machinery Equipment	WHST	Wholesale Trade and Comission
META	Basic and Fabricated Metal	WOOD	Wood and Cork Products

Figure 1.16: Labor Share by Sectors

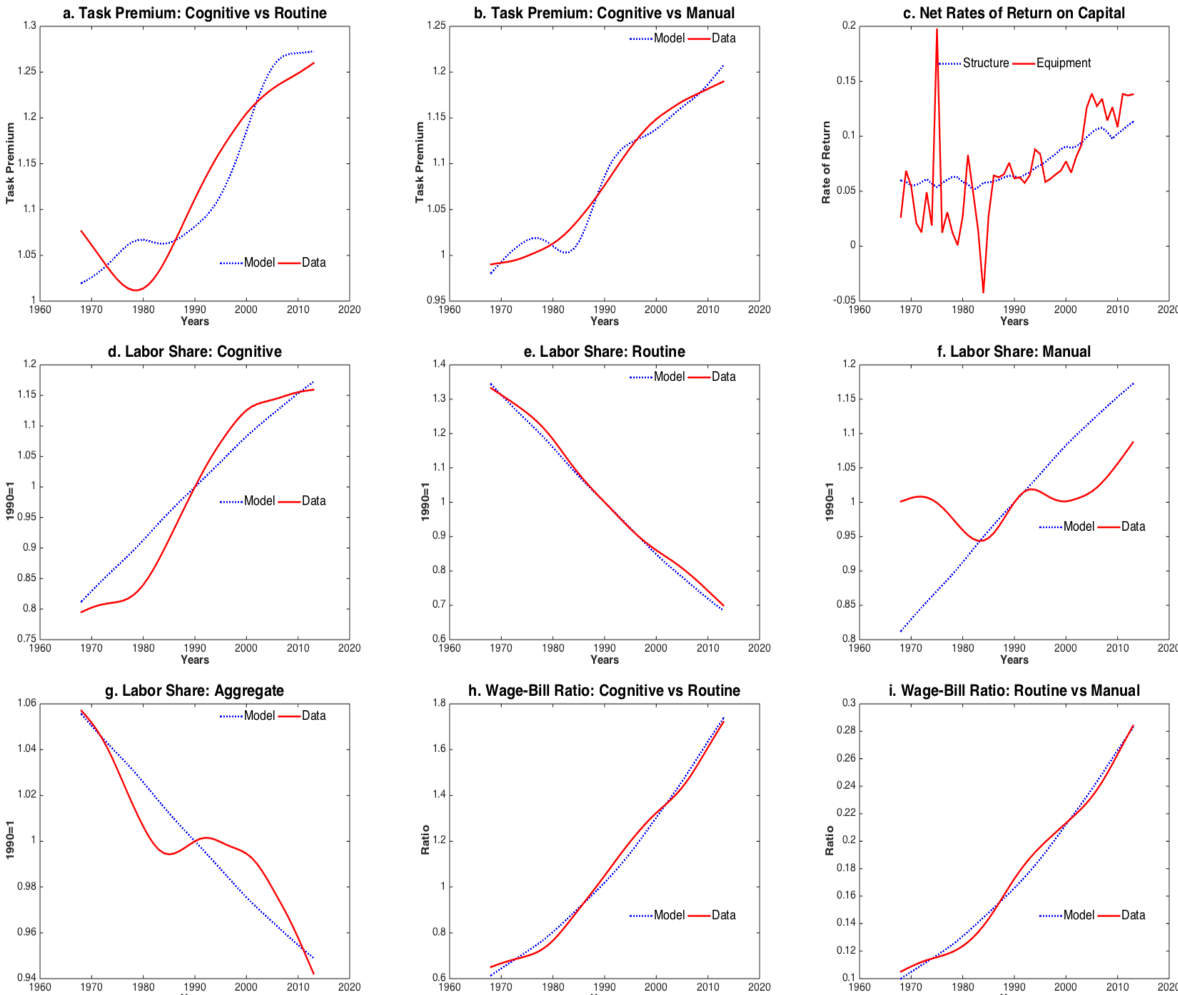
Figure A.2: Labor Share by Sectors

Figure 1.17: Labor Share Trend Coefficients by the Sectors and the Tasks



Note: Due to the small number of data for manual labor for many sectors, cognitive and manual labor are aggregated as non-routine labor.
Source: Author's calculations from labor and output files of WORLD-KLEMS and CPS data sets.

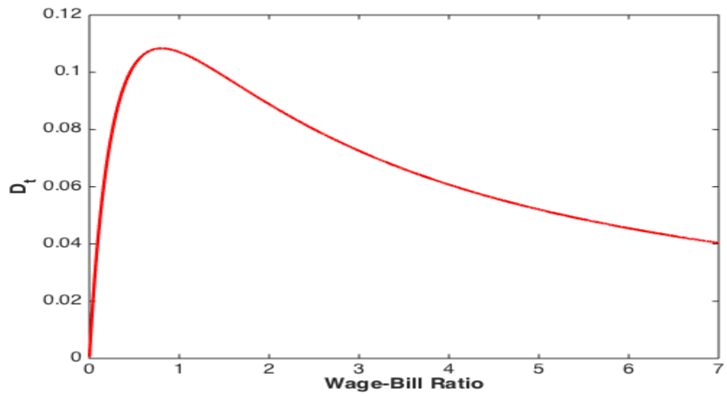
Figure 1.18: Model Fit and Data for the Cobb-Douglas Specification



Note: The series are HP-trends.

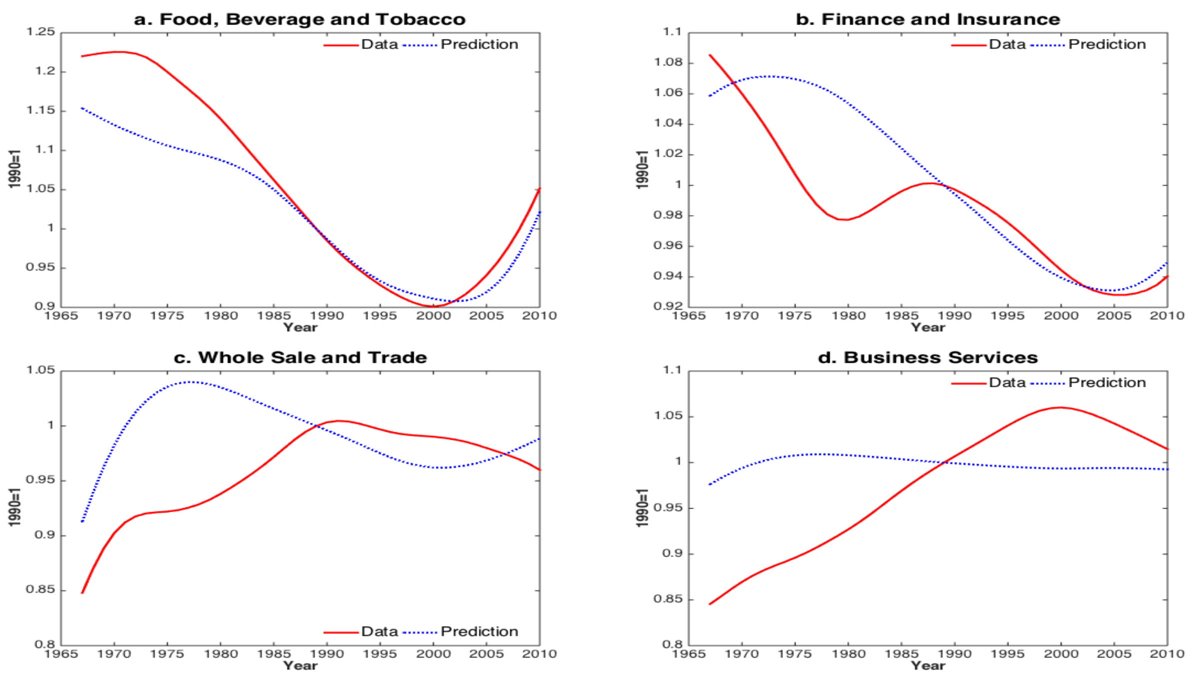
The model plots are derived from the estimation of the model with Cobb-Douglas specification as in equation 1.14

Figure 1.19: Effect of the Changes in Wage-Bill Ratio on Labor Share Growth



Note: The figure shows the coefficient of the changes in wage-bill ratio in equation 1.17.

Figure 1.20: Labor Share Generated by the Wage-Bill Ratio Series for Selected Sectors



Note: The series are HP-trends.

The figure shows the model fit when equation 1.17 is fed with the wage-bill ratios and γs calibrated for each sector.

Table 1.10: List of Model Parameters

Parameter	Description	Value	Source
α	Compensation share of structural capital	0.1058	Bayesian Inference
$\frac{1}{1-\sigma}$	Elasticity of subst. b/w routine task and equipment capital	2.40	Bayesian Inference
γ	Share of equipment capital in partial Cobb-Douglas	0.3879	Bayesian Inference
$\frac{1}{1-\kappa}$	Elasticity of subst. b/w final good and manual service consumption	0.87	Regression
χ	Share of final good in consumption composite	0.9410	Regression
δ_s	Depreciation rate of structural capital	0.0275	BEA Tables
δ_e	Depreciation rate of equipment capital	0.1460	BEA Tables
Γ	Discount factor	0.96	Literature
S	Measure of skilled households	0.361	CPS Data
μ	Share of routine task in outer CES	0.4160	Calibration
b	Relative scale of routine task efficiency of unskilled agents	0.6493	Calibration
ζ	Cognitive task efficiency of skilled agents	1.8681	Calibration
p_0	Initial relative equipment capital price	0.8302	Calibration
	Parameters Specific to Extended Model		
α_1	Compensation share of structural capital in goods sector	0.1355	EU-KLEMS Data
α_2	Compensation share of structural capital in service sector	0.0921	EU-KLEMS Data
γ_1	Share of equipment capital in partial Cobb-Douglas in goods sector	0.5043	EU-KLEMS Data
γ_2	Share of equipment capital in partial Cobb-Douglas in service sector	0.2653	EU-KLEMS Data
μ_1	Share of routine task in outer CES in good sector	0.4039	Calibration
μ_2	Share of routine task in outer CES in service sector	0.3276	Calibration
$\frac{1}{1-\nu}$	Elasticity of subst. b/w intermediate sectors	0.87	Regression
ξ	Share of good sector in final good aggregator	0.3727	Regression

1.9.2 Derivations and Equations

1.9.2.1 Representative Firm's First Order Conditions

Below first order conditions are with respect to cognitive, routine and manual tasks and structural and equipment capitals in this specific order.

1.9.2.2 General functional form

$$w_c = (1-\alpha)(1-\mu)\theta(1-\lambda)\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}}\right)} \times \left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}-1}\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}-1}\frac{L_c^\rho}{h_c} \quad (1.53)$$

$$w_r = (1-\alpha)\mu\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}}\right)}\frac{L_r^\sigma}{h_r} \quad (1.54)$$

$$w_m = (1-\alpha)(1-\mu)(1-\theta)\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}}\right)} \times \left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}-1}\frac{L_m^\beta}{h_m} \quad (1.55)$$

$$r_{str} = \alpha\frac{Y}{K_{str}} \quad (1.56)$$

$$r_{eq} = (1-\alpha)(1-\mu)\theta\lambda\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}}\right)} \times \left(\theta\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}} + (1-\theta)L_m^\beta\right)^{\frac{\sigma}{\beta}-1}\left[\lambda K_{eq}^\rho + (1-\lambda)L_c^\rho\right]^{\frac{\beta}{\rho}-1}K_{eq}^{\rho-1} \quad (1.57)$$

Cobb-Douglas specification:

$$w_c = (1-\alpha)(1-\mu)\delta\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left[L_c^\delta K_{eq}^\gamma L_m^{1-\gamma-\delta}\right]^\sigma\right)}K_{eq}^{\sigma\gamma}L_m^{\sigma(1-\delta-\gamma)}\frac{L_c^{\sigma\delta}}{h_c} \quad (1.58)$$

$$w_r = (1-\alpha)\mu\frac{Y}{\left(\mu L_r^\sigma + (1-\mu)\left[L_c^\delta K_{eq}^\gamma L_m^{1-\gamma-\delta}\right]^\sigma\right)}\frac{L_r^\sigma}{h_r} \quad (1.59)$$

$$w_m = (1-\alpha)(1-\mu)(1-\delta-\gamma)\frac{Y}{\left(\mu L_r^{\sigma} + (1-\mu)\left[L_c^{\delta} K_{eq}^{\gamma} L_m^{1-\gamma-\delta}\right]^{\sigma}\right)} K_{eq}^{\sigma\gamma} L_c^{\sigma\delta} \frac{L_m^{\sigma(1-\delta-\gamma)}}{h_m} \quad (1.60)$$

$$r_{str} = \alpha \frac{Y}{K_{str}} \quad (1.61)$$

$$r_{eq} = (1-\alpha)(1-\mu)\gamma \frac{Y}{\left(\mu L_r^{\sigma} + (1-\mu)\left[L_c^{\delta} K_{eq}^{\gamma} L_m^{1-\gamma-\delta}\right]^{\sigma}\right)} K_{eq}^{\sigma\gamma-1} L_m^{\sigma(1-\delta-\gamma)} L_c^{\sigma\delta} \quad (1.62)$$

1.9.2.3 Relationship between Labor Share and Wage-Bill Ratio

$$LS_t = \frac{w_{r,t}h_{r,t} + w_{c,t}h_{c,t} + w_{m,t}h_{m,t}}{Y_t} \quad (1.63)$$

$$LS_t = (1-\alpha)\frac{\mu L_{r,t}^{\sigma} + (1-\mu)\delta K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)} + (1-\mu)(1-\gamma-\delta) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\left(\mu L_{r,t}^{\sigma} + (1-\mu)\left[K_{eq,t}^{\gamma} L_{c,t}^{\rho} L_{m,t}^{1-\delta-\gamma}\right]^{\sigma}\right)} \quad (1.64)$$

$$LS_t = (1-\alpha)\frac{\mu L_{r,t}^{\sigma} + (1-\mu)(1-\gamma) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\left(\mu L_{r,t}^{\sigma} + (1-\mu)\left[K_{eq,t}^{\gamma} L_{c,t}^{\rho} L_{m,t}^{1-\delta-\gamma}\right]^{\sigma}\right)} \quad (1.65)$$

Multiplying both denominator and numerator of the right hand side by $\frac{1}{\mu L_{r,t}^{\sigma}}$

$$LS_t = (1-\alpha)\frac{1 + \frac{(1-\mu)(1-\gamma) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}}}{1 + \frac{(1-\mu) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}}} \quad (1.66)$$

Multiplying the second term in the denominator by $\frac{1-\gamma}{1-\gamma}$:

$$LS_t = (1-\alpha)\frac{1 + \frac{(1-\mu)(1-\gamma) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}}}{1 + \frac{(1-\mu) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}} \frac{1-\gamma}{1-\gamma}} \quad (1.67)$$

$$LS_t = (1-\alpha)\frac{1 + \frac{(1-\mu)(1-\gamma) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}}}{1 + \frac{\frac{(1-\mu)(1-\gamma) K_{eq,t}^{\sigma\gamma} L_{c,t}^{\sigma\delta} L_{m,t}^{\sigma(1-\delta-\gamma)}}{\mu L_{r,t}^{\sigma}}}{1-\gamma}} \quad (1.68)$$

Substituting the wage-bill ratio between non-routine and routine tasks:

$$wbr_t = \frac{(1-\mu)(1-\gamma)K_{eq,t}^{\sigma\gamma}L_{c,t}^{\sigma\delta}L_{m,t}^{\sigma(1-\gamma-\delta)}}{\mu L_{r,t}^{\sigma}} \tag{1.69}$$

$$LS_t = (1-\alpha)\frac{1+wbr_t}{1+\frac{wbr_t}{1-\gamma}} \tag{1.70}$$

1.9.2.4 Labor Share in Difference Terms

Below, the variables with a hat denote growth rate of the variable from period $t-1$ to t. Equation 1.70 can be written in growth terms as follows:

$$\widehat{LS}_t = (\widehat{1+wbr_t}) - \left(\widehat{1+\frac{wbr_t}{1-\gamma}}\right) \tag{1.71}$$

$$\widehat{LS}_t = \frac{wbr_t}{1+wbr_t}\widehat{wbr}_t - \frac{\frac{wbr_t}{1-\gamma}}{1+\frac{wbr_t}{1-\gamma}}\widehat{wbr}_t \tag{1.72}$$

$$\widehat{LS}_t = \frac{wbr_t}{1+wbr_t}\widehat{wbr}_t - \frac{wbr_t}{1-\gamma+wbr_t}\widehat{wbr}_t \tag{1.73}$$

$$\widehat{LS}_t = \frac{(1-\gamma)wbr_t + wbr_t^2}{(1-\gamma)+wbr_t+(1-\gamma)wbr_t+wbr_t^2}\widehat{wbr}_t - \frac{wbr_t + wbr_t^2}{(1-\gamma)+wbr_t+(1-\gamma)wbr_t+wbr_t^2}\widehat{wbr}_t \tag{1.74}$$

$$\widehat{LS}_t = \widehat{wbr}_t\left[\frac{wbr_t - \gamma wbr_t + wbr_t^2 - wbr_t - wbr_t^2}{(1-\gamma)+wbr_t+(1-\gamma)wbr_t+wbr_t^2}\right] \tag{1.75}$$

$$\widehat{LS}_t = -\widehat{wbr}_t\left[\frac{\gamma wbr_t}{(1-\gamma)+(2-\gamma)wbr_t+wbr_t^2}\right] \tag{1.76}$$

$$\widehat{LS}_t = -\widehat{wbr}_t\left[\frac{\gamma}{wbr_t+(2-\gamma)+\frac{(1-\gamma)}{wbr_t}}\right] \tag{1.77}$$

1.9.3 Hours and Wage Data

1.9.3.1 Measuring Labor Hours and Wage Rates

This methodology closely follow from Krusell et al. (2000) and Domeij and Ljungqvist (2006). Labor data is obtained from March Current Population Survey (CPS) integrated by IPUMS (Flood et al. (2015)). The availability of a consistent occupational definition limits the period of study to 1967-2013. Number of annual observations in raw data ranges from 130,476 (1996) to 218,269 (2001). However, after dropping out some observations, we are left with numbers ranging from 55,721 (1996) to 96,184 (2001). I record every person whose age is between 16 and 70. Consistent with the literature, self employed people, unpaid family workers and agricultural and military workers are dropped from the sample. Furthermore, people who reported zero usual hours worked per week last year are dropped as well.

For each person, I record their personal characteristics: *age*, *sex*, *race*, occupation (*occ50ly*); employment statistics: class of worker (*classwly*), weeks worked last year (*wkswork1* and *wkswork2*), usual hours worked per week last year (*uhrswork* and *hrswork1*); income: total wage and salary income last year (*incwage*) and CPS personal supplement weights: *wtsupp*.[51] Three task groups are obtained from the occupation series based on the classifications in the literature. The details of this can be found in the following subsection. Then, each person is assigned to one of 198 groups created by age, race, sex and task. Age is divided into 11 5-year groups: 16-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, 66-70. Race is divided into three: white, black, others. Finally, occupation is divided into three task groups: cognitive, routine and manual.

Before calculating the annual hours worked and hourly wage rates, topcoded income values are adjusted using the "revised income topcodes files" published by Census Bureau (and compiled by IPUMS) to swap topcoded values in 1976-2010 CPS files with these revised values. This procedure replaces the topcoded values with new values based on the Income Component Rank Proximity Swap method, which was introduced in 2011. Hence, throughout the whole 1975-2013 period, the topcoding methodology is consistent and comparable. This also eliminates the jumps in task premium that researchers observe due to the change in topcoding methodology in some years. Unfortunately, swap values are not available for earlier years. Therefore, following Krusell et al. (2000), I tried both leaving the topcoded

[51] IPUMS recodes the CPS series on occupation into the 1950 Census Bureau occupational classification system. This provides consistent occupational codes for the jobs respondents reported working during the previous calendar year, for 1968 forward.

values as they are and also multiplying them by 1.45 for the years before 1975. This does not change any of the results of the paper.

For the CPS years after 1975, CPS has usual hours worked per week and weeks worked last year. Thus, calculating the annual hours for a person is straightforward: I simply multiply weeks worked last year by usual hours worked. Hence, for CPS years 1976 and afterwards, total hours are:

$$hours_{i,t-1} = wkswork1_{i,t-1} \times uhrswork_{i,t-1}$$

where, i is individual observation and t is the CPS year.

For earlier years I need to do two adjustments. First, weeks worked are available only as intervals and I need to approximate a scalar value for each interval. Fortunately, both the intervals and actual weeks are available for years after 1975. Therefore, we can calculate the average weeks worked after year 1975 for each interval and replace the earlier years with those values. In this context, the following approximations are used:

Interval	**Approximation**
1-13	8.1
14-26	21.5
27-39	33.6
40-47	42.6
48-49	48.3
50-52	51.8

Second, I have to use hours worked last week variable as a proxy to usual hours worked per week last year. However, there are many agents who were not employed last week, or who were employed but not at work for some reason, despite reporting a positive income for last year. Rather than dropping those observations, I replaced the hours they worked per week with the average of the hours worked by the people in their group in that particular year. I also paid attention to whether the person was part time or full time employed when doing this replacement.

Hourly wage is calculated as:

$$wage_{i,t-1} = \frac{incwage\_swapped_{i,t-1}}{hours_{i,t-1}}$$

Later, observations with $hours_{i,t-1} < 260$ (quarter of part time work) and $wage_{i,t-1} < 0.5 \times minimum\_wage_{t-1}$ are dropped to smooth out the effect of externalities and misreportings. Following this, for each groups and year, I calculate group weights as: $\mu_{g,t} = \sum_{i \in g} \mu_{i,t}$ where, $g \in G$ is set of groups. Then average hours and wage measures for each group and year are calculated:

$$\begin{aligned} hours_{g,t-1} &= \frac{\sum_{i \in g} \mu_{i,t} \times hours_{i,t-1}}{\mu_{g,t}} \\ wage_{g,t-1} &= \frac{\sum_{i \in g} \mu_{i,t} \times wage_{i,t-1}}{\mu_{g,t}} \end{aligned}$$

To aggregate across groups into aggregate task groups, the group wages of 1980 are used as the weights. Letting $j \in \{C, R, M\}$, where C, R and M represent the cognitive, routine and manual occupations respectively, then for each task group j, we have total hours:

$$N_{j,t-1} = \sum_{g \in G_j} hours_{g,t-1} \times \mu_{g,t} \times wage_{g,80}$$

and average hourly wage is:

$$W_{j,t-1} = \frac{\sum_{g \in G_j} hours_{g,t-1} \times \mu_{g,t} \times wage_{g,t-1}}{N_{j,t-1}}$$

Finally task premium between cognitive and routine tasks is calculated as $\frac{W_{C,t-1}}{W_{R,t-1}}$.. The other task premiums are found in the same way.

1.9.3.2 Occupational Classification

I follow Autor et al. (2003), Acemoglu and Autor (2011) and Autor and Dorn (2013) -among many other studies in the literature- to classify the occupations into different tasks. Occupations are divided along two dimensions: cognitive vs manual and routine vs non-routine.

Table 1.11 provides detailed explanations and examples for each of these categories.[52] In short, cognitive and manual jobs are characterized by the differences in the extent of mental versus physical activity. On the other hand, routine and non-routine jobs are differentiated based on the codifiability of the work. Routine tasks are the ones that can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures. In contrast, when a task requires instant decision making, flexibility, taking initiatives, problem solving, creativity and personal interaction, then it is classified as non-routine.

Table 1.11: Occupational Classification

	Non-Routine	**Routine**
Cognitive	Managerial, professional, technical workers (i.e. physicians, public relations managers, financial analysts, computer programmers, economists)	Sales and office and administrative support (i.e. secretaries, bank tellers, retail salespeople, travel agents, mail clerks, data entry keyers)
Manual	Service jobs (i.e. janitors, gardeners, manicurists, bartenders, home health asides)	Blue collar jobs (i.e. machine operators and tenders, mechanics, dress makers, fabricators and assemblers, cement masons, and meat processing workers)

For the purpose of this study- and as common in the literature- I classify all the routine occupations in one single category: "Routine", whether they are cognitive or manual. This group represents the tasks implemented by the "middle skill" labor. These occupations are not necessarily mechanical nor computerized and they might even require personal interaction. The common characteristic of the tasks labeled as routine is that they can be replaced

[52]This table is borrowed from Jaimovich and Siu (2012)

by technological improvement or can be offshored. For instance, as online sales became more widespread, many sale jobs have been lost. As another example, most of the call centers started employing labor that is physically in India.

Non-routine occupations are divided into two categories. I label cognitive non-routine occupations as "Abstract", which tends to be "high skill" labor. These are mainly managerial, professional, executive and technical jobs. Finally, manual non-routine occupations are classified as "Manual" occupations. These occupations represent the lowest tail of the skill distribution and they are termed as "service occupations" by Autor and Dorn (2013) and Firpo et al. (2011).

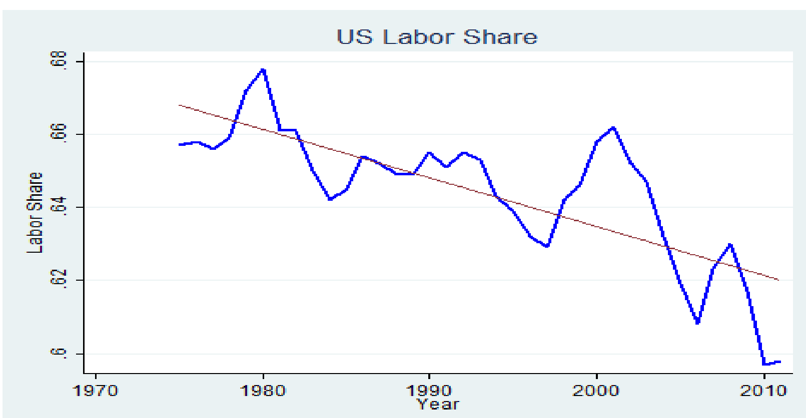
CHAPTER 2

Impact of Information Technology on the Labor Share: Evidence from the U.S. Sectoral Data

2.1 Introduction

Until recently, labor's share of income (henceforth, the labor share) in the U.S. economy has been considered to be nearly constant. However, recent studies have documented that this fact does not describe the U.S. economy anymore, as the labor share in the U.S. has been falling over the last few decades. This decline has substantially accelerated since the early 2000s (Figure 2.1).

Figure 2.1: U.S. Labor Share: Non-farm Business Sector



Source: Karabarbounis and Neiman (2014b).

The aggregate decline in the labor share is important on its own and is the subject of a vast literature trying to unravel the causes of this new phenomenon. In Chapter 1, I discussed that the co-existence of technological progress and capital-task complementarity is a key explanation for the recent decline of the aggregate labor share. Nevertheless, the aggregate picture masks the accurate experiences of each segments of the labor market. First of all, as Figure 2.2 below and Figure 1.16 in Section 1.9.1 both reveal, the decline in the aggregate labor share has been mostly driven by the majority of the manufacturing sectors; while the labor share has either remained roughly the same or even exhibited an increase in most of the service sectors.[12] Furthermore, as Figure 2.3 demonstrates, the decline in the labor share is almost solely due to the losses of a specific type of labor doing routine tasks, while the workers in non-routine occupations have actually enjoyed a substantial rise in their share of total income.[3]

The decline in the aggregate labor share has coincided with a period when the price of capital have declined substantially. In particular, the price of information and communication technologies (ICT) capital, which is the most technology intensive definition of capital and hence can proxy the technological advancement better than other types of capital, ex-

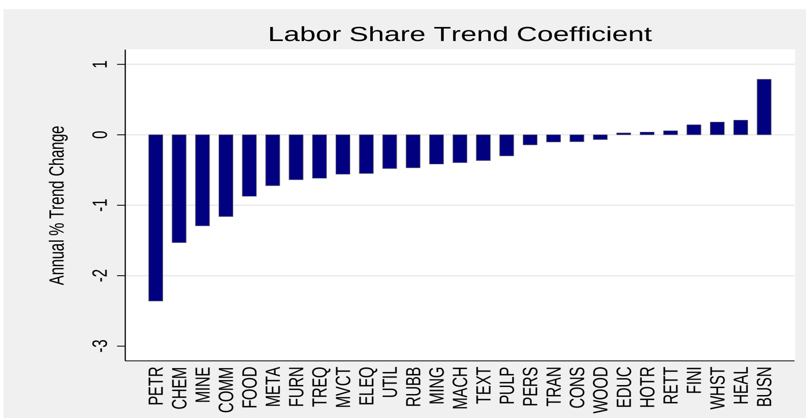
[1]Figure 2.2 shows the labor share trends for each sector for the period 1977-2007. Labor share trends are defined as the slope coefficient of a regression of the log of the labor share on a time variable. Thus, they can be interpreted as annual percentage changes in the labor share. Figure 1.16, on the other hand, displays the whole time series of the labor share in each sector.

[2]Sectors studied in this paper and the abbreviations used can be found in Table 1.9 in Section 1.9.1.

[3]Section 1.9.3 provides explanation and examples of both types of labor. In short, routine tasks are the ones that can be summarized as a set of specific activities accomplished by following well-defined instructions and procedures. These tasks can be replaced by machines, computers or even be offshored. In contrast, when a task requires instant decision making, flexibility, taking initiatives, problem solving, creativity and personal interaction, then it is classified as non-routine.

hibited the most notable trend decline.[4] Not surprisingly, this has been coupled with the rise of the share of ICT capital among all capital from almost 0 percent to around 35 percent. Meanwhile, whether we define skill by years of education or by the task-content of occupations, both the employment share of skilled labor in production and the skill premium rose considerably.[5] All these, along with the fact that the decline in the labor share has been unique to “unskilled” labor as shown in Figure 2.3, imply that most of the developments in labor markets have been consistent with the predictions of the theory of capital-skill complementarity (CSC). Hence, any attempt to explain the decline in the labor share would be incomplete and inconsistent with the rest of the labor market developments if the role of capital-skill complementarity is ignored.

Figure 2.2: Labor Share Trend Coefficient by Sectors



Source: Author’s calculations from EU-KLEMS data set.

[4]ICT is an umbrella term that includes any communication device or application, encompassing: radio, television, cellular phones, computer and network hardware and software, satellite systems and so on, as well as the various services and applications associated with them, such as videoconferencing and distance learning. Therefore, each sector might be using different subsets of ICT capital and thus face differing prices per unit of ICT capital consumed.

[5]Regardless of how we define skill, skill premium is defined as the wage of skilled labor divided by that of unskilled.

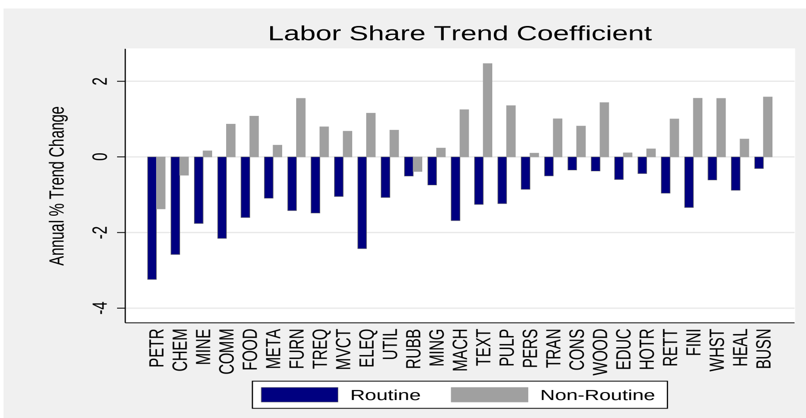
Nevertheless, the literature on the labor share mainly focuses on one type of capital and labor when investigating the role of falling capital prices (which is a proxy to technological progress) in the decline of the labor share. Bulk of the studies in this literature completely ignore the skill composition of labor and hence, the capital-skill complementarity. This literature has not arrived at an agreement on the impact of the decline in capital prices on the labor share yet. For instance, while Karabarbounis and Neiman (2014b) attribute half of the decline in the labor share to the decline in capital prices, Oberfield and Raval (2014) claim that the price of capital cannot account for the decline in the labor share on its own.

This paper is an attempt to reconcile these conflicting conclusions about the impact of the decline in capital prices on the labor share. By exploiting the sectoral heterogeneities in several dimensions, and incorporating skill composition of labor into the picture, I aim at characterizing the conditions, under which, the decline in capital prices would lead to a rise or fall in the labor share at the sectoral and aggregate levels.[6] Splitting the capital as ICT vs non-ICT and labor input as routine vs non-routine has several advantages. Above all, this setup will enable us to break the labor share into two components: routine and non-routine and inferring a mechanism from this disaggregation that explains why the decline in capital prices impacted sectors differently. This mechanism also has implications for the decline in the aggregate labor share as we can model it as the transition of the economy from a state, where initially some sectors were overloaded with routine labor, to a new one where most of the sectors complete their adjustment in their production process by substituting routine labor with non-routine ones and ICT capital.

[6] In this sense, just like Chapter 1, this chapter also marries the labor share literature with capital-skill complementarity and job polarization literatures to shed light on the link between technological progress and the labor share. The reader is encouraged to read Section 1.2 for a detailed review of each of these three strands of literature.

To investigate the role of technological progress on the labor share, I first compile capital and hours data for 28 U.S. sectors from various sources. Then I use a two-stage Bayesian Estimation method that has been described in detail in Chapter 1 to estimate the elasticities of substitution between ICT capital and two different labor inputs in each sector and at the aggregate level.[7]. To estimate the elasticities, I used the standard production function of Krusell et al. (2000), which allows capital-skill complementarity. Later, I do both panel and trend regression analysis to analyze the effect of the decline in the price of ICT capital on the labor share, when we control for the initial routine task intensities and the degree of capital-skill complementarities in each sector.

Figure 2.3: Labor Share Trend by Sectors: Routine vs Non-Routine Labor



Source: Author's calculations from EU-KLEMS data set.

The main finding of this paper is that factor prices alone cannot explain the decline in the aggregate labor share. As a matter of fact, the empirical findings suggest that the

[7]I also re-estimate the elasticities using the two-stage simulated pseudo-maximum likelihood (SPML) methodology as in Krusell et al. (2000) This version of the paper reports only the results obtained by the Bayesian Estimation technique. Using two-stage SPML methodology does not alter any of the conclusions of this paper.

decline in ICT capital price must have actually affected the labor share favorably. This is possible in our set up as there are two groups of labor and as data reveals, one of these are on the losing side, while the others are enjoying increases in their share of total income. Consistent with this, significant capital skill-complementarity is documented at each sector. This finding is not surprising since the price of ICT capital investment fell in every sector and each sector responded by increases in their skill premium and a decline in share of routine task hours, along with substantial rise in ICT capital services per hour. Hence, we can say that experiences of sectors in terms of the course of their skill premia and changes in skill compositions are consistent with the theory of capital-skill complementarity (or with its reinterpreted version: routinization biased technological change (RBTC)).[8] Nonetheless, sectors are found to exhibit considerable heterogeneity in terms of their degree of capital-skill complementarity, and more important than that, in terms of absolute complementarity between ICT capital and skilled labor. This, in part, explains why some sectors faced declining labor shares while the others did not.

Existence of capital-skill complementarity is necessary and sufficient alone to generate a model outcome similar to that in Figure 2.3 in the sense that the labor share increases for a certain group, while declining for the unskilled group. However, capital-skill complementarity alone does not justify the widely differing magnitudes in trend changes of the income shares of each type of labor across sectors. It also does not guarantee a fall or rise in the overall labor share in a sector. Our panel and trend regression analysis show that if anything, decline in price of capital have positive impact on the labor share in a sector. However, this positive impact on the labor share is weakened or even reversed when (i) the sector initially has a very large share of routine workers, or (b) the complementarity between capital and

[8] Jung and Mercenier (2014) define RBTC as "a reinterpretation of the role of technical progress in shaping labor markets: technology- and computers in particular- can replace labor in routine tasks (those tasks that involve step-by-step procedures and can therefore be codified) but not in non-routine tasks." This term was first advocated by Autor et al. (2003), who also provided evidence in favor of it using the U.S. data.

skilled hours is weak. In these cases, the loss of the routine labor will dominate the gain of non-routine ones and thus, the sector will experience a declining labor share.

In this framework, the decline in ICT capital prices can be thought of as the main factor triggering a structural transition within sectors to a new steady state with less routine labor. Each sector will experience similar patterns for sub-components of the labor share but the ones with a large bulk of labor on the losing side will experience a decline in the aggregate labor share simply due to the larger weight of losing group in total labor hours. Over time, as the share of unskilled labor in production falls to reasonably low levels, the positive impact of capital-skill complementarity on the labor share will start dominating and decline in the labor share might slow down or even revert back. Similarly, if the gains of one skilled labor is not large enough relative to the losses of one unskilled labor, then again the sector will be more likely to experience a fall in the labor share. This, in turn, mainly depends on the elasticity of substitution between skilled labor and ICT capital. However, if a long enough time period is considered, this effect will be reversed as both the labor and producers can complete their adjustments and more labor can benefit from the extra gains that come with the decline in capital prices.

This story has crucial implications for the economy-wide aggregate labor share. In one hand, the initial routine-task intensity is high for the aggregate economy as well. Furthermore, I document that the elasticity of substitution between ICT capital and skilled hours is larger than 1 at the aggregate level. Combined together, these two explain why the labor share is falling when the price of ICT capital is rising. If we focus on structural shift story, on the other hand, the aggregate decline is still consistent with our explanation as most of the sectors- especially the manufacturing ones- are the ones with high initial routine task intensity and weak complementarity between ICT capital and skilled hours. These sectors also constitute a large share of total value added and they experience largest declines in their labor shares. Two good news stand out for the future. First, share of these sectors in value added is declining fast.[9] Second, within those sectors, share of routine labor is falling fastest and hence the decline in the labor share should cool down in near future.

Finally, a modest contribution of the paper is to provide new elasticity measures when capital is split as ICT and non-ICT capital and skill is defined by the routine task intensity of occupations. KORV's elasticities of substitution are used commonly in job polarization literature as well. Given that capital-skill complementarity and job polarization literatures use different capital and skill definitions, a study investigating the effects of computer technology on the polarization of job markets might cause misleading conclusions on the skill premium and the skill composition if the appropriate parameters are not employed. As reported later, I still document strong capital-skill complementarity at the aggregate level when one uses ICT capital as the proxy of technology and the task-based definition of skill. However, despite implying strong capital-skill complementarity, new estimates show that ICT capital and skilled labor are not absolute complements as the elasticity of substitution between them is above 1, unlike 0.67 reported by KORV. This difference is crucial as this elasticity plays the key role in shaping the trend of the labor share in response to declining capital price. As a matter of fact, the inconsistency of KORV's model's prediction in terms of the labor share is corrected once we use these new elasticities and capital and skill definitions.

This paper is constructed as follows. In Section 2.2, data is introduced and empirically analyzed. This will be followed by description of model used in estimation in Section 2.3. Section 2.4 will report the key findings. Finally, Section 2.5 will conclude the paper.

[9] This "between component" is not considered in this paper as we ignore sectoral shifts at this point. However, I showed in Chapter 1 that the role of sectoral shifts has been negligibly small for the last two decades. However, as the sectors complete their adjustments by reducing their routine labor employment, between sector effects might gain importance again.

2.2 Data and Facts

In this section, I will first explain the reasons behind my choice of capital and skill definitions. Later, data sources and an outline of methodology used in calculation of labor hours will be described. Finally, some facts and empirics from data will be presented.

2.2.1 Choice of capital and skill definition

Unlike the standard capital-skill complementarity literature, this paper splits the capital as ICT capital (rather than equipment capital as it is common in the literature or one single investment good) and non-ICT capital. This choice of capital has two advantages over using equipment capital. First, the price of ICT capital has declined enormously over the last four decades. This decline accelerated especially from mid 90s to early to mid 2000s. In this short period, share of ICT capital among all capital also more than tripled. This was followed by the acceleration in the decline in the labor share in 2000s. As a consequence, the fall in the price of ICT capital and the following increase in ICT capital intensity emerge as the natural candidates for linking technological advancement and the labor share.

Secondly, differentiating the capital as ICT versus non-ICT capital will enable us to analyze the causes of the trend decline in the labor share in consistence with another recent phenomenon of the U.S. labor markets: job polarization.[10] To my knowledge, the link between job polarization and the labor share has not been studied yet. Finally, as it is demonstrated in Figure 1.1, despite its success in explaining the skill premium, the theory of capital-skill complementarity is incapable of explaining the decline in the labor share in past decade when equipment capital is used as the proxy of technology and skill is defined

[10]Here, job polarization refers to the growth in the employment share of high skill and low skill occupations, while that of middle skill occupations erodes. One common explanation for job polarization is the advances in computer technology, which replaced the labor working in occupations that have high routine task intensity. In this sense, job polarization literature can be thought of as a sub branch of capital-skill complementarity literature. However, the definitions of capital and skill are different in two literatures.

by years of education. On the other hand, once we change our definition of capital as ICT capital, we see that capital-skill complementarity becomes more consistent with the trends in both the skill premium and the labor share.

In line with our choice of capital, I define skilled hours as hours worked in non-routine occupations, in contrast to bulk of the capital-skill complementarity and the labor share literatures, where various education levels are used as proxies to skill. One obvious advantage of this choice of skill definition is ensuring the consistency with the *"RBTC"* hypothesis, which was described earlier. More detailed arguments in favor of use of task-based skill definition are provided in Section 1.3.

2.2.2 Data sources

2.2.2.1 Labor input and wage data

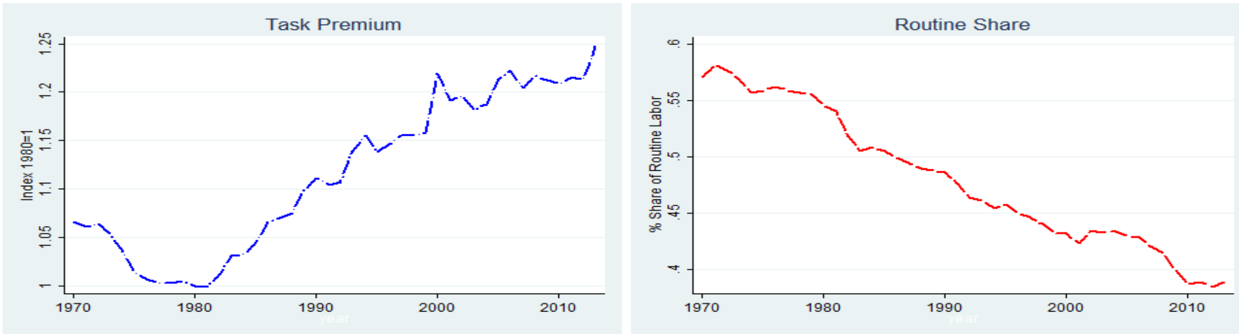
The source of wage and skill composition data is March Supplement of Current Population Survey (CPS) for the years between 1970 and 2007.[11][12] The details of constructing labor input and wage series are described in detail Section 1.9.3. The task premium series constructed exhibits an increasing trend for about two decades after 1980 before finally flatting out in early 2000s (left panel of Figure 2.4).[13] This period coincides with the ICT boom that started cooling down following late 1990s (Figure 6 below). This strengthens our reasoning for choosing ICT capital and task based skill classification: routine vs non-routine.

[11]CPS data is compiled and published by IPUMS (Flood et al. (2015)). For 1970 to 2007 data, we used CPS from 1971 to 2008.

[12]Wage and skill composition data are available up to the year 2013. However, I restricted this study to 1970-2007 period since capital stock and price data are consistently available for only this period.

[13]Consistent with our choice of skill classification, task premium and skill premium are used interchangeably throughout this paper.

Figure 2.4: Task Premium and Task Composition in U.S.: 1970-2013



Source: Author's calculations from CPS.

Labor input series calculated from CPS for both types of labor are used only to determine the share of routine labor in total hours, which is presented in the right panel of Figure 2.4. Actual total labor hours, on the other hand, are taken from EU-KLEMS files for the sake of consistency with the capital series.[14] These hours are then multiplied by the shares of each type of labor to allocate total hours into either of two skill groups.

2.2.2.2 Capital stock and prices

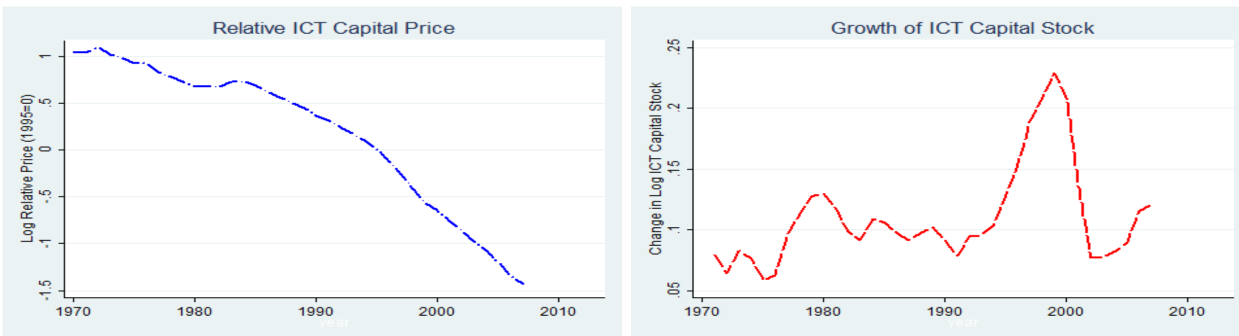
Capital stock series are taken from EU-KLEMS data set. This data set provides quality-adjusted capital stock series, investment flows and price of investment for both ICT and non-ICT capital. The main advantage of EU-KLEMS data set is that it provides capital series for up to 72 industries, which enables us to do sectoral analysis. I aggregate those sectors into 27 groups, excluding agriculture, public administration and military and real estate activities.[15]

[14]For the same reasoning, value added and compensation of employees for each sector are taken from EU-KLEMS data set as well.

[15]Sectoral classification of CPS data and EU-KLEMS data do not match one-to-one as the former is based on NAICS classification while the latter uses ISIC Rev. 4 to classify the industries. To match these two, I took the EU-KLEMS aggregations and aggregated the CPS sub-industries at three digit levels into two digit

The main disadvantage of the EU-KLEMS data set is that it does not enable us to study the corporate business sector only, which is usually the main focus of the studies in labor share literature. However, we can distinguish between market economy and non-market services, and excluding the non-market services from our study does not alter our main findings.[16]

Figure 2.5: ICT Capital: Relative Price and Growth Rate of Stock



Source: EU-KLEMS.

As depicted in the left panel of Figure 2.5, the relative price of ICT capital has declined substantially throughout the entire period of our study.[17] This process has accelerated in 1990s as discussed earlier. Consistent with this, ICT capital stock growth reached at historically unprecedented high levels in mid 90s before slowing down in early 2000s (the right panel of Figure 2.5). This is the period that we call as “ICT boom” and the acceleration in

levels consistent with ISIC classification.

[16]Some of the non-market activities such as public administration, defense and real estate activities are already excluded in our analysis. When I drop the two other non-market services -education and health- as well, the key messages of the paper remain intact.

[17]This relative price series will be fed into our model as a proxy to technological improvement as explained earlier.

the decline in the labor share followed this period. That is the main reason why ICT capital is the focus of this study and our skill definition is based on tasks, as some tasks are highly vulnerable to computerization.

2.2.3 Facts

When we only focus on the aggregate picture, what we see is both a decline in the labor share and a substantial fall in the price of ICT capital. At first glance, this might have been interpreted as an evidence supporting Karabarbounis and Neiman (2014b) and others who claim that most of the decline in the labor share can be attributed to the decline in capital price. However, when the economy is disaggregated into 27 sectors, our conclusion about the link between capital prices and the labor share changes its direction. As both panels of Figure **??** reveal, the sectors that faced the largest decline in relative ICT capital prices and the largest increases in ICT capital per value added are the ones that have experienced the smallest decline in their labor share.[18][19] The negative relation between ICT capital and the labor share gets even stronger when we drop a few outlier sectors from our sample. Furthermore, if we deflate relative ICT prices by average wages in each sector, the favorable impact of relative ICT prices on the labor share gets even stronger (Figure 2.14).

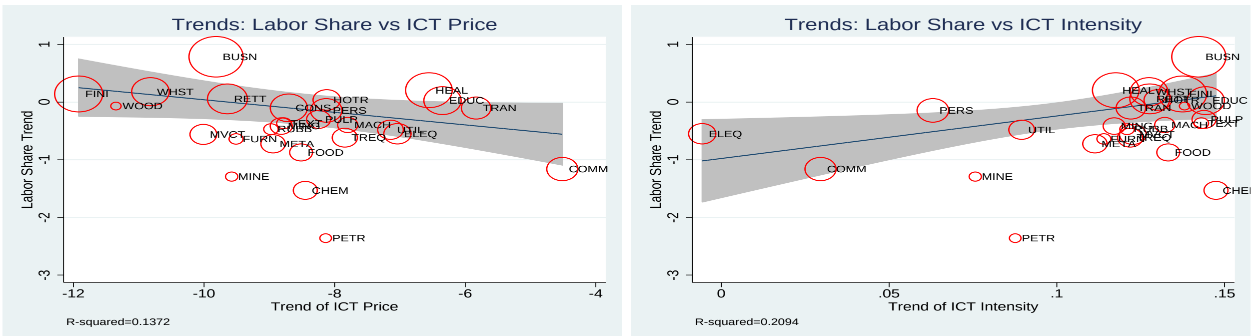
It is true that the labor share declined for most of the sectors when ICT capital prices were falling substantially at each sector. However, this does not mean that the decline in ICT prices were the main reason behind the decline in the labor share. On the contrary,

[18] In this study, I mostly focus on long term trend decline in the labor share. Hence, most of the scatter plots show the trend coefficients against other variables of interest. Trend coefficients are obtained by the regression of a logarithmic variable on a time variable and a constant. The coefficient of the time variable is interpreted as the annual percentage in the dependent variable.

[19] At this point, it would be useful to remind again that ICT is an umbrella term covering different types of computer, software, communication and other devices and each sector use a different subset of ICT capital. Hence, even though all sectors face declining ICT capital prices, the magnitude of the decline might substantially differ across sectors.

sectoral experience tells us that, assuming everything else is the same, decline in ICT capital prices worked in a way to alleviate the decline in the labor share.

Figure 2.6: Labor Share Trend vs ICT Price and Stock Trends Across Sectors



Note: ICT capital intensity is defined as ICT capital stock per unit of value added generated in a sector.
Source: Author's calculation from the EU-KLEMS data set.

Figure 2.6 shows the negative relationship between ICT capital and the labor share in longer horizon as it only focuses on the trend changes during the entire period of study. Alternatively, when we run a regression of the labor share on relative ICT capital prices, we still obtain a significant negative relationship between ICT prices and the labor share, when we use either relative ICT prices or relative ICT prices deflated by sectoral wage rates (Table 2.3).[20] Table 2.4 in Section 2.6 shows that the sign of the relationship remains the same when all data is differentiated or HP-detrended. However, in this case, reported coefficients are no longer significant.

[20]The panel regressions have both time and cross-sectional fixed effects. Alternative methods are tested as well and fixed effects are proven to be statistically the most appropriate specification. Furthermore, even though it is not reported in Table 2.3, several other control variables such as capital stocks, wage rates, labor hours and value added among a few more were also included among regressors as well. Inclusion of them affects neither the sign nor the significance of coefficients reported here. Finally, all the regressions are in logarithmic terms.

To sum it up, whether we consider only the long term or focus on the relationship over time and across sectors at the same time, the first fact we derive from the data is that **capital price and the labor share seem to be negatively correlated**. In this sense, this paper agrees more with Oberfield and Raval (2014) than Karabarbounis and Neiman (2014b).

If the labor share and ICT prices are negatively related, one would naturally ask why we had been observing a decline in both of them at the same time. That question can be answered better if we zoom into the disaggregated picture. As already discussed earlier, there are two groups of labor in our setup: routine and non-routine. Capital-skill complementary predicts that, the former will experience a relative deterioration in their share of income as the ICT prices decline. As shown in Figure 2.3 earlier, sectoral data confirms this prediction. As a matter of fact, what sectoral data points out is a stronger statement: not only routine labor does relatively worse in terms of the labor share; they also lose their share of income in absolute terms, while that of non-routine group increases.

As each sector has one losing and one winning group in terms of the labor shares and more or less experience similar trend decline in ICT capital prices, then the sectors for which the group of routine labor is initially high, the losses are more likely to dominate the gains of a smaller group. This is a simple accounting identity that would hold regardless of the model specification.

Assume that relative ICT capital prices are falling and sectoral production functions exhibits capital-skill complementarity. If we define, wage-bill ratio as the relative wage bills of two types of workers, then CSC would predict that wage-bill ratio will be rising at each sector, which is also confirmed in data. Wage-bill ratio is also equivalent to the ratio of labor shares and it is expected to rise due to: (i) rise in task premium, (ii) rise in the share of non-routine hours in total hours.

$$wbr = \tfrac{labsh_{nr}}{labsh_{r}} = \tfrac{w_{nr}}{w_{r}} \times \tfrac{h_{nr}}{h_{r}} \uparrow$$

Here, w_{nr} and w_r represent wage rates of non-routine and routine labor. Similarly, $labs_{nr}$

and $labs_r$ stands for labor shares, and h_{nr} and h_r hours of each group. Finally, wbr denotes wage-bill ratio.

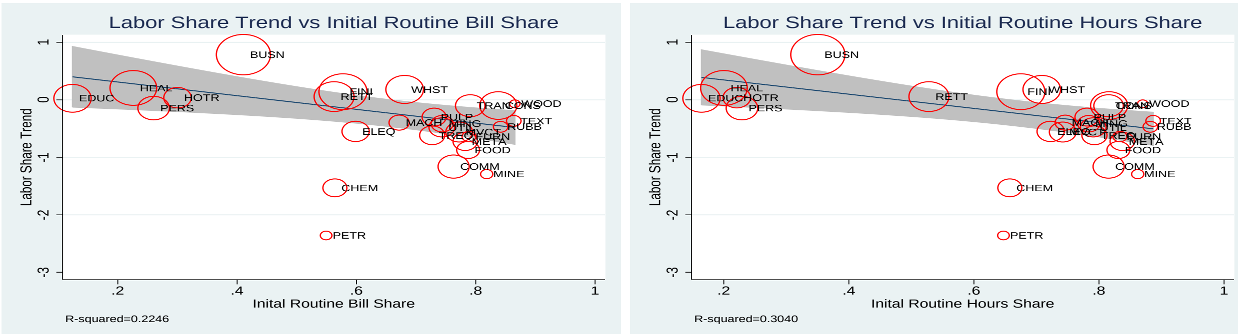
I am aware that rise in wage-bill ratio does not mean one group will benefit, while the other will lose in terms of the labor share. They can also both lose or benefit at the same time. However, one thing is certain: one group is relatively worse-off and the larger the share of this group, the more limited the sector's overall gain will be. In other words, sector with higher initial routine labor share will be less favorably affected by the decline in ICT capital prices. If we write the labor share as sum of its two components and log-linearize it, we would obtain:

$$labsh = labsh_r + labsh_{nr}$$
$$\widehat{labsh} = \tfrac{labsh_r}{labsh}\widehat{labsh_r} + \tfrac{labsh_{nr}}{labsh}\widehat{labsh_{nr}}$$
$$\widehat{labsh} = R\widehat{labsh_r} + (1-R)\widehat{labsh_{nr}}$$

Here, R is defined as the original wage bill share of routine labor. If R is large in a sector, the effect of the labor share of routine labor will dominate. Considering that we almost always observe a negative labor share trend for this group, we would expect to see that the sectors that have the largest negative labor share trend will be the ones with largest initial routine wage-bill share. As a matter of fact, data confirms this. Figure 2.7 plots the labor share trends against both initial (1977) routine bill share and routine hours share. This figure reveals our second fact from data: **sectors that initially had the largest employment and wage-bill shares of routine labor are the ones with largest trend decline in their overall labor share.** [21]

[21] When we multiply the trend changes of each group by their respective initial shares (R for routine labor share and $1-R$ for non-routine labor share), we see that sectors whose labor share declined the most have almost monotonically largest weighted trend decline in routine labor share and smallest weighted non-routine share trend increase. This is depicted in Figure ??, which is a weighted average version of Figure 2.3.

Figure 2.7: Labor Share Trend vs Initial Routine Task Intensities



Note: ICT capital intensity is defined as ICT capital stock per unit of value added generated in a sector.
Source: Author's calculations from EU-KLEMS and CPS data sets.

Up to this point, I stated out two facts: (i) a larger decline in capital prices are associated with smaller a trend decline in the labor share, and (ii) sectors with initially high routine bill shares have experienced the largest trend decline in their labor shares. The next step is to estimate the elasticities of substitution in each sector to document the degrees of capital-skill complementarity at each of them. Using these estimates and the initial routine task intensities across sectors, I will try to characterize the conditions under which decline in capital prices causes a fall or rise in the sectoral and aggregate labor shares.

2.3 Model and Estimation

2.3.1 Model

The production function that is used to estimate the elasticities of substitution is similar to the one used in Chapter 1 except for the fact that we have only two types of labor inputs: routine and non-routine, rather than three types as in Chapter 1.[22] This production function is estimated separately for each sector and for the aggregate economy. The model targets are also different in this chapter as we use the labor share as one of the moments that we

[22] In this paper, both cognitive and manual non-routine types of labor are aggregated into a single type as "non-routine".

target to obtain the parameters.[23] Due to these -and also notational- differences, the model is re-introduced in this section.

As before, to simplify the estimation, the paper abstracts from the household sector and uses the profit maximizing decisions of a representative firm choosing from among four factors production. The equations to be used in estimation comes from the standard production function of Krusell et al. (2000), which exhibits capital-skill complementarity and is extensively used in this literature. The four factors of production are ICT capital, non-ICT capital and, routine and non-routine labor inputs. The elasticities of substitution between ICT capital and two types of labor are allowed to be different.

Even though not modeled explicitly, two other sectors provide input to our model equations. First, a household sector is assumed to own two types of capital used in production. The investment decisions of the household between two types of capital provide us with a no-arbitrage condition between the returns on them. Combined with firm's first order conditions with respect to capital inputs, this constitutes our third equation used in estimation. Secondly, we implicitly assume that there are perfectly competitive firms producing the ICT capital and their profit maximization decision allows us to model the technological advancement as decline in price of ICT capital.

Before introducing the details of the model economy, it is important to clarify that this version of the paper does not model aggregation of the sectors into a single economy. In contrast, our strategy is treating every sector as a single economy and run separate estimations for each. Thus, we do not need to worry about the relative prices of the output of each sector. Furthermore, with this approach, we can also assume differing prices and

[23] In Chapter 1, the goal was to find parameters of a production that is consistent with the U.S. wage and employment trends and check if these parameters would explain the decline of the labor share. Thus, the labor share has been kept as one of the model outcomes, rather than being one of the targets. In this chapter, on the other hand, we are trying to estimate the elasticities of substitution that are consistent with the labor share trends in each sector. Thus, the labor share replaces one of the two task premiums used in Chapter 1.

returns on ICT capital across sectors. This approach is consistent with the purpose of our paper since at this point we are only interested in understanding the link between ICT capital prices a sector faces and the trend of the labor share in that particular sector and how this link might have been affected by various heterogeneities.

2.3.2 Final Good Production Technology

Letting i denote the sector, the production technology for sector i is defined as follows:

$$\begin{aligned} Y_{i,t} &= A_{i,t} G(K_{nc,i,t}, K_{ict,i,t}, h_{r,i,t}, h_{nr,i,t}; \phi_{r,i,t}, \phi_{nr,i,t}; \Upsilon_i) \quad (2.1) \\ G(.) &= K_{nc,i,t}^{\alpha_i} \{\mu_i u_{i,t}^{\sigma_i} + (1-\mu_{i,t})[\lambda_i K_{ict,i,t}^{\rho_i} + (1-\lambda_i) s_{i,t}^{\rho_i}]^{\frac{\sigma_i}{\rho_i}}\}^{\frac{(1-\alpha_i)}{\sigma_i}} \end{aligned}$$

According to this production function, the value added at time t in sector i is a function of four factors of production: ICT capital $K_{ict,i,t}$, non-ICT capital $K_{nc,i,t}$, routine (unskilled) hours worked in efficiency units $u_{i,t}$ and non-routine (skilled) hours worked in efficiency units $s_{i,t}$. These efficiency hours are defined as follows, respectively:

$$s_{i,t} = \varphi_{s,i,t} h_{nr,i,t} \quad (2.2)$$

$$u_{i,t} = \varphi_{u,i,t} h_{r,i,t} \quad (2.3)$$

where, $\varphi_{u,i,t}$ and $\varphi_{s,i,t}$ are efficiency levels of each type of workers at time t and industry i and $h_{r,i,t}$ and $h_{nr,i,t}$ are respective raw hours worked. Furthermore, $A_{i,t}$ is the neutral technological change in industry i. Finally, production functions are allowed to differ across sectors by the set of parameters $\Upsilon_i \in \{\sigma_i, \rho_i, \alpha_i, \mu_i, \lambda_i\}$. Here, σ_i and ρ_i are the key parameters that shape the elasticities of substitution between ICT capital and two types of workers: routine and non-routine, respectively.

Using the definition of KORV, the elasticity of substitution between ICT capital and routine (unskilled) hours is $\frac{1}{1-\sigma_i}$, while the elasticity of substitution between ICT capital and non-routine (skilled) hours is defined as $\frac{1}{1-\rho_i}$.[24] The parameter α_i determines the share

[24]This definition of elasticities are based on the assumption that all other factors are constant. When other factors change, elasticities of substitution might change as well.

of non-ICT capital compensation in value added and can easily be calibrated from our data set, even though I estimate it along with the rest of the parameters. Finally, μ_i and λ_i govern the compensation shares of the remaining three factors of production.

The representative firm in industry i maximizes its profits by choosing the four factors of production $K_{ict,i,t}$, $K_{nc,i,t}$, $h_{r,i,t}$ and $h_{nr,i,t}$, while taking the efficiencies of the two skill groups $\varphi_{u,i,t}$ and $\varphi_{s,i,t}$; and the wage and rental rates as given. Using the final good and non-ICT capital as the numeriare and hence setting the price of final good as 1, the profit of the representative firm in sector i and at time t is as follows:[25]

$$\Pi_{i,t} = Y_{i,t} - r_{nc,i,t}K_{nc,i,t} - r_{ict,i,t}K_{ict,i,t} - w_{r,i,t}h_{r,i,t} - w_{nr,i,t}h_{nr,i,t} \tag{2.4}$$

where, $r_{nc,i,t}$ and $r_{ict,i,t}$ are sector specific rental rates of non-ICT and ICT capital respectively. Similarly, $w_{r,i,t}$ and $w_{nr,i,t}$ denote the hourly wage rates of routine and non-routine labor in sector i and time t.

As discussed in Chapter 1, capital-skill complementarity requires $\sigma_i > \rho_i$, meaning that $\frac{1}{1-\sigma_i} > \frac{1}{1-\rho_i}$: the elasticity of substitution between ICT capital and routine hours is larger than that between ICT capital and non-routine hours. In other words, when there is technological improvement (modeled as the fall in the price of ICT capital) and hence ICT capital intensity increases, we would expect the share of routine hours in total employment to fall, while that of non-routine employment to rise. Meanwhile, if the increase in relative supply of non-routine labor does not keep up with the rise in relative demand for non-routine labor, we would expect the skill premium and wage bill ratio (defined as the ratio of total wage bill of non-routine labor to the total wage bill of routine labor) to rise as well. Considering the enormous decline in ICT prices (substantial improvement in technology) over last decades, demand effect is expected to dominate, thereby increasing the skill premium and wage bill

[25] We are assuming here that 1 unit of final good in each sector can be transformed to 1 unit of non-ICT capital, while ICT capital is produced using a different technology that will be explained soon. To validate this assumption, data reveals that price of final good and non-ICT goods have a correlation of almost 1 in every sector.

ratio. Finally, note that in this specification of the production function, elasticity of substitution between two types of labor is assumed to be equal to the elasticity of substitution between ICT capital and routine labor.[26]

Two of the equations I will use in estimation are derived from the first order conditions of the firm's problem. Before discussing the details of equations to be used, first order conditions need to be defined:[27]

$$\begin{aligned}
w_{nr} &= (1-\mu)(1-\alpha)(1-\lambda)\frac{Y}{\{\mu u^{\sigma}+(1-\mu)[\lambda K_{ict}^{\rho}+(1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}}\}} && (2.5)\\
&\quad \times[\lambda K_{ict}^{\rho}+(1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}-1}\frac{s^{\rho}}{h_{nr}} \\
w_{r} &= \mu(1-\alpha)\frac{Y}{\{\mu u^{\sigma}+(1-\mu)[\lambda K_{ict}^{\rho}+(1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}}\}}\frac{u^{\sigma}}{h_{r}} && (2.6)\\
r_{nc} &= \alpha\frac{Y}{K_{nc}} && (2.7)\\
r_{ict} &= (1-\mu)(1-\alpha)\lambda\frac{Y}{\{\mu u^{\sigma}+(1-\mu)[\lambda K_{ict}^{\rho}+(1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}}\}} && (2.8)\\
&\quad \times[\lambda K_{ict}^{\rho}+(1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}-1}K_{ict}^{\rho-1} && (2.9)
\end{aligned}$$

2.3.2.1 Wage-Bill Ratio

One of the three equations used in estimation is the wage-bill ratio, which is defined as the ratio of the total wage bill received by non-routine labor to the total wage bill received by

[26]Alternatively, we could have assumed that the elasticity of substitution between routine and non-routine labor equals to the elasticity of substitution between ICT capital and non-routine labor. This specification would require amending the production fucntion as: $G(.) = K_{nc,i,t}^{\alpha_i}\{\mu_i s_{i,t}^{\rho_i}+(1-\mu_{i,t})[\lambda_i K_{ict,i,t}^{\sigma_i}+(1-\lambda_i)u_{i,t}^{\sigma_i}]^{\frac{\rho_i}{\sigma_i}}\}^{\frac{(1-\alpha_i)}{\rho_i}}$. I repeated the estimation using this specification as well. However, the match of the model was substantially weaker under this specification. Especially, the predictions of this specification in terms of labor share could not match the data. Therefore, this specification does not seem to be describing the sectors or the overall economy.

[27]For the sake of simplicity, I will not use time and subscripts from now on. Yet, the reader should keep in mind that each equation is time and sector specific.

routine labor.[28] Wage-bill ratio in data is calculated using the sectoral wages and hours for two skill groups. On the other hand, wage rates coming from the first order conditions give us the skill premium in model as in equation 2.10 below. Multiplying both sides of this equation by the relative supply of non-routine hours give us the wage-bill ratio (equation 2.11).

$$
\begin{aligned}
sp &= \frac{w_{nr}}{w_r} \\
&= \frac{(1-\mu)(1-\lambda)[\lambda K_{ict}^{\rho} + (1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}-1} s^{\rho} h_r}{\mu u^{\sigma} h_{nr}} \qquad (2.10)\\
wbr &= \frac{w_{nr} h_{nr}}{w_r h_r} \\
&= \frac{(1-\mu)(1-\lambda)[\lambda K_{ict}^{\rho} + (1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}-1} s^{\rho}}{\mu u^{\sigma}} \qquad (2.11)
\end{aligned}
$$

Following the steps in KORV for the skill premium, I first log-linearize and differentiate the wage-bill ratio equation with respect to time. This yields:

$$
\begin{aligned}
\ln(wbr) &= \lambda \frac{\sigma-\rho}{\rho} (\frac{K_{ict}}{s})^{\rho} - \sigma \ln(\frac{h_r}{h_{nr}}) + \sigma \ln(\frac{\phi_{nr}}{\phi_r}) \qquad (2.12)\\
\widehat{wbr} &\simeq \sigma(\widehat{h_{nr}} - \widehat{h}_r) + \sigma(\widehat{\phi}_{nr} - \widehat{\phi}_r) \qquad (2.13)\\
&\quad + (\sigma-\rho)\lambda(\frac{K_{ict}}{s})^{\rho}(\widehat{K}_{ict} - \widehat{h_{nr}} - \widehat{\phi}_{nr})
\end{aligned}
$$

where the variable with a hat represents growth rate of the relevant variable.

As KORV describes in more detail for skill premium, equation 2.13 decomposes the growth rate of wage-bill ratio into three components. For a detailed description, one should see Krusell et al. (2000). Briefly, the first component, $\sigma(\widehat{h_{nr}} - \widehat{h}_r)$, which KORV names as *the relative quantity effect*, tells that the faster the growth rate of non-routine hours relative to

[28] Alternatively, we could have used the skill premium instead of wage-bill ratio as in KORV. Wage-bill ratio is the skill premium multiplied by relative supply of non-routine hours. Hence, there is no difference in estimation outcomes when either one of these two is used. For the matter of convenience, I am choosing wage-bill ratio as one of the equations I am trying to match.

routine hours, the faster the increase in wage-bill ratio (and the skill premium). As a matter of fact, during the entire period of this study, this effect has always positively contributed to the increase in skill premium and wage-bill ratio. Moreover, this effect is positive and significant in almost all the sectors (except for hotels and restaurants) and hence does not contribute significantly to sectoral heterogeneity in terms of the labor share trends. Second effect represented by $\sigma(\widehat{\phi}_{nr} - \widehat{\phi}_r)$ is what KORV terms as *the relative efficiency effect*. When $\sigma > 0$, an increase in the relative efficiency of non-routine labor raises both the skill premium and wage-bill ratio. This effect is not measurable from the data as we cannot observe the efficiencies. However, considering the fact that the skill premium exhibited similar trends across sectors, implying the mobility of labor across sectors in this entire period, might indicate that relative efficiencies of two types of labor should not have differed across sectors. Hence, I would not expect this component to play a key role in explaining the differences across sectors.

The last but the most important component is what we call as the *capital-skill complementarity effect*:$(\sigma - \rho)\lambda(\frac{K_{ict}}{s})^{\rho}(\widehat{K}_{ict} - \widehat{h_{nr}} - \widehat{\phi}_{nr})$. We know that ICT capital experienced enormous growth rates in the period of study, while the labor hour growth rates remained substantially lower than that. When $\sigma > \rho$ (capital-skill complementarity), faster growth in ICT capital tends to increase both the skill premium and wage-bill ratio. Therefore, the existence of capital-skill complementarity is crucial in explaining the trend increase in skill premium and wage-bill ratios across sectors. However, the degree of the increase in wage-bill ratio (and skill premium) is mainly affected by the $(\frac{K_{ict}}{s})^{\rho}$ term. If $\rho > 0$ (ICT capital and non-routine hours are absolute substitutes), the effect of the relative growth of ICT capital will accelerate over time, thereby increasing the wage-bill ratio further as more ICT capital accumulates relative to the non-routine hours in efficiency units. On the other hand, if $\rho < 0$ (ICT capital and non-routine hours are absolute complements), the effect of the relative growth of ICT capital on wage-bill ratio will slow down as ICT capital accumulates. In that case, the growth rate of the skill premium and wage-bill ratio will be bounded at the limit. The latter case is what KORV founded in their study, where they find $\rho = -0.49$. Remember that the labor share predicted in their model, as well as the labor share in data in the period covered in their study are pretty stable in the long run. We will soon argue that the parameter ρ plays the key role in determining the response of wage-bill ratio and hence that of the labor shares across sectors. Proposition 1 states that the larger the substitutability between ICT capital and non-routine (skilled) hours, the faster the rise in wage-bill ratio. Later, Proposition 2 will discuss how this is translated into a faster decline in the labor share.

Proposition 1. *If there is capital-skill complementarity ($\sigma > \rho$) and we assume that unobserved efficiency of worker types move together across sectors; then, when the relative price of ICT capital falls, wage-bill-ratio (wbr) will rise faster in sectors where the substitutability between ICT capital and non-routine (skilled) hours is larger.*

Proof. Following from equation 2.13, the proof is straightforward and intuitive. First, when the substitutability between ICT capital and non-routine labor is larger in a sector, the growth rate of ICT capital per non-routine hour ($\widehat{K}_{ict} - \widehat{h_{nr}}$) would be larger as well in that sector for a given change in relative ICT capital prices. This, in turn, will strengthen the capital-skill complementarity effect. Second, within a sector, the larger the elasticity parameter ρ is, the larger the multiplier $(\frac{K_{ict}}{s})^{\rho}$ in capital-skill complementarity effect is. Either of these two would lead to a faster rise in wage-bill ratio. □

Even though not presented in this paper, data reveals that both the fall in ICT capital prices and the rise in ICT capital intensity (ICT capital per hours) in entire period of study are similar across almost all sectors. Therefore, the important implication of Proposition 1 is that the larger the parameter governing the elasticity of substitution between ICT capital and non-routine hours, the faster and larger the rise in wage-bill ratio is. I will now explain why and how wage-bill ratio is related to the labor share, which is the core variable of interest of this paper.

2.3.2.2 Labor Share

The second equation that will be used in estimation is the labor share, which is the main focus of this study. Labor share in a sector i at time t is defined as the total wage bills of two types of labor divided by the value added of that sector. Letting *labs* denote the labor share, we define it as:[29]

$$labs = \frac{w_{nr}h_{nr} + w_r h_r}{Y}$$

When we plug the first order conditions of the representative firm's problem and the definition for the value added, we obtain the labor share as a function of the three factors of production: K_{ict}, h_{nr} and h_r; and efficiencies of two skill groups:

$$labs = \frac{(1-\alpha)\{(1-\mu)(1-\lambda)[\lambda K_{ict}^{\rho} + (1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}-1}s^{\rho} + \mu u^{\sigma}\}}{\{\mu u^{\sigma} + (1-\mu)[\lambda K_{ict}^{\rho} + (1-\lambda)s^{\rho}]^{\frac{\sigma}{\rho}}\}} \tag{2.14}$$

Rearranging equation 2.14 as in Section 1.9.2 yields:

$$labs = (1-\alpha)\frac{1+wbr}{\{1+wbr+wbr\frac{\lambda}{1-\lambda}(\frac{K_{ict}}{s})^{\rho}\}} \tag{2.15}$$

Equation 2.15 shows that the labor share depends on two variables: wage-bill ratio and ICT capital per effective skilled hours. First of all, other things remaining the same, a rise in wage-bill ratio will cause a fall in the overall labor share. This can be proven mathematically by checking the first partial derivative of the labor share equation with respect to wage-bill ratio, which is always negative.[30] However, the effect of the second component on the labor share is uncertain as the sign of the partial derivative of the labor share with respect to ICT

[29] Note that I continue dropping the i and t subscripts for the sake of simplicity in presentation.

[30] $\frac{\partial labs}{\partial wbr} = (1-\alpha)[\frac{-\frac{\lambda}{1-\lambda}\left(\frac{K_{ict}}{s}\right)^{\rho}}{\left(1+wbr+\lambda\frac{wbr}{1-\lambda}\left(\frac{K_{ict}}{s}\right)^{\rho}\right)^{2}}] < 0$

capital per efficient non-routine hours depends on the sign of ρ.[31]

When $\rho > 0$, meaning that ICT capital and non-routine (skilled) hours are absolute substitutes, the rise in $\frac{K_{ict}}{s}$ will have a larger impact on the labor share and hence we will expect the labor share to fall. Asymptotically, the labor share can fall all the way to 0. On the other hand, when $\rho < 0$, the effect of $(\frac{K_{ict}}{s})$ term will vanish as it gets larger and the labor share will increase, converging asymptotically to $1-\alpha$. Thus, the parameter ρ, which governs the elasticity of substitution between ICT capital and non-routine hours plays the key role in the determination of the labor share in response to ICT capital specific technological progress and the resulting rise in ICT capital in a particular sector. Proposition 2 summarizes this relationship between the parameter ρ and the labor share.

Proposition 2. *If there is capital skill complementarity ($\sigma > \rho$), the larger the substitutability between non-routine(skilled) hours and ICT capital (the larger the parameter ρ) is, the faster the decline in the labor share is for a given level of rise in ICT capital per effective non-routine hours $\frac{K_{ict}}{s}$.*

Proof. The substitutability between non-routine hours and ICT capital affects the labor share through two channels. The direct channel follows from the discussion above regarding equation 2.15. When ρ is greater than 0, a rise in $\frac{K_{ict}}{s}$ ratio will amplify the denominator of the labor share equation. For a given level of this ratio, the larger the parameter ρ is, the faster the fall in labor share will be.

There also exist a second and indirect channel that links the parameter ρ and the labor share. This directly follows from Proposition 1. We already showed that when there is

[31]

$$\begin{aligned}
\frac{\partial labs}{\partial(\frac{K_{ict}}{s})} &= -\rho(\frac{K_{ict}}{s})^{\rho-1}\lambda wbr\frac{1-\alpha}{1-\lambda}\frac{1+wbr}{\left(1+wbr+(\frac{K_{ict}}{s})^{\rho}\frac{\lambda}{1-\lambda}wbr\right)^2} \\
&< 0 \text{ if } \rho > 0 \qquad (2.16) \\
&> 0 \text{ if } \rho < 0 \qquad (2.17)
\end{aligned}$$

capital-skill complementarity ($\sigma > \rho$), the larger the parameter ρ is, the stronger the impact of a rise in ICT capital intensity on wage-bill ratio is. Since the increase in wage-bill ratio always translates into a fall in the labor share as discussed above, a larger substitutability between ICT capital and non-routine hours would lead to a faster decline in the labor share. $\square$

To sum it up, all the discussions in this subsection imply that the key parameter explaining the differences across sectors in terms of the labor share trends is expected to be the parameter ρ, which govern the elasticity of substitution between ICT capital and non-routine hours. To be more specific, we expect to document existence of capital-skill complementarity at every sector, while finding absolute complementarity between ICT capital and non-routine hours in service sectors for which the labor share is either stable or rising and documenting absolute substitutability for the goods sectors, which drive the fall in the aggregate labor share.

2.3.3 ICT Capital Production Technology

Similar to the model in Section 1.4, we assume that one unit of investment good is converted into one unit of non-ICT capital. Hence, price of both final good and non-ICT capital are both normalized as 1. On the other hand, ICT capital is assumed to be produced by perfectly competitive firms, converting part of the final good invested in ICT capital into q_t units of ICT capital, where, q_t is the relative productivity of ICT capital producing sector. A rise in q_t would imply technological progress in ICT capital producing sector.

As before, perfect competition in this sector guarantees that $p_{ict,t} = \frac{1}{q_t}$ and I will proxy ICT capital-specific technological advancement by a fall in $p_{ict,t}$ since q_t is not available from data.

2.3.4 Household's Problem

The household problem is also the same as in Section 1.4 and thus, is not discussed in detail here. The only difference here is that instead of investing in equipment and structural capital as in Chapter 1, the representative household in this chapter allocates its investment between ICT and non-ICT capitals. Equating the expected rates of return on both types of capital gives us a "no-arbitrage condition", which is used as our third and the last target in estimation:

$$E(\frac{p_{ict,t+1}}{p_{ict,t}})=\frac{1}{(1-\delta_c)}[A_{t+1}G_{K_{nc,t+1}}+(1-\delta_{nc})-\frac{A_{t+1}G_{K_{ict,t+1}}}{p_{ict,t}}] \tag{2.18}$$

where, $G_{K_{nc,t+1}}$ and $G_{K_{ict,t+1}}$ are partial derivatives of the production function with respect to non-ICT and ICT capitals, respectively. Moreover, E denotes expected value and δ_{nc} and δ_c represent the depreciation rates of each types of capital.

2.3.5 Estimation

The two-stage Bayesian Estimation methodology used in this chapter to estimate the aggregate and sectoral production functions is the same as in Chapter 1, where the reader can find a detailed description of both the estimation strategy and the Metropolis Hastings-MCMC algorithm employed. To avoid the repetition, this section presents only the differences in estimation.

As in Chapter 1, our partial equilibrium model is reduced into a non-linear state space model. The three measurement equations are 2.11 (wage-bill ratio), 2.14 (labor share) and 2.18 (no-arbitrage condition in capital markets). Nevertheless, we now have one less transition equation since we have only two types of labor, rather than three.

$$\log(\varphi_{nr,t}) = \log(\varphi_{nr0}) + \eta_{nr,t} \tag{2.19}$$

$$\log(\varphi_{r,t}) = \log(\varphi_{r0}) + \eta_{r,t} \tag{2.20}$$

where, φ_{nr0} and φ_{r0} are constants specifying the average efficiency levels of non-routine and routine labor, respectively and η_t is a 2×1 vector of shocks, which are assumed to have a multivariate normal distribution with zero mean and covariance matrix $\Sigma = \sigma_\eta^2 I_2$.[32]

The list of parameters that needs to be estimated are presented in Table 2.5. Since μ, ω, φ_{nr0} and φ_{r0} are all scaling parameters, one of them is fixed as a normalization as in Chapter 1: φ_{nr0}. Depreciation rates are both sector and time specific and I use the depreciation rates published by EU-KLEMS for the period 1977-2007.[33] For earlier years, depreciation rates of year 1977 are employed. These leave us with 8 parameters to be estimated.[34] Table 2.6 presents the prior distributions used in the Bayesian estimation stage. Finally, it should be clarified that all the parameters in Table 2.5 will be independently estimated for the overall economy, as well as for each sector. In other words, I will let the shock processes for efficiencies to be independent from the shocks in other sectors or in overall economy.

2.4 Findings

2.4.1 Estimation Results

2.4.1.1 Aggregate Economy

The parameters of the aggregate economy is estimated using the two-stage Bayesian Estimation method described in previous section. As a reminder, the first stage is fitting IV

[32] Even though sector specific subscripts are ignored for notational ease, one should keep in mind that we repeat the algorithm for each sector.

[33] Alternatively, I use fixed depreciation rates for all the sectors and time periods and set them as $\delta_{ict} = 0.3$ and $\delta_{nc} = 0.1$ as common in the literature. All of our findings are robust to either way of setting the depreciation rates.

[34] The parameter α, which determines the compensation share of non-ICT capital, can also be calibrated from data as we have both value added and compensation of each type of capital from EU-KLEMS data set. The estimated and calibrated parameters are almost the same and dropping α from the estimation all together did not alter any of the rest of the parameters. Hence, α is kept as part of the estimation process.

Table 2.1: Estimation Results: Overall Economy

	σ		ρ	
Data	**KORV**	**Estimation**	**KORV**	**Estimation**
KORV	0.401	0.459	−0.495	−0.378
(1963-1992)	(0.234)	(0.023)	(0.048)	(0.046)
EU-KLEMS		0.820		0.1619
(1970-2007)		(0.017)		(0.030)

Note: The values reported in parenthesis are standard errors.

instruments for labor inputs, while the second stage is the Metropolis-Hasting MCMC algorithm described earlier. To convince the reader that our findings are not methodology driven, I also estimated the model of Krusell et al. (2000) with Bayesian methodology and compared our findings to theirs. To reinstate, KORV's data set and mine differ in three dimensions: (i) unlike their skill definition based on years of education, I defined skill based on tasks perfomred, (ii) while they differentiate between structural and equipment capital, we divided capital stock as ICT and non-ICT capital in this paper, and (iii) time periods covered are different. Table 2.7 summarizes these differences.

First of all, our estimates using KORV's data set are quite close to theirs and considering that estimation methodologies are not the same, the differences in two estimates are reasonably small (Table 2.1). The only difference is that the parameter ρ, which governs the elasticity of substitution between equipment capital and skilled labor hours, is overestimated but the capital-still complementarity is still strong and equipment capital and skilled labor hours are absolute complements. Hence, the substantial difference we get in our estimates for ICT capital and task-based defined skilled hours will be attributed to the differences in data set, skill and capital definitions and time period, rather than methodological differences.

The last row of Table 2.1 documents that there is still very strong capital skill complementarity in overall economy when skill is defined based on task content of occupations and capital is divided as ICT and non-ICT capital. As Table 2.1 shows, $\sigma = \mathbf{0.82}$ is significantly larger than $\rho = \mathbf{0.16}$, which proves the existence of capital-skill complementarity.[35] However, compared to the elasticities used in job polarization literature, which are mostly based on KORV's work, we find significantly stronger substitutability between capital and each type of labor. More interestingly, technology intensive capital and skilled labor turns out to be absolute substitutes rather than being complements. Thus, any study using elasticities not consistent with these numbers while still using task-based skill definition and ICT capital might lead to misleading conclusions.

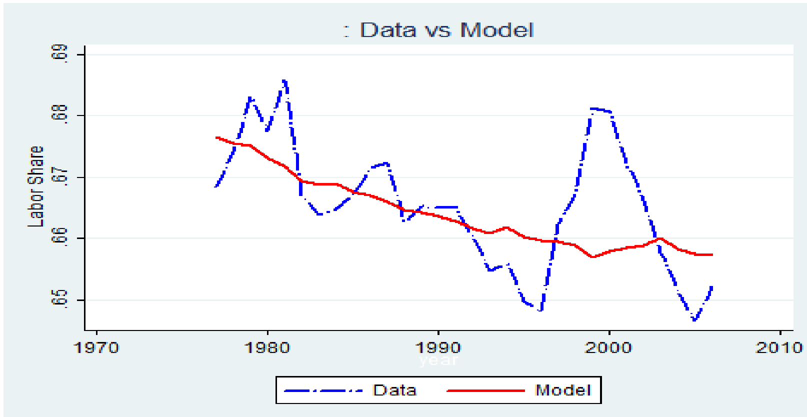
This difference between KORV's and our estimates has important implications for the labor share as well. As discussed earlier, especially the differences in complementarity between capital and skilled labor, which is governed by parameter ρ is crucial as this elasticity plays the key role in shaping the trend of the labor share in response to declining capital prices. As a matter of fact, the inconsistency of KORV's model's prediction in terms of the labor share is substantially corrected once we use these new elasticities and capital and skill definitions (Figure 2.8). In this sense, a modest contribution of this paper is providing new elasticity measures that are more consistent with the labor share and the skill premium trends as observed in past three decades.

2.4.1.2 Sectoral Findings

I estimated the model for each of the 27 sectors. Before going into details of estimation results, I want to summarize the main findings as follows: (i) Strong capital-skill complementarity is documented at each sector, albeit at differing degrees. Depending on how we

[35] One would notice that these estimates are significantly different from what were found in Chapter 1. However, this is an expected outcome as this chapter focuses on a one particular type of capital, which is produced by the most rapidly progressing technology.

Figure 2.8: Aggregate Labor Share: Data vs Model



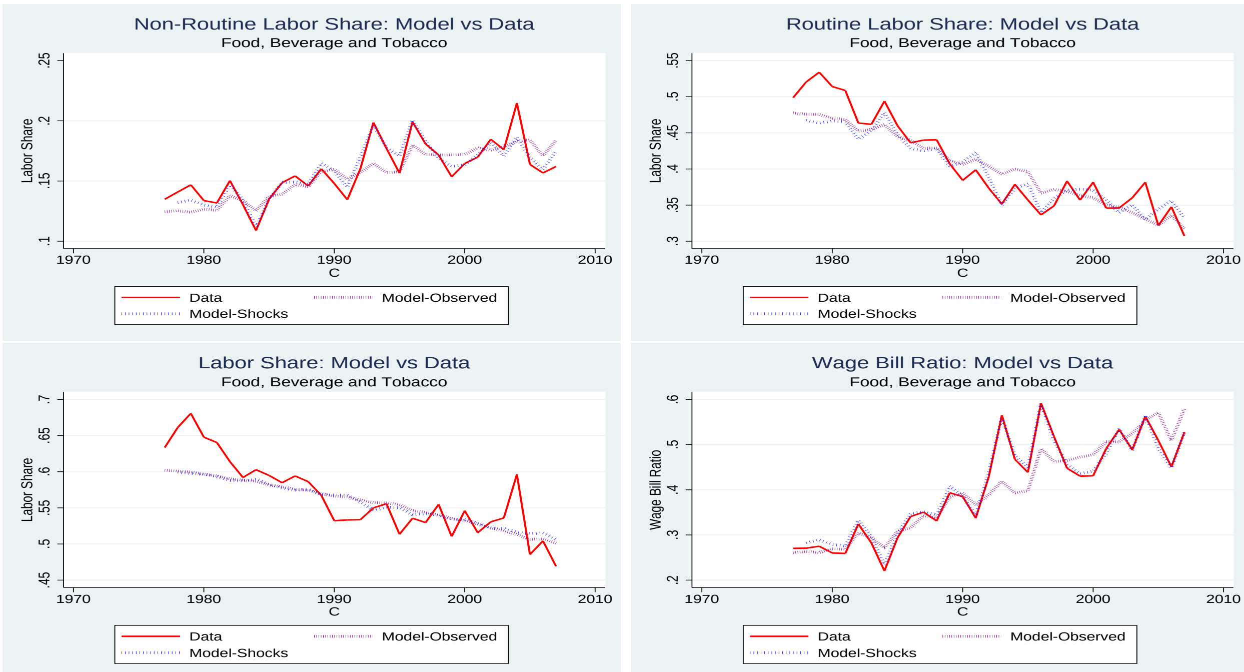
define degree of capital-skill complementarity, sectors with stronger capital-skill complementarity are the ones that experienced the largest decline in the labor share. (ii) Sectors are quite heterogeneous in terms of absolute complementarity between ICT capital and skilled hours, which is governed by the parameter ρ. (iii) Sectors exhibiting decline in the labor share are the ones that use a technology with higher substitutability between ICT capital and skilled hours while sectors in which skilled labor is more complementarity with ICT capital, the labor share did not fall or even exhibited a rise during the period of study.

Before reporting the estimated parameters, it would be useful to first present the fit of the model in terms of the labor shares and wage-bill ratios. In Figure 2.9, the graphs for four series for the Food, Tobacco and Beverage sector are displayed. This is one of the sectors that experienced the largest decline in the labor share, while share of non-routine labor has been increasing and that of routine workers has been exhibiting a substantial decline.

In each panel, there are three series. The red lines show the data for the sector. The dotted blue lines are the model's fit when we include the i.i.d. shocks to efficiencies of two labor types. Finally, when we set those shocks equal to 0 in each period, what we obtain are purple dotted lines. These lines can be interpreted as the model's predictions that are due entirely to the observable factors.

Figure 2.9: Labor Shares and Wage-Bill Ratio: Data vs Model

Food, Tobacco and Beverage



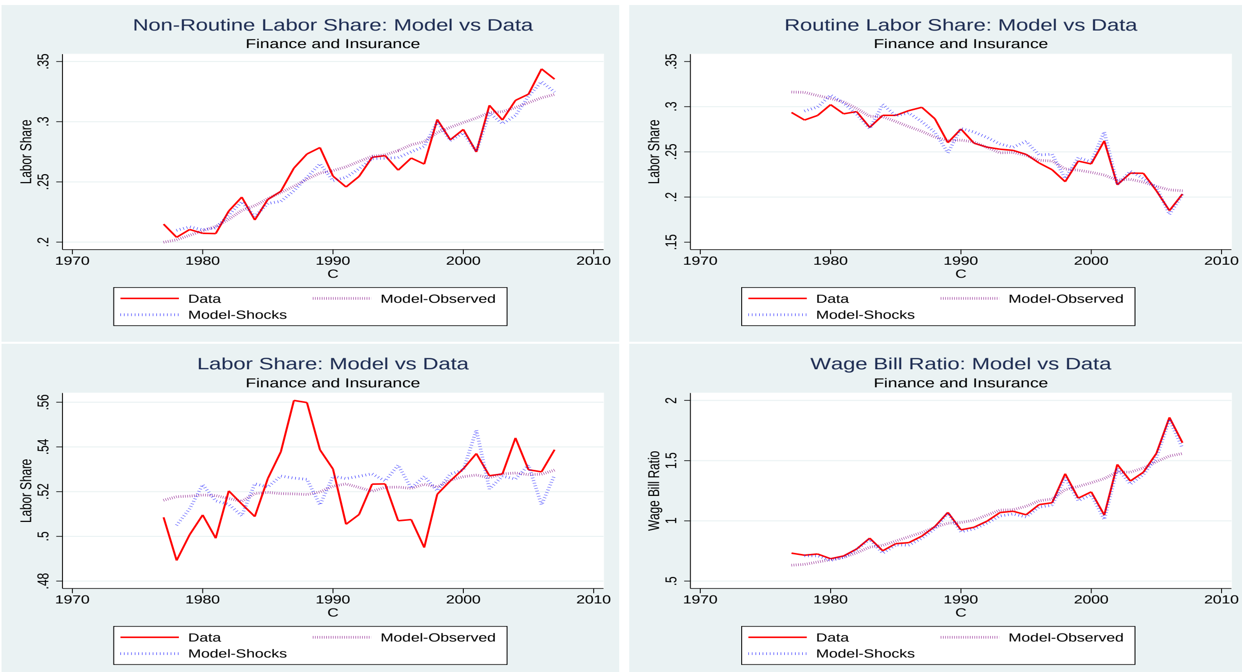
What Figure 2.9 tells us is that the model is able to capture the behavior of both the labor share and wage-bill ratio (and the skill premium) at the same time. When we look at the disaggregated labor shares, we can see that the model is also consistent with what we had seen earlier in Figure 2.3: one group is losing in terms of their share of income, while the other group is actually experiencing a rise.[36] In Figure 2.10, I present the same series for Finance and Insurance sector, for which the sectoral labor share has been rising. Similar to Food, Tobacco and Beverage sector, the labor share of non-routine labor has been rising, while that of routine labor was falling. Despite this similarity, aggregate labor share in this sector did not fall. Graphically, we can see that this difference arises from the faster rise in the share of non-routine labor. This, in turn, depends on the magnitude of the parameter ρ, which is negative for Finance and Insurance sector (implying absolute complementarity

[36] As a matter of fact, the fit of the model has improved considerably when I used both types of the labor share series rather than an aggregate labor share series in estimation procedure.

between ICT capital and non-routine hours) but positive and large for the Food, Tobacco and Beverage sector.

Figure 2.10: Labor Shares and Wage-Bill Ratio: Data vs Model

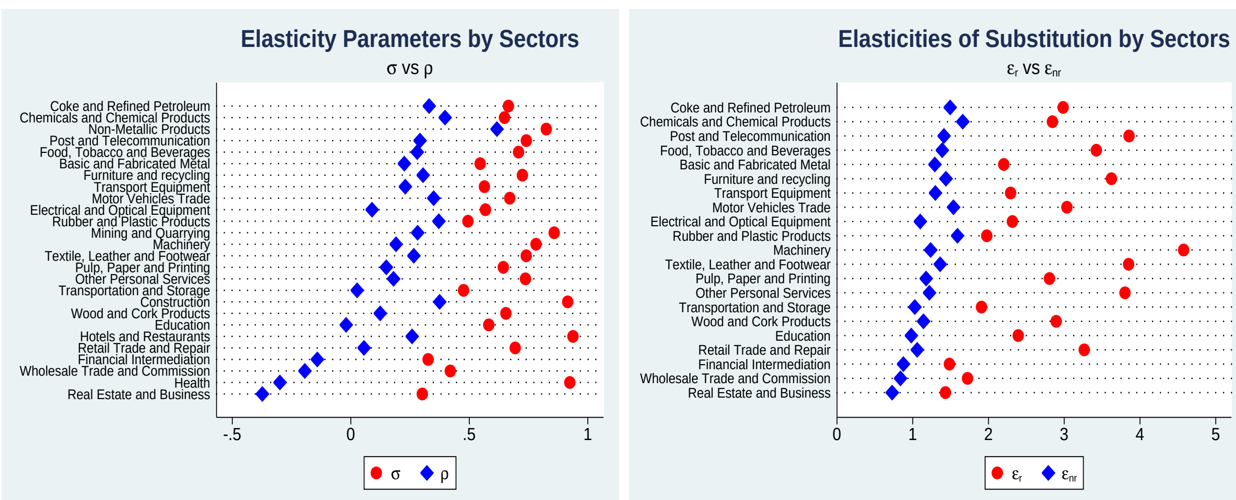
Finance and Insurance



To measure how much of the volatility of the labor shares can be explained by observed data and our model, I computed correlation coefficients between data and model's prediction for each draw of the posterior. To do so, I set the shocks to efficiencies equal to zero at every period and construct a distribution of fitted labor shares for each draw of the second half of the posterior. Then, I HP-detrend both data and model fits and compute correlation coefficients. The correlations for non-routine and routine labor are both positive and significant for most of the sectors. Here, I report only two of them. The correlations between model fit and data for non-routine labor are 0.6463 and 0.5583 for Food, Tobacco and Beverage sector and for Finance and Insurance sector, respectively. The correlations for routine labor are lower: 0.4998 and 0.3381, respectively.[37] Thus, inferring only from these two sectors, we can say that around 60% of the movements of non-routine labor share can be attributed to observed variables. This value is around 40% for routine labor shares.

Figure 2.11 reports the estimated parameters for each sector. In both panels, sectors are placed in descending order by the trend decline in their labor shares. The left panel shows parameters governing the elasticities of substitution between ICT capital and two types of labor: σ and ρ. Remember that $\sigma > \rho$ implies capital-skill complementarity. Right panel, on the other hand, reports elasticities of substitution between ICT capital and routine hours ($\frac{1}{1-\sigma}$) and non-routine hours ($\frac{1}{1-\rho}$). Since for each sector we have $\sigma > \rho$ (or $\frac{1}{1-\sigma} > \frac{1}{1-\rho}$), we can say that capital-skill complementarity is found in each sector. Even though not reported here, the standard errors are very low and thus, capital-skill complementarities are significant.

Figure 2.11: Estimated Elasticities by Sectors

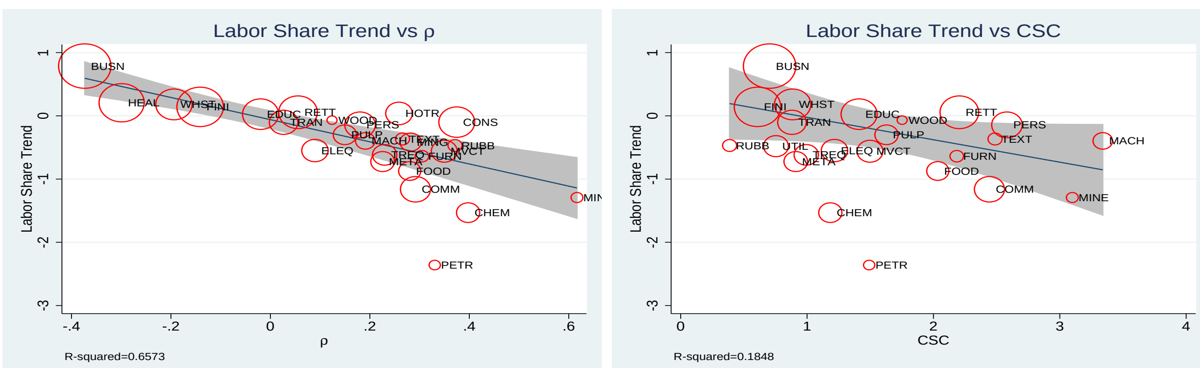


Note: Left: ρ (blue), σ (red); Right: $\frac{1}{1-\rho}$ (blue), $\frac{1}{1-\sigma}$ (red).
Sectors on the vertical axes are sorted by their labor share trend coefficients in ascending order.

[37] Even though not reported here, standard errors of the coefficient correlations are very small.

A few interesting patterns emerge from Figure 2.11. First, there is a visible correlation between labor share trend and the parameter ρ that governs the elasticity of substitution between ICT capital and non-routine occupations. The same is true if we look at the elasticities instead. However, because of the scaling in right panel, it is not as easily observable. On the other hand, we do not observe a relationship between labor share trends and the parameter σ or elasticity of substitution between ICT capital and routine hours ($\frac{1}{1-\sigma}$). Left panel of Figure 2.12 quantifies this relationship between labor share trends and elasticity of substitution between ICT capital and skilled labor. The larger the substitutability between ICT capital and non-routine labor hours is, the larger the decline in the labor share is. The decline is limited or positive but small when ρ is negative.

Figure 2.12: Labor Shares vs Elasticities



Note: Horizontal axes: ρ (Left); CSC (Right).

Right panels of both Figure 2.11 and Figure 2.12 show a similar relationship between the labor share trend and capital-skill complementarity (CSC). If we define the degree of capital-skill complementarity as the difference between two elasticities, $\frac{1}{1-\sigma} - \frac{1}{1-\rho}$, the stronger the CSC is, the larger the decline in the labor share is. However, it should be reminded at this point that this relationship depends on how we define the "degree" of capital-skill complementarity.[38]

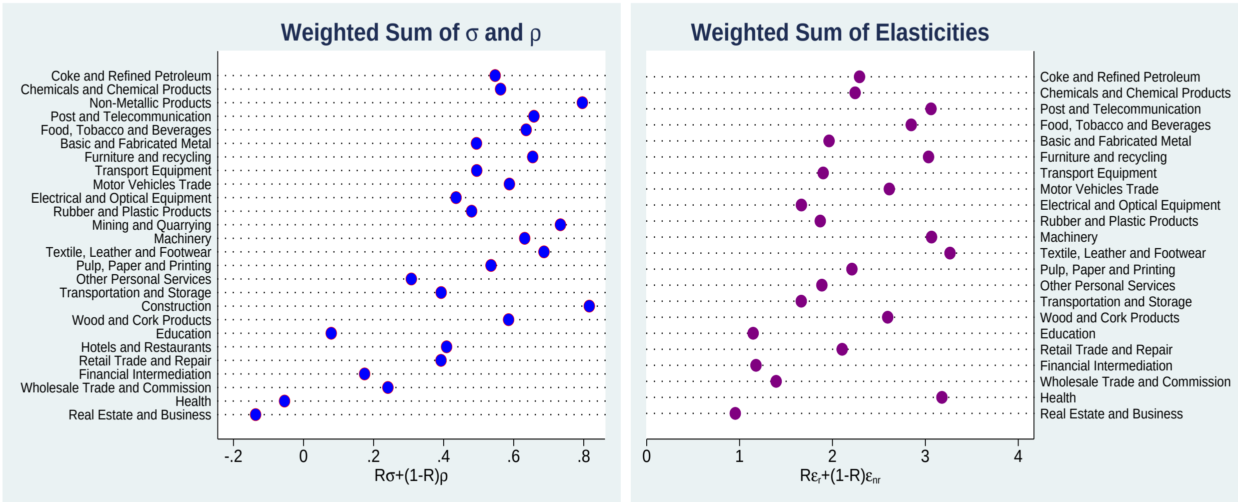
We had already discussed that the initial routine bill shares play an important role in decline in the labor shares. Therefore, I constructed an index of elasticity of substitution between ICT capital and average labor hours in sectors, using the initial share of routine and non-routine hours as their respective weights. I calculated two measures: (i) $R\sigma + (1-R)\rho$ and, (ii) $R\frac{1}{1-\sigma} + (1-R)\frac{1}{1-\rho}$, where R is the initial share of routine hours. As Figure 2.13 shows, the larger the weighted average of elasticities is, the larger the decline in the labor share is. Right panel of Figure 2.13 indicates that if the average elasticity of substitution between ICT capital and average labor hours is above 1.5, then the labor share declines in that sector. In that sense, 1.5 can be considered as a threshold, as opposed to the threshold in the labor share literature, which is 1. However, we have a different type of capital here and two different labor types. Under this set up, some sectors can experience increase in the labor share, while still having an elasticity of substitution between capital and labor larger than 1. This can be better seen in Figure 2.16, which displays the fit of the regression of the labor share trends on these measures.

2.4.2 Regression Analysis

We had started by stating a puzzle coming out of the inspection of the sectoral data: sectors that faced the faster decline in ICT capital prices have experienced the smallest decline in

[38] Alternatively, we could have defined degree of capital-skill complementarity as $\sigma - \rho$ as some of the literature does. However, this definition is problematic. Imagine two sectors with following parameters, one with $\sigma_1 = 0.8$ and $\rho_1 = 0.2$ and the other with $\sigma_2 = 0.4$ and $\rho_2 = -0.2$. In this case, the degree of capital-skill complementarity will be measured the same: $\sigma_1 - \rho_1 = \sigma_2 - \rho_2 = 0.6$. However, the individual elasticities of substitution in two sectors are different and they should have different implications for the skill premium and the labor share for a given trend decline in ICT capital prices. Hence, I am using the other definition: $\frac{1}{1-\sigma} - \frac{1}{1-\rho}$. However, one should be cautious when interpreting the results based on CSC as the specification of "degree" might matter considerably.

Figure 2.13: Weighted Sum of Elasticity Parameters



Note: Left: $R\sigma + (1 - R)\rho$; Right: $R\frac{1}{1-\sigma} + (1 - R)\frac{1}{1-\rho}$, where R is the initial routine hours share in that sector. Sectors on the vertical axes are sorted by their labor share trend coefficients in ascending order.

their labor shares. Later, I showed that if a sector: (i) initially had a high load of routine labor, and (ii) has strong capital-skill complementarity (or weak complementarity between ICT capital and non-routine hours), it is more likely that the labor share will be declining in this sector. In this subsection, I report the outcomes of panel and simple OLS regressions of the labor shares on ICT capital prices and some interaction variables. Our purpose here is to investigate how the impact of ICT capital prices on the labor share might be affected by various factors such as the initial routine shares and degree of capital-skill complementarity. With this exercise, we can partially explain why we are seeing the labor share falling if the decline in ICT capital prices actually impact the labor share favorably.

Table 2.2 reports the outcome of the panel regression of the labor shares on relative ICT capital prices, and its interaction with: (i) initial routine wage-bill share, and (ii) a measure of capital-skill complementarity.[39] The regressions reported in Table 2.2 are fixed-effects,

[39] Alternatively, we could have interacted with the parameter ρ, which governs the elasticity of substitution between ICT capital and non-routine hours. The regression outcomes for this version are reported in Table 2.8. Using ρ instead of capital-skill complementarity substantially strengthens our results discussed

Table 2.2: Panel Regression of the Labor Shares on Relative ICT Prices

Independent	**I**	**II**	**III**	**IV**
$log(P)_{ICT,i,t}$	$-.1342$	$-.2709$	$-.1401$	$-.2715$
	(.0132)	(.0153)	(.0185)	(.0150)
$log(P)_{ICT,i,t} * wbrsh77$		.2235		.2162
		(.0163)		(.0160)
$log(P)_{ICT,i,t} * CSC$			.0286	.0244
			(.0046)	(.0041)
$constant$	$-.6725$	$-.6853$	$-.6310$	$-.6495$
	(.0231)	(.0204)	(.0230)	(0.0207)
$R^2 - within$	0.1983	0.3758	0.2434	0.4085
$R^2 - between$	0.1175	0.1123	0.0947	0.093
$F - value$	5.26	12.38	6.61	13.75
Observations per group:	31		Groups:	23

weighted panel regressions, where we control for both cross-sectional and time effects.

The first column of Table 2.2 shows that the labor share and relative ICT capital prices are negatively correlated. Considering that ICT capital prices were declining substantially, this means that the labor share should have been increased as well. In columns II and III, I interact the relative ICT prices with initial routine bill share and a measure of capital-skill complementarity. In both cases, the coefficient of relative ICT price gets more negative and interaction coefficients are positive. Among those two, the influence of the initial routine share is substantially larger than that of capital-skill complementarity. As a matter of fact, when I use two interactions in the same regression, the coefficient of relative ICT price and R^2s are not affected significantly.

here.

The main message of the regression analysis in Table 2.2 is that even though decline in capital prices works in favor of the labor share by benefiting some fraction of the total labor force, the losses of the other group might dominate the benefits of declining capital prices if the sector has a high load of workers in the losing side and if the complementarity of ICT capital and non-routine labor is weak. In either of these cases, the losses of routine labor will outweigh the benefits of non-routine and hence sector's aggregate labor share will rise. The fact that we see the labor share declining in most of the sectors and at the aggregate level, is not contradicting with this story as the majority of the sectors fall in this category.

The lesson we draw from this analysis is valuable. If the share of routine labor hours is this crucial in affecting the behavior of the labor share, the steady decline in routine shares in recent decades should be considered as good news. We can consider the current behavior of the labor share as an outcome of a transition period, in which, sectors are replacing their routine labor with computers. Over time, as the economy reaches to a new steady state with a low(er) share of routine employment, the decline in the labor share should stop or even revert back. As a matter of fact, if I repeat the regression above for trend coefficients only, I find that the capital-skill complementarity plays no role in trend decline (Table 2.9).[40] We can interpret the outcome of this regression as longer-term relation between the labor share and ICT capital prices and interacting variables. In the longer run, more labor can adjust their skills and switch to non-routine occupations, while firms also complete most of their adjustments and offer more of this type of employment opportunities. Hence, a good strategy for governments would be subsidizing training programs for labor rather than fighting the advancements in ICT technology. Similarly, labor should also invest more in their skills to benefit from increased rewards and employment opportunities some occupations offer. Our

[40]Table 2.9 reports the outcome of the OLS regression of trend decline in labor share on the trend decline in relative ICT capital prices and its interactions with initial routine bill share and degree of capital-skill complementarity.

results indicate that the within-sectoral adjustments can correct the decline in the labor share over the medium to longer run.

2.5 Conclusion

The decline in the U.S. labor share has coincided with a period where massive advancements in information and communication technology have been experienced. Since a group of workers in labor force are vulnerable to this type of technological advancement due to the nature of tasks their occupations require, the decline in ICT capital prices emerged as a natural candidate for the explanation of the behavior of the labor share. However, the story is not this simple if we examine the disaggregated economy, or split the labor shares into shares of two skill groups. In particular, what we observe is that the aggregate decline is driven by some sectors, while the others experienced either a limited fall or even a rise in their labor shares. Furthermore, the loss in the labor share is unique to a group of workers who are working in routine tasks in almost every sectors.

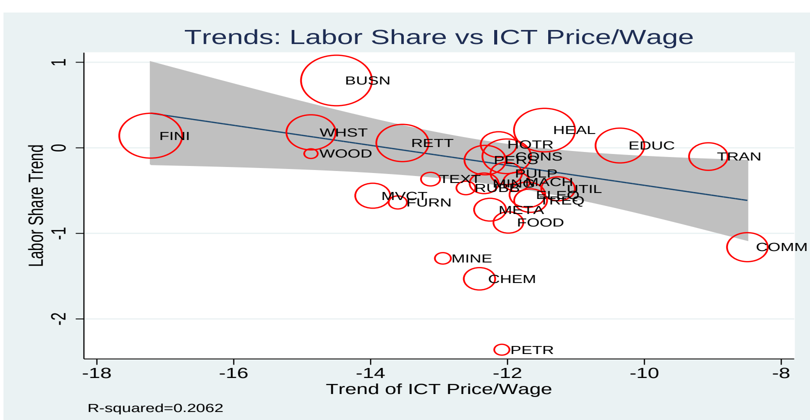
This paper provides and answer to the question whether the decline in ICT capital prices can account for the decline in the labor share. By exploiting the sectoral heterogeneity in terms of labor share trends, and the opposing behavior of the labor shares of two skill groups, we tried to offer a simple mechanism that can explain the decline in the aggregate labor share, increase in the skill premium and different responses of sectors in terms of their labor shares, all at once.

Unlike what we expected at the start, the decline in ICT capital prices turned out to be positively impacting the labor shares. This is not as odd as it sounds at the beginning. When ICT capital prices are falling and there is capital-skill complementarity, one group of workers will be hurt while the others gain. If the gains of one group dominates the losses of the other, then a decline in ICT capital prices might actually cause the labor share to rise. The regression analysis unraveled that if a sector has initially high load of unskilled labor or if the ICT capital and skilled labor are not strong complements, then loss of routine labor share dominates the gains of non-routine labor. Since these two characterizes most of the sectors, the losses of unskilled labor have dominated in almost every sector, thereby reducing the total labor share in that sector and thus, for the whole U.S. economy.

There are positive implications of these discussions. In the near future, there is nor reason to expect a significant slowdown in the fall in ICT capital prices. Over time, as sectors complete their adjustments and reach a level where the share of routine labor is at reasonably low levels, then the fall in the labor shares should slow down or even revert back. Thus, we can consider the current phase as a transition to a new steady state with more skilled employment. In the long run, the existing labor should benefit from this. Meanwhile, the government should subsidize training programs for labor and, routine workers should invest in their skills to benefit from the increased rewards and employment opportunities that come with advancements in ICT capital. To sum it up, this paper implies that the advancements in information technology will not be harmful overall once the economy completes its adjustment to this new world of information.

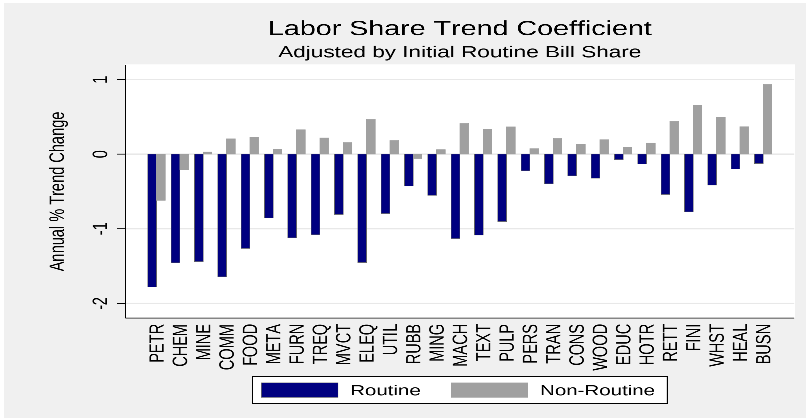
2.6 Appendix: Additional Figures and Tables

Figure 2.14: Labor Share Trend vs Relative ICT Price Deflated by Sectoral Wages



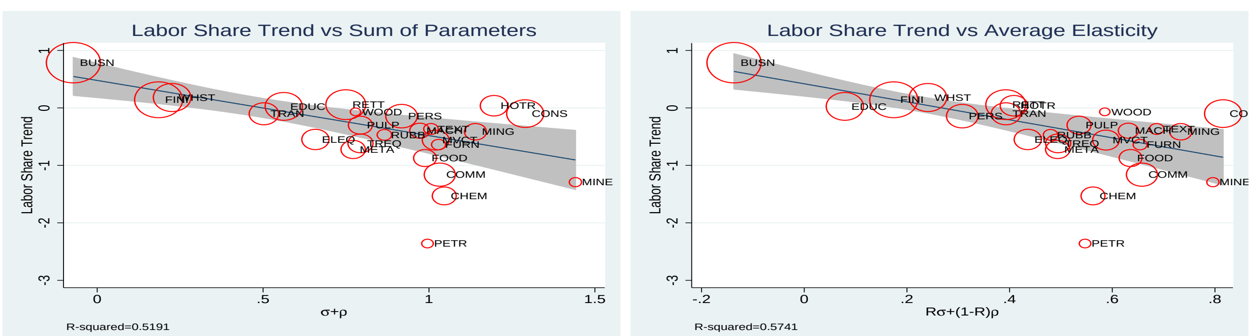
Note: ICT capital intensity is defined as ICT capital stock per unit of value added generated in a sector.
Source: Author's calculation from the EU-KLEMS data set.

Figure 2.15: Labor Share Trends: Routine vs Non-Routine (weighted)



Note: The trends are weighted by initial routine bill shares.

Figure 2.16: Labor Share Trends vs Weighted Sum of Elasticity Measures



Note: Horizontal axes: $R\sigma + (1-R)\rho$ (Left); $R\frac{1}{1-\sigma} + (1-R)\frac{1}{1-\rho}$ (Right), where R is the initial routine hours share in that sector.

Table 2.3: Panel Regression of the Labor Share on Relative ICT Price

$log(labs_{i,t})$	**I**	**II**
Dependent	$log(P_{ICT_{i,t}})$	$log(\frac{P_{ICT_{i,t}}}{Wage_{i,t}})$
Specification	Level	Level
Coefficient	$-.040935$	$-.0670154$
p-value	**0.024****	**0.000*****
R^2-within	0.2381	0.2489
R^2-between	0.1587	0.3009
$F-test$ for $u_i = 0$	258.68	226.6

Table 2.4: Panel Regression of the Labor Share on Relative ICT Price (detrended series)

$log(labs_{i,t})$	**I**	**II**	**III**	**IV**
Dependent	$log(P_{ICT_{i,t}})$	$log(\frac{P_{ICT_{i,t}}}{Wage_{i,t}})$	$log(P_{ICT_{i,t}})$	$log(\frac{P_{ICT_{i,t}}}{Wage_{i,t}})$
Specification	Diff.	Diff.	HP	HP
Coefficient	$-.0143877$	$-.031343$	$-.0323428$	$-.0586793$
p-value	0.553	0.105	0.265	**0.007*****
R^2-within	0.09	0.10	0.10	0.10
R^2-between	0.02	0.03	0.01	0.03
$F-test$ for $u_i = 0$	1.18	1.16	0.00	0.00

Note: Here the variables are differenced in columns I and II, and HP-detrended in columns III and IV.

[h]

Table 2.5: Parameters to be Estimates

$\frac{1}{1-\sigma}$	Elasticity of subst. b/w ICT capital and routine hours
$\frac{1}{1-\rho}$	Elasticity of subst. b/w ICT capital and non-routine hours
α	Compensation share of Non-ICT capital
μ	Share of routine labor in outer CES
λ	Share of ICT capital in inner CES
φ_{nr0}	Initial efficiency of non-routine worker
σ_{ε}^2	Variance of measurement errors
σ_{η}^2	Variance of transition equation errors

Table 2.6: Prior Distributions

Parameter	**Distr.**	**Mean**	**Std.**	**Range**
σ	Normal	0.57	0.25	$[-2, 1]$
ρ	Normal	-0.75	0.25	$[-2, 1]$
α	Normal	$-$	0.1	$[0, 1]$
μ	Normal	0.5	0.2	$[0, 1]$
ω	Normal	0.5	0.2	$[0, 1]$
φ_{nr0}	Normal	2	0.15	$(0,\infty)$
σ_e^2	Gamma	0.3	0.01	$(0,\infty)$
σ_η^2	Gamma	0.4	0.01	$(0,\infty)$

Table 2.7: Comparison of KORV and This Study

	Capital	**Skill**	**Period**
KORV(2000)	Equipment	by education	1963-1992
Our paper	ICT	by occupation	1970-2007

Table 2.8: Panel Regression of the Labor Shares on Relative ICT Prices:

Using ρ as Interaction Variable

Independent	**I**	**II**	**III**	**IV**
$log(P)_{ICT,i,t}$	$-.0859$	$-.2330$	$-.0555$	$-.1542$
	(.0132)	(.0158)	(.0115)	(.0161)
$log(P)_{ICT,i,t} * wbrsh77$		.2079		.1290
		(.0149)		(.0153)
$log(P)_{ICT,i,t} * \rho$			.1543	.1166
			(.0094)	(.0101)
constant	$-.5863$	$-.6283$	$-.5536$	$-.5877$
	(.0223)	(.0201)	(.0193)	(0.0189)
$R^2 - within$	0.1109	0.2896	0.3389	0.3941
$R^2 - between$	0.1587	0.1888	0.0949	0.1326
$F - value$	3.13	9.91	12.46	15.31
Observations per group:	31		Groups:	27

Table 2.9: OLS Regression of the Labor Share Trends on Relative ICT Price Trends

Independent	**I**	**II**	**III**	**IV**
$log(P)_{ICT,i,t,trend}$	$-.1470$	$-.4650$	$-.0876$	$-.3825$
	(.0101)	(.0309)	(.0209)	(.0298)
$log(P)_{ICT,i,t,trend} * wbrsh77$		.5193		.5770
		(.0493)		(.0494)
$log(P)_{ICT,i,t,trend} * csc$			-0.0187	-0.0703
			(.0141)	(.0114)
constant	-1.4467	-3.0126	$-.6035$	-1.9878
	(.0920)	(.2431)	(.2002)	(0.2458)
R^2	0.2279	0.5369	0.2960	0.6009

CHAPTER 3

Job Polarization, Skill Accumulation and Wealth Inequality

3.1 Introduction

It has been well documented that the U.S. wage inequality has been persistently rising over the past three decades. A relatively recent literature following the works of Autor et al. (2003) and Autor et al. (2006) links the rise in wage inequality to the concepts of job and wage polarization, which have been characterizing the U.S. labor markets beginning from the 1980s.[1] Most of the studies in this literature have mainly focused on documenting the existence of job and wage polarization and investigated whether the trend had been unique to the U.S. or to some certain period alone. Another line of studies tried to explain the factors leading to this polarization process.[2] The most popular explanation has been the *"routinization"* hypothesis of Autor et al. (2003).[3] This paper focuses on this explanation

[1]Here, job polarization refers to the growth in the employment share of high and low skill occupations, while that of middle skill occupations erodes. Similarly, wage polarization refers to the rise in relative wages of both high and low skill occupations compared to the middle skill ones.

[2]Among those, some studies explain job and wage polarization with globalization and offshoring Grossman and Rossi-Hansberg (2008); Costinot and Vogel (2010); Goos et al. (2011); Monte (2011); Das (2012); Jung and Mercenier (2014).

[3]Similar to Chapter 1, the occupations are divided into three categories following Autor et al. (2003): abstract, routine and manual. Here, the first group represents high skill occupations while the other two represent middle and low skill occupations respectively. According to the routinization hypothesis, tech-

and tests its predictions in terms of wage inequality, skill accumulation and wealth inequality in an incomplete markets environment with heterogenous agents.

Most of the studies in the job polarization literature are abstracted from market imperfections. Therefore, this literature fails to analyze the saving behavior of the households and hence, the link between job polarization literature and wealth inequality has not been established yet. Furthermore, other than the trade models, the literature solely focuses on 'demand' side effects on skilled labor, while ignoring the increase in 'supply' of skilled labor that has been observed in data. In this paper, I will incorporate an otherwise standard task-based production function into a Bewley (1977) type heterogenous agents model with incomplete markets. This will contribute to the existing literature on job polarization and wage inequality in two ways: first, incomplete markets will enable us to study the accumulation of savings and hence implications of job and wage polarization for wealth distribution. Second, having savings in the model will enable us to introduce a simple mechanism of education choice, thereby making the supply of skilled labor endogenous. This will help us to generate the desired increase in the supply and employment share of skilled labor that most of the studies in job polarization fail to address.

The strategy of this paper is as follows: First, I build and calibrate a heterogenous agents DSGE model with incomplete markets and job and wage polarization ingredients, that matches different aspects of the U.S. wage and employment data in the base year of the study, which is 1981. Later, keeping the calibration same as in 1981, I change the productivity of ICT capital capital for 2011, which will be computed by the decline in ICT

nological change arrives in the form of replacement of routine task intensive occupations, which we call as "routinization biased technological change (RBTC)". New technology in this context takes the form of either an exogenous decline in the price of information and communication technology (ICT) capital or an exogenous increase in the productivity of ICT capital producing sector, which is assumed to be relative substitute with middle skill tasks and relative complement with high skill tasks. Larger demand for high skill labor following a technological improvement drives the relative wages of this group up and hence induces an increase in the demand for low skill service occupations as well. As a consequence, the shares of abstract (high skill) and manual (low skill) occupations increase.

capital prices in data over the sample period. Comparing these two periods will enable us to make inferences on how well the routinization hypothesis alone does in generating job and wage polarization as observed in data. Moreover, comparing the wealth distribution for these two years, we can analyze the contribution of job and wage polarization processes in explaining the continues accumulation of college educated labor and recently discussed *middle class squeeze* in terms of wealth holdings.

The paper is organized as follows: Section 3.2 provides a brief literature review, special focus being on the papers linking job polarization and wage inequality. Section 3.3 presents data and facts, while the model is introduced in Section 3.4. Section 3.5 presents our quantitative exercise, the parameterization, solution algorithm and main findings. Section 3.6 introduces a two-sector extension of the model that could potentially improve the findings of the baseline model in terms of matching the U.S. employment data. Finally, Section 3.7 concludes the paper.

3.2 Literature Review

Job polarization, which is defined as the rise in the employment shares of high and low skill occupations, relative to that of middle skill occupations, has been documented for the U.S. by many studies Autor et al. (2003); Acemoglu and Autor (2011, 2012); Jaimovich and Siu (2012); Autor and Dorn (2013). Similar employment shifts has been found for the U.K. as well Goos and Manning (2007); Bisello (2013). Furthermore, job polarization has been observed for Germany Spitz-Oener (2006); Dustmann et al. (2009); Kampelmann and Rycx (2011) and Japan Ikenaga and Kambayashi (2010).

The findings about rest of the European countries are more heterogenous. Goos et al. (2011) investigate 16 Western European countries and find a similar employment polarization pattern for the period between 1993 and 2006 for most of these countries. On the other hand, Nellas and Olivieri (2012), introducing labor market frictions in terms of unionization, find that in continental Europe, differently from the U.S. and the U.K., the fall in the share of middling paid occupations has not come with an increase in the share of low-paid employment. Similarly, Fernandez-Macias (2012) argues that rather than a pervasive process of polarization, there was a plurality of patterns of structural employment change across Europe for the period between 1995 and 2007.

As far as wage polarization is concerned, it seems more like a phenomena almost unique to the U.S. For instance, Dustmann et al. (2009) and Antonczyk et al. (2010) demonstrate that relative rise in the wages of low skill occupations observed in the U.S. was not evident for Germany even though the wage movements at the top of wage distribution have been similar for 1980s and 1990s. Similarly, Stewart (2012) and Holmes and Mayhew (2010) show that wage of low skill occupations relative to middle skill occupations remained stable, while relative wages of high skill occupations relative to middle skill occupations grew persistently. Finally, Naticchioni et al. (2014) conclude that there are no wage polarization trends in Europe, neither at the industry nor at the individual country level.

Earlier researchers successfully explained wage inequality and increasing demand and supply of skilled labor observed in 1980s using skill biased technological change (SBTC) hypothesis. Some influential papers in this area are Katz and Murphy (1992), Greenwood et al. (1997) and Krusell et al. (2000). However, SBTC hypothesis alone is incapable of explaining the growth of employment share and relative wage of low skilled occupations, which has been mainly the issue of 1990s.[4] As a reaction, Autor et al. (2003) introduced routinization hypothesis, which is a nuanced and task-based version of SBTC to explain the phenomenon of job polarization, focusing on the impact of computerization on the different categories of workplace tasks Bisello (2013). In a recent paper, Autor and Dorn (2013) employ a model of changing task specialization in which "routine"clerical and production tasks are displaced by automation. The main focus of their paper is the sources of the changing shape of the lower-tail of the U.S. wage and employment distributions. They find that the twisting of the lower tail is substantially accounted for by a single proximate cause - rising employment

[4]The limitations of SBTC - an its canonical model- are further explored by Acemoglu and Autor (2011).

and wages in low-education, in-person service occupations. Furthermore, they conclude that in labor markets that were initially specialized in routine-intensive occupations, employment and wages polarized after 1980, with growing employment and earnings in both high-skill occupations and low-skill service jobs.

As briefly mentioned in the introduction, routinization is not the only explanation for job and wage polarizations. Even though they are less popular in the literature, other explanations include trade, globalization and offshoring, which is the relocation of some parts of production process to low wage countries. Goos et al. (2011) explore the role of technology, offshoring and institutions and conclude that technology plays the most important role in employment polarization. Other studies focusing on these alternative explanations are Grossman and Rossi-Hansberg (2008), Blinder (2009), Costinot and Vogel (2010), Monte (2011), Das (2012) and Jung and Mercenier (2014). Also, Acemoglu and Autor (2011) propose a Ricardian task-based model as an alternative to the canonical model of SBTC. Recently, Jaimovich and Siu (2012) used a search model that links job polarization to recent jobless recoveries phenomena. Their paper is among one of the few that endogeneize the skill accumulation, thereby successfully generating increase in both the supply and demand for skilled labor.

3.3 Data and Facts

3.3.1 Data

The main source of wage and employment data is March Supplement of Current Population Survey (CPS) for the years between 1981 and 2011[5]. I used only the data for the head of households between the ages of 16 and 64. As it is common in the literature, only full time-full employment labor data has been employed. In other words, observations with

[5]Selected CPS data is reported by IPUMS (Flood et al. (2015)). For 1981 to 2011 data, we used CPS from 1982 to 2012.

working time less than 40 weeks a year and 35 hours per week were dropped. Moreover, self employed households and family workers are excluded. In addition, observations with either no income or zero income reported were eliminated. These, on average, left us around $31,000$ observations per year.

The main variable of interest is the real hourly wage rates. To obtain this, I first generated nominal hourly wages, which is calculated as annual wage income and salary divided by total hours worked in a year. Here, total hours worked is derived by multiplying the weeks worked by the usual hours worked per week. Finally, real hourly wages are obtained by deflating the nominal hourly wages by Personal Consumption Expenditures (PCE) Index of Bureau of Labor Statistics (BLS).

CPS income data is topcoded, meaning that observations above a certain threshold are censored to ensure confidentiality. However, topcoding practice has drastically changed starting from the 1996 CPS. Prior to 1996, all the topcoded observations were being replaced by the same value that equaled to the threshold value. On the other hand, beginning from 1996, one can observe values larger than the topcode amount, since observations above the topcode amount have started to be replaced by the mean income of the families with similar characteristics. Due to this shift in topcoding practice, income data prior to and after 1996 were not comparable. To overcome this difficulty and ensure consistency between the compared periods, I kept the topcoding practice same as in pre-1996 period and replaced all observations above the top code amount with the threshold of the relevant year. It should be emphasized here that this adjustment biased the wage inequality, when measured by Gini coefficient, downward. It also surpassed the relative wages of the high skill labor compared to other skill groups. Nonetheless, the wage inequality trends still remains consistent with the existing evidence from the literature.

In addition to the adjustment at the top of the wage distribution, I also replaced the bottom 1% of the wages with $1st$ percentile value, with the aim of eliminating outliers and misreportings in data. Finally, I used CPS provided weights for individuals in all calculations.

Once data is cleaned as explained above, labor input is assigned into one of the following three occupations: abstract (high skill), routine (middle skill) and manual (low skill) as in Chapters 1 and 2. Details of occupational classification are presented in Section 1.9.3 and thus, will not be discussed again here. Interested reader can find several examples of each types of occupations in Table 1.11.

3.3.2 Facts

3.3.2.1 Wage inequality

Our data confirms the already documented trend in wage inequality: it has been on the rise in the past three decades. This can be seen using various measures of inequality. Figure 3.1 demonstrates two of them: Gini coefficient on the left and 90/10 ratio on the right.[6][7] It is clear from the figure that the rise in wage inequality has been relatively modest during the last decade.

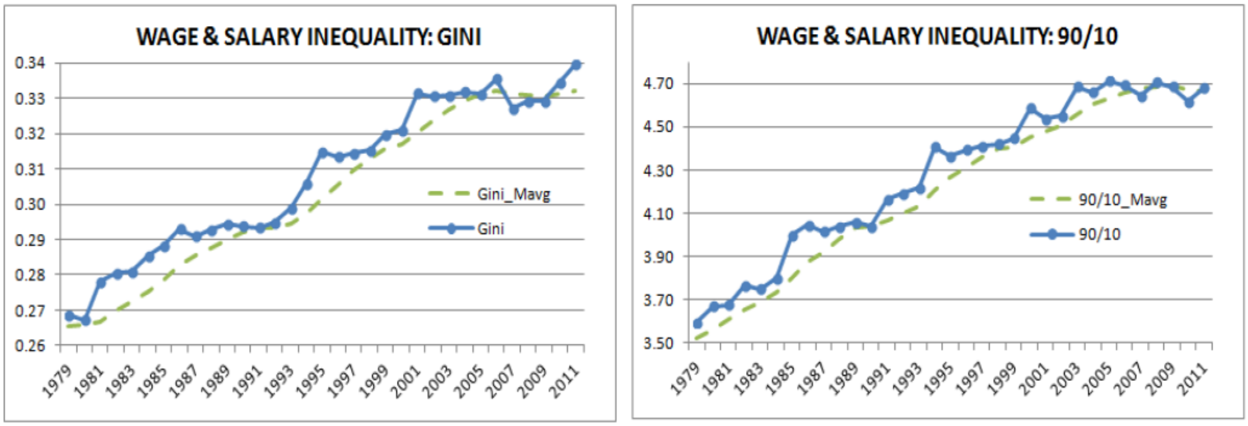
3.3.2.2 Job polarization

When we use the occupational classification described earlier, we see that employment has shifted from routine occupations to both abstract and manual occupations (Figure 3.2) in last three decades. Left panel of the Figure 3.2, which shows the average annual percentage change in employment shares of each occupation type for different periods, reveals that job

[6] 90/10 ratio is commonly used in the literature. Unlike Gini, it is less sensitive to extremely low and high values. It is measured as the 90th percentile of income distribution divided by 10th percentile. A similar ratio, 90/50 ratio, which has special focus on the upper tail of the income distribution also reveals similar findings.

[7] 'Mavg' represents 'moving average'. It is the five-years moving average of the relevant variable and included to smooth the effects of survey data related problems out.

Figure 3.1: Wage Inequality in the U.S.



Source: Author's calculations from the CPS data.

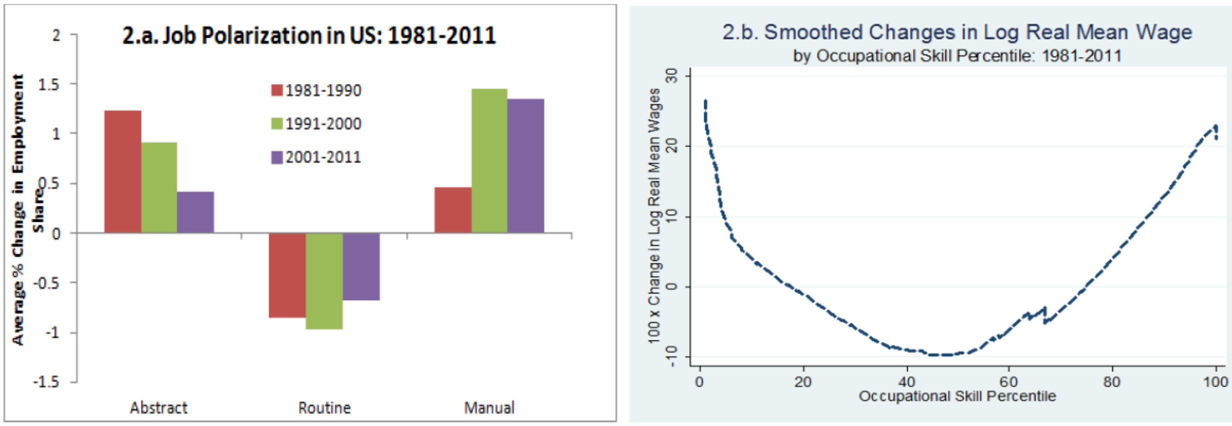
polarization trend has continued in all three decades since 1980s.[8] In absolute terms, the share of routine occupations has declined by about 22% during the entire sample period. Meanwhile, the share of abstract jobs has increased by around 29% and the share of manual occupations has risen by almost 41%.

At this point, one can question the robustness of this finding to the classification chosen. As a reaction to this, I obtained smoothed changes in employment shares by 1981 occupational skill percentile rank, using a locally weighted smoothed regression (right panel of the Figure 3.2).[9] Similar to the case with only three groups of occupations, we see that employ-

[8]Employment shares are measured using the total hours worked by each group. As usual, sample weights are used.

[9]Wage distribution of 1981 was used as a proxy to the skill distribution. There is a strong assumption underlying this: jobs are paid according to the skill level they require. Therefore, lowest paid job as of 1981 has been assigned as the lowest skill job and so on. Sorting occupations based on their log mean wages as of 1981, employment weighted percentiles are constructed. Then, the employment shares of each bin are recalculated for 2011. Finally, using a locally weighted smoothed regression (bandwith 0.8 with 100 observations), smoothed changes in employment shares by skill percentile rank are obtained.

Figure 3.2: Job Polarization in the U.S.: 1981-2011



Source: Author's calculations from the CPS data.

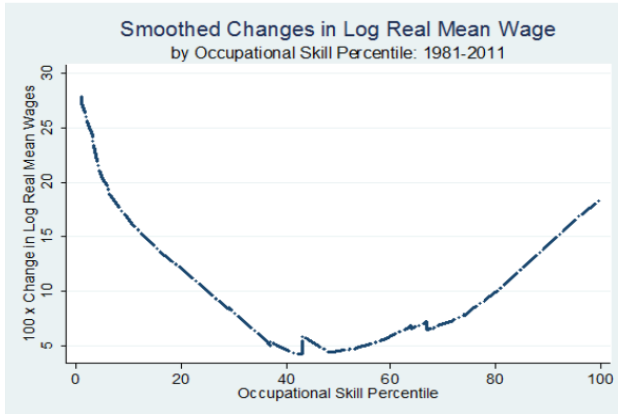
ment shares increased in both tails, while decreasing in the middle. Hence, the existence of job polarization during the entire sample period does not seem to be contingent on a certain choice of classification.

3.3.2.3 Wage Polarization

Job polarization process during the 1981-2011 period has also been coupled with polarization of the wage structure. As Figure 3.3 reveals, relative wages of the middle skill occupations have declined compared both to the highest and the lowest skill occupations.

Figure 3.3 implies that growth in relative wages of low skill occupations was larger than that of high skill occupations. Yet, one should keep the topcoding problem in mind before reaching a firm conclusion on this. As a matter of fact, when our three-tasks classification is concerned, we see that relative mean wage of high skill occupations compared to the middle skill occupations have increased by around 16% (from 1.31 to 1.53), while the mean wage of low skill occupations relative to those of middle skill ones rose only by 6.7% (from 0.74 to 0.79) during the entire sample period.

Figure 3.3: Wage Polarization in the U.S.: 1981-2011

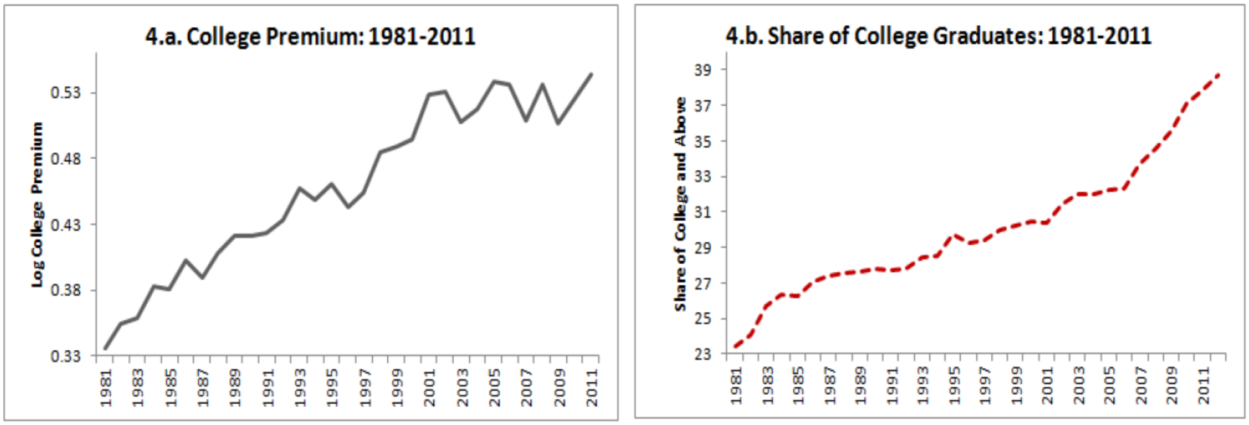


Source: Author's calculations from the CPS data.

3.3.2.4 College Premium and Supply of Skill

College premium, defined as the mean wage of labor with a college degree or above divided by the mean wage of labor without a college degree, has been rising during most of the sample period (left panel of Figure 3.4). This rise has been more pronounced during the 1980s and 1990s. This finding is not surprising since job and wage polarization would imply a substantial rise in the demand for skilled labor, coupled with an increase in the relative wage of this group. Meanwhile, relative supply of skilled labor - labor with a college degree and above- has increased by around 65% (right panel of Figure 3.4). The growth in the share of college educated labor has accelerated during the last decade. Brought together, these two figures suggest that the increase in demand for skilled labor has been significantly larger than the rise in the supply of skilled labor especially during the first two decades of our sample.

Figure 3.4: College Premium and Share of Skilled Labor



Source: Author's calculations from the CPS data.

3.4 Model

3.4.1 Environment

Our model brings various elements of standard models of skill biased technical change (SBTC) and job polarization literatures together, taking the model of Aiyagari (1994) as the basic starting point. Agents are heterogenous in the sense that they receive idiosyncratic labor productivity shocks and set of occupations available to them. Markets are assumed to be incomplete, meaning that agents face a borrowing constraint and thus, engage in precautionary savings to smooth their consumption.

Labor can be either one of two skill groups: skilled (college) and unskilled (non-college), which are denoted as S and U respectively. There is one single final good, which is produced using both the skilled and unskilled labor in one of three tasks: Abstract (L_a), Routine (L_r) and Manual (L_m). Along with two types of capital -ICT capital (K_c) and structural (non-ICT) capital (K_s)- there are five factors of production in the economy: L_a, L_r, L_m, K_c and K_s. It should be noted at this point that SBTC literature misses the task based approach. On the contrary, job polarization literature abstracts from structural capital to keep the models simple and analytically tractable. Our model combines all of these in the same production function as well as introducing incomplete markets.

3.4.2 Households

There exists a continuum of agents of total mass equal to 1. Every period each household receives either a high (good) or low (bad) labor productivity shock. These shocks are denoted as z_h and z_l, respectively and hence, the set of possible shocks is summarized by Z such that $Z = \{z_l, z_h\}$. The productivity shocks follow a Markov process with a transition matrix of the form: $P = \begin{bmatrix} q_{ll} & 1 - q_{ll} \\ 1 - q_{hh} & q_{hh} \end{bmatrix}$, where q_{ll} is the probability of staying in low state, given that we were already in low state, and q_{hh} is the same for high state. In another representation: $\Pr(z' = z_l | z = z_l) = q_{ll}$ and $\Pr(z' = z_h | z = z_h) = q_{hh}$, where a variable with a prime denotes the variable for the next period. The probability of switching from one state to another is totally independent from the past history of the productivity shocks.

Each agent maximizes its preferences defined over a stochastic process for consumption given by the following utility function:

$$E[\sum_{t=0}^{\infty} \beta^t u(c_t)] \text{ , where } \beta \in (0, 1)$$

$$\text{and, } u(c_t) = \frac{c_t^{1-\lambda} - 1}{1-\lambda}$$

where, $\lambda > 1$ is the relative risk aversion coefficient.

Agents smooth their consumption by accumulating a single risk free asset during the good times and dissaving their assets during the bad times. We will interpret this risk free asset as a one-period-ahead sure claim on consumption goods. a units of assets saved this period yields $(1+r)a$ units of consumption goods next period. In terms of general equilibrium, this asset holdings should be balanced by the structural capital demand of the producers and thus r should be set in a way to equate asset demand by producers to the asset supply by households. The effective incompleteness of our model arises from the existence of a *credit limit*. I impose the restriction that credit balances of an individual should always remain above a certain credit limit $\underline{a} < 0$ and hence agents have precautionary saving motives.[10]

Each worker i is endowed with a vector of three efficiency sets: $E_i = (a_i, r_i, m_i)$, where a_i represents the efficiency of the agent in abstract task and so on. We are assuming the following efficiency vectors for skilled and unskilled labor respectively: $E_{S,i} = (\xi, 0, 0))$ and $E_{U,i} = (0, \eta_i, 1)$ where subscripts S and U indicate whether the variable in question belongs to skilled or unskilled labor. These vectors imply that only skilled labor can work in abstract tasks and also skilled labor cannot work in routine nor manual tasks. Since efficiency of a skilled labor in abstract tasks, ξ, is the same across all agents in this group, they all receive the same wage rate: w_a.

Unskilled labor can supply its one unit of labor endowment to either routine or manual tasks. Once employed in manual task, all the agents are homogenous, meaning that they have the same efficiency and receive the same wage: w_m. On the other hand, when they are employed in routine task, they are heterogenous with agent-specific relative efficiency: η_i. Wages in routine tasks are also different for each agents since they will receive $w_r \eta_i$. Routine task efficiency units are assumed to be distributed with density $f(\eta)$, such that $\int_0^\infty f(\eta) d\eta = 1$.

Labor supply decision of skilled labor is quite standard as she inelastically supplies one unit of labor to abstract task and receives w_a. On the other hand, unskilled labor supplies routine labor if her wage in routine task exceeds that in manual task: $w_r \eta_i \geq w_m$. This decision rule yields a cutoff efficiency level, $\eta^* = \frac{w_m}{w_r}$, above which unskilled agent supplies all of its labor to routine task.

Within this framework, one period budget constraint of the skilled and unskilled agent becomes:

[10]As Aiyagari (1994) argues, a borrowing limit is required as long as $r < 0$. Otherwise the problem will not be well posed and there will not exist a solution. Since the present value of life time earnings is infinite, nothing will prevent the agents from running a Ponzi scheme. On the other hand, when $r > 0$, a less restrictive borrowing constraint would suffice. For instance, imposing present value budget balance, along with non-negativity of consumption necessarily imply a borrowing constraint.

S :

$$c_S + a'_S \leq (1+r)a_S + w_a l_a z$$

U :

$$c_U + a'_U \leq (1+r)a_U + \max\{w_r \eta_i l_r, w_m l_m\}z$$

$$c \geq 0 \text{ and } a \geq \underline{a}.$$

where, a' stands for asset holdings next period.

To incorporate a simple skill choice to our model, I introduce exogenous death following the approaches of Blanchard (1985) and Zambrano (2013). Every period, households die with a probability of ψ. The dead household is immediately replaced by a newcomer, who inherits the assets of the dead. The newcomer draws a routine task efficiency endowment η_i from the probability distribution $f(\eta)$. The newcomer is assumed to have the same productivity level as the dead and follows the same Markov process. Observing her efficiency, inherited asset level and the fixed cost of education (φ), the newcomer makes a choice whether to acquire a college degree or not if she has enough resources for that. In other words, if the newcomer does not have enough resources to cover education expenses, she automatically becomes unskilled. Therefore, the value function at the beginning of the life of a newcomer i will be:

$$v_0(a', z'; h, e, r, w) = \max\{v(a', z'; U, e, r, w), v(a' - \varphi, z'; S, e, r, w)\}$$

$$\text{if } a - \varphi \geq -\underline{a}, \text{ and}$$

$$v_0(a', z'; h, e, r, w) = v(a', z'; L, e, r, w)$$

$$\text{otherwise.}$$

where e represents the efficiency endowment vector, r is the interest rate, h represent the skill level such that $h \in \{S, U\}$ and w is the set of wages $\{w_a, w_r, w_m\}$.[11]

[11] Zambrano (2013) provides a lemma (Lemma 2) that suggests that if the cost of education is lower than

In summary, altruistic agents that maximize lifetime utility of the household will have the following value function:

$$
\begin{aligned}
& v(a, z; h, e, r, w) \\
= & \max_{c,a'} \{u(c) + \beta\psi[P(z,z)v(a', z; h, e, r, w) + (1 - P(z,z))v(a', z'; h, e, r, w)] \\
& +\beta(1-\psi)[P(z,z)v_0(a', z; h, e, r, w) + (1 - P(z,z))v_0(a', z'; h, e, r, w)]\} \qquad (3.1)
\end{aligned}
$$

subject to

$$c + a' \leq (1 + r)a + w(h, e)l_{h,e}z$$

$$c \geq 0 \text{ and } a' \geq \underline{a}$$

From now on, I will assume that all the assumptions and theorems in Stokey and Lucas (1996) that are necessary for this process to have a unique solution are valid. Let the state vector describing an agent's position at a time be denoted as $x \in X$ such that $x = (a, z)$. Then, the individual state space is $X = A \times Z$, where $A = [\underline{a}, \infty]$ and Z is as described above. Thus, assuming that a bounded measurable solution v to the equation 3.1 exists, then that v is the optimal value function. Then, the functions $c : X \times R_{++} \to R_{+}$ and $a : X \times R_{++} \to A$ are optimal decision rules provided that $c(x; h, e, r, w)$ and $a(x; h, e, r, w)$ are measurable, feasible, and satisfy the value function $v(x; h, e, r, w)$.

3.4.3 Final Good Producing Firms

Final good is produced by employing five factors of production mentioned earlier by perfectly competitive firms renting skilled and unskilled labor and structural and computer capital.

a threshold, only poor individuals that can afford it will attend college. Similarly, if the cost of college is larger than an upper threshold, only the rich individuals will attend college. When the cost of education is between these two thresholds, then individuals with asset holdings that are not neither too high nor too low will attend college. This lemma follows from the concavity of value function as well as the fact that $v(a', z'; S, r, e) - v(a', z'; U, r, e)$ is decreasing in assets.

I incorporate the task-based approach of the job polarization literature into an otherwise standard production function that is common in the SBTC literature - to be more specific, the production function of Krusell et al. (2000):

$$Y = K_s^{\alpha}\{\mu {L_r}^{\sigma} + (1-\mu)[\omega(\xi L_a)^{\rho} + (1-\omega){K_c}^{\rho}]^{\sigma/\rho}\}^{\gamma/\sigma} L_m^{1-\gamma-\alpha} \tag{3.2}$$

where, $\alpha, \gamma \in (0,1)$ and $\alpha + \gamma < 1$ are shares of structural capital and non-manual tasks combined with computer capital, respectively. Also μ and ω are the parameters that govern the income shares, while ρ and σ govern the elasticities of substitution across factors.

This production function yields the following cross-elasticities between factors:

$$\begin{aligned} \varepsilon_{L_a,K_c} &= \frac{1}{1-\rho} \\ \varepsilon_{L_r,K_c} &= \frac{1}{1-\sigma} \\ \varepsilon_{L_m,K_c} &= 1 \end{aligned}$$

If the routinization hypothesis is valid, K_c and L_a should be relative complements ($\varepsilon_{L_a,K_c} < 1$), while K_c and L_r are relative substitutes ($\varepsilon_{L_r,K_c} > 1$). Furthermore, K_c will be less complementary with L_m than with L_a and less substitutable with L_m than with L_r since $\varepsilon_{L_m,K_c} = 1$. This is a realistic assumption since advancements in technology affect demand for manual services indirectly through its effects on relative wages and employment of abstract labor. Thus, manual services are expected to be affected less favorably than abstract occupations. However, they will still be relatively better than routine occupations since these low skill jobs are not completely replaceable by the machines and computers yet.

When elasticities satisfy the restrictions above, a decrease in the price of computer capital will reduce the relative demand for routine task, while increasing the demand for other two. This, in turn, will put downward pressure on the relative wages paid to routine task compared to other two tasks.

3.4.4 ICT Capital Producers

As it is standard in job polarization literature, computer (ICT) capital (K_c) is produced by perfectly competitive firms, using some part of the final good. Production technology is:

$$K_c = Y_c e^{\nu_t}/\theta$$

where, Y_c is part of final good used in production of computer capital. Hence, we have $Y = Y_c + C + I_s$, where I_s is the investment on structural capital. Furthermore, ν_t is the growth rate of computer capital productivity (or equivalently rate of decline of computer capital price), while $\theta = e^{\nu_0}$ is an efficiency parameter. We also assume that computer capital fully depreciates between periods ($\delta_c = 1$). This assumption is not as unrealistic as it seems at first glance when computer capital is interpreted as computer and information technology a firm rents each year. Thus, price paid to this good can be interpreted as rent paid to technology a firm hires.

Perfect competition guarantees that:

$$p_c = \frac{Y_c}{K_c} = \theta e^{-\nu_0}$$

Since we assumed that $\theta = e^{\nu_0}$, initial price of computer capital will equal to 1 ($p_c = 1$). In this paper, I will not make ν time dependent. Rather, I will introduce technological change by an exogenous increase in ν, or an exogenous fall in p_c. This, as explained earlier, will trigger the polarization process as cheaper computer replaces routine tasks and induce a higher demand for other tasks.

3.4.5 Structural Capital

Structural (non-ICT) capital (K_s) in the model is the standard capital in most of the economic models. It can be produced from final output on a one-to-one basis. The stock of structural capital evolves according to standard law of motion:

$$K_s' = (1 - \delta_s)K_s + I_s$$

Table 3.1: Model Summary

Endogenous Variables	**Exogenous Variables**
Wage rates	Price of computer capital
Interest rate	Efficiency endowments
Factor demands	
Cutoff efficiency	
Relative supply of skilled labor	

where $0 < \delta_s < 1$ is the depreciation rate.

Structural capital is assumed to be owned by households and rented to the final good producers at the rate $r + \delta_s$.

3.4.6 Summary of the Variables

Table 3.1 summarizes the basic variables of interest in our model. I will keep the price of computer capital as exogenous and investigate the effects of changing it on wages and employment shares.

3.5 Quantitative Exercise

In this section, I will solve the model quantitatively for two different states and, by comparing them, test how well routinization hypothesis does in explaining the employment and wage shifts and skill accumulation observed in data. To begin with, I will parameterize the model targeting task shares, wage ratios and factor income shares for the year 1981. Then, price of computer capital will be fed into the model for the year 2011, while all the parameters are kept the same. However, both the borrowing limit and cost of education will be adjusted for 2011 to keep the results comparable. Finally, supply of skills, employment shares and asset distribution will be compared for two periods.

3.5.1 Parameterization

3.5.1.1 Household

Parameters related to the household problem will mainly be borrowed from Huggett (1993) and Aiyagari (1994). Unlike Huggett (1993), who follows the approach of Imrohoroglu (1989) and interprets z_h and z_l as earnings when employed and not employed, I follow Aiyagari (1994) and assume that idiosyncratic shocks are productivity shocks. Thus, I set $z_h = 1$ and $z_l = 0.4$ following Aiyagari (1994). Consistent with this, I use the transition matrix implied by Aiyagari (1994): $P = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}$, which yields invariant probability distribution $\pi = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$, meaning that agents have high productivity half of the time. Note that one period in our model is 1 year.

As it is standard in the literature, discount factor β is set as 0.96. Following Mehra and Prescott (1985), the coefficient of relative risk aversion λ is set to 1.5. Regarding the credit limit, I set it equivalent to the average income of one year. To keep the results comparable between two years, I adjust $\underline{a}$ to be equal to one year's average income as we change the price of computer capital. Death rate is set as 0.0083 from data as 0.83% of the total population die every year in the U.S.

A key parameter to set is φ, cost of education. In this exercise I set it equal to 3.16 times the median wage. This follows from the 2012 College Board Report estimate for the cost of four-years college in a private nonprofit university. When this parameter changes, the share of agents who obtain education is affected significantly. Therefore, results are not robust to choice of φ in terms of absolute values obtained. For instance, if we had used cost of public universities instead (1.86 instead of 3.16), a larger share of agents would prefer getting education and this would affect employment shares and relative wages. However, even in that case, all the key variables would still change in the same direction following a decline in the price of computer capital.

Following the job polarization literature Autor and Dorn (2013), I assume that routine task efficiency endowments have an exponential distribution with parameter κ: $f(\eta_i) = \kappa e^{-\kappa\eta_i}$ for $\eta_i \in [0, \infty)$. This distribution (with $\kappa = 1$) is used extensively in the literature since exponential distribution is easy to solve analytically. For our purpose, I do not need exponential distribution and it should be disciplined by data since choice of distribution might affect some of the findings. Yet, when Pareto distribution has been used instead of exponential distribution, main messages of the paper remains the same.

Table 3.2 summarizes the parameters of the household problem. At this point, κ is missing and it will be calibrated in the following subsections.

Table 3.2: Parameters of the Household Problem

Parameter	Explanation	Value	Source
β	Discount factor	0.96	Huggett (1993)
ψ	Death rate	0.0083	Data
λ	CRRA coefficient	1.5	Mehra and Prescott (1985)
$\underline{a}$	Borrowing limit	$w\_average$	Model
φ	Cost of Education	$3.16 \times w\_median$	College Board Report
P	Transition Matrix	$\begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}$	Aiyagari (1994)
e	Productivity Endowments	$\begin{bmatrix} 1 \\ 0.4 \end{bmatrix}$	Aiyagari (1994)

3.5.1.2 Firms

Most of the parameters of the production side are taken from the SBTC literature. Share of structural capital is estimated by Krusell et al. (2000) as 0.117. They also estimate elasticity of substitution between equipment capital and unskilled labor as 1.6694 and between equipment capital and skilled labor as 0.6689. Even though they do not have task based approach, I assume here that their skilled labor and our abstract task, which could be implemented only by skilled labor, can be used interchangeably. Following this assumption, we can assume that their unskilled labor and our routine task match to a great extent as well.

It should be noted here that the equipment capital in Krusell et al. (2000) is not exactly the same as our computer (ICT) capital here since we assume it totally depreciates every period, but their equipment capital accumulates even though it appreciates much faster than the structural capital. Nevertheless, the equipment capital in Krusell et al. (2000) and Greenwood et al. (1997) covers computer capital as well and this component of the equipment capital is the main driver of the decline in equipment capital prices. Therefore, l assume that two definitions can be interpreted as the same variable. Thus, elasticity of substitution between routine task and computer capital is set to 1.6694 and that between computer capital and abstract task is set to 0.6689. Note that these parameters make abstract task and computer capital relative complements, while routine task and computer capital relative substitutes as routinization hypothesis requires.

Following Greenwood et al. (1997), I choose 0.05 as the depreciation rate of structural capital. As mentioned earlier, δ_c is assumed to be equal to 1.[12]

We had assumed that price of computer capital to be equal to 1, which is also the price of final good for the base year 1981. For 2011, we need to calculate the price of computer capital again since we exogenously change it to compare two periods. To obtain p_c for 2011, we need to find the growth rate of productivity of computer capital or deflation rate of computer capital price. Starting from 1988, I used Information Technology, Hardware and

[12] Greenwood et al. (1997) estimate the depreciation rate of equipment capital as 0.125.

Services Index of BLS, which decreased 9.7% on average between the years 1988 and 2011. Prior to 1988, I used estimate of Greenwood et al. (1997) for the growth of equipment capital productivity, which is 3.24%. At first glance, these two values might seem incomparable. However, the decline rate of Information Technology, Hardware and Services Index in the early years is close to 3.24% as well. The decline rate in index jumps to very high levels in 90s and 2000s, thereby increasing the average to 9.7%.

Table 3.3 summarizes the parameters chosen for the problem of firms.

Table 3.3: Parameters of the Producer Problem

Parameter	Explanation	Value	Source
α	Share of K_S	0.117	Krusell et al. (2000)
δ_s	Depreciation rate	0.05	Greenwood et al. (1997)
$\frac{1}{1-\sigma}$	ε b/w R & K_c	1.6694	Krusell et al. (2000)
$\frac{1}{1-\rho}$	ε b/w A & K_c	0.6689	Krusell et al. (2000)
ν	% Decline in p_c	3.24% until 1988	Greenwood et al. (1997)
		9.7% from 1988	BLS

3.5.1.3 Missing and Calibrated Parameters

After the parameterization described so far, we are still missing five parameters: $\mu, \omega, \gamma, \xi, \kappa$. The first two of them are the parameters governing the income shares. γ is the share of three factors of production combined (L_a, L_r and K_c) in the production function. ξ is the efficiency of abstract labor in production. Finally, κ is the parameter of the exponential distribution that governs the routine task efficiency distribution. To estimate these parameters, we have six targets to match from the data for the year 1981. Those targets are summarized as follows:

$$
\begin{aligned}
Share\_Manual &= 0.13 && (3.3)\\
Share\_Abstract &= 0.29 && (3.4)\\
\frac{w_A}{w_R} &= 1.31 && (3.5)\\
Capital\_Income\_Share &= 0.3 && (3.6)\\
\eta^* &= \frac{w_M}{w_R} = 0.71 && (3.7)\\
\xi &= E(\eta) \times 0.9333^{**} && (3.8)
\end{aligned}
$$

Target 3.8 follows from the estimate of Acemoglu (2002) for the year 1980. Until mid 1980s, skilled labor was less efficient than unskilled labor. Over time, both the relative and absolute efficiency of unskilled labor fell considerably.[13] Estimate of Acemoglu (2002) is also consistent with that of Caselli and Coleman (2006) and Unel (2010).

Note that we have six moments to target but five parameters to calibrate. Therefore, we have to release one of the targets. Fortunately, when we drop the target 3.4, we calibrate parameters yielding a very close value for the target 3.4 as well. It should be noted here that I assumed that 33.2% of the agents are skilled as it is observed in CPS data for the year 1981 when estimating the missing parameters.[14] Later, when solving the model, I let the share of skilled labor to change endogenously and see if we can obtain a share close to 33.2% or not.

Table 3.4 presents the results of our estimation.

3.5.2 Algorithm

In this section, algorithm used to solve the quantitative model is summarized briefly. We have two loops; outer loop being for the interest rate r, while inner loop is over the relative

[13] Here, I implicitly assumed that skilled labor of Acemoglu (2002) matches our abstract labor, while his unskilled labor coincides with our routine labor.

[14] I assume that college graduates refer to "college equivalent" definition of Autor et al. (1998). College equivalent is defined as those with a *college degree* $+0.5\times$ *those with some college*.

Table 3.4: Calibrated Parameters

Parameter	Explanation	Calibrated Value
μ	Share of R in outer CES	0.5626
ω	Share of A in inner CES	0.3281
κ	Parameter of exponential distribution	0.6
γ	Share of abstract, routine and computer capital in production	0.8125
ξ	Efficiency of abstract labor	1.5537

wage rate $\frac{w_a}{w_r}$. I begin with an initial guess of r, that is within the range likely outcomes of interest rate.[15] I also pick an initial guess for the relative wage between abstract and routine tasks. The range chosen is between 1 and 3. Employing our initial guesses of r and $\frac{w_a}{w_r}$, we solve for optimal decision rules for asset holdings using the Value Function Iteration (VFI) methodolgy.

Once, we get the decision rules, Ie simulate the economy for 1,000,000 agents to compute invariant asset distribution and share of agents willing to get college education. Using this share of skilled labor, I compute the implied wage ratio. If this ratio is larger than our initial guess, I increase our guess for $\frac{w_a}{w_r}$ using the bisection methodology. Similarly, when the implied wage ratio is lower, I decrease the initial guess. Once $\frac{w_a}{w_r}$ is updated, I repeat the VFI and simulation parts again until $\frac{w_a}{w_r}$ converges.

After $\frac{w_a}{w_r}$ converges, I check for the excess demand for asset holdings. Demand for holdings comes from the firm's choice of structural capital. On the other hand, supply of asset is obtained from the simulation. If excess demand is positive, I update r upward using bisection methodolgy. Likewise, negative excess demand requires updating r downward. I repeat the whole process until r converges (or until excess demand for asset holdings is around 0).

[15] According to Aiyagari (1994), this interest rate should lie between complete markets interest rate ($\frac{1}{\beta}$) and $-\delta_S$.

3.5.3 Findings

3.5.3.1 Job and Wage Polarization

Our model does a remarkably good job in matching the data for the year 1981 (Table 3.5). This results from the ability of the model to generate share of skilled labor matching the college equivalent in data we used in our parameter estimation. Once the share of skilled labor has been predicted correctly, rest of the variables match the data since the parameters have already been estimated for that particular level of the share of college educated labor. Model is also fairly successful in predicting the rise in the share of abstract jobs, even though it overshoots it a little. Rather than increasing to 39% as in data, share of abstract jobs increase to 44.4% in the model. On the other hand, the direction of wage polarization in the model is the same as in data. However, relative increase in the wage of abstract tasks is significantly above that in data. This mainly stems from the fact that model falls short of data in terms of the share of college equivalent workers. This results in higher wages for the abstract task since supply of skilled labor is not as abundant as in data.

Table 3.5: Findings: Data vs Model

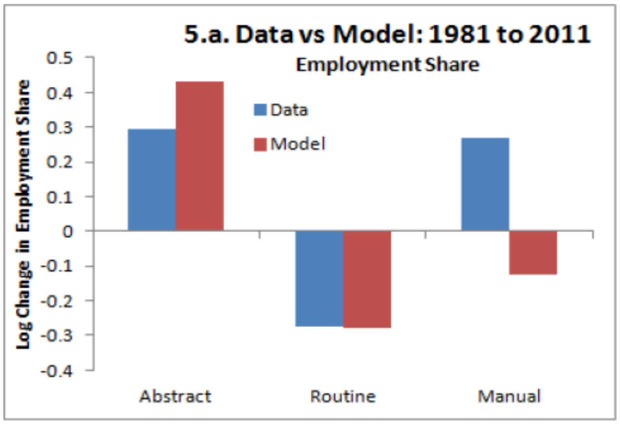
	1981		2011	
	Data	Model	Data	Model
Share_A	29	28.8	39	44.4
Share_R	58	58.1	44	44.0
Share_M	13	13	17	11.5
$\frac{w_A}{w_R}$	1.31	1.31	1.56	1.79
$\frac{w_M}{w_R}$	0.71	0.71	0.81	0.84
Share_College	33.2%	33.12%	53.3%	49.6%

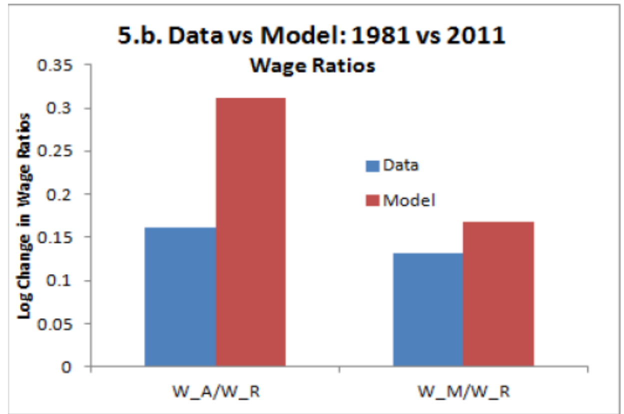
As both Table 3.5 and the left panel of Figure 3.5 demonstrate, the sole failure of the model is its inability to generate the rise in the share of manual occupations. On the contrary, share of this group even declines in the model. There might be two explanations for this failure. First, exponential distribution assumption for efficiency endowments might not be representative of the actual data. When the relative wage of the manual jobs increase in our model (due to the increased demand for manual task), this does not generate a sufficient increase in the supply of manual task. Second, our model misses an additional demand channel for the manual labor. According to the routinization hypothesis, when the demand for and supply of abstract task increase, coupled with an increase in relative wage of this group, there will be higher demand for manual jobs such as cleaners, baby-sitters, janitors and similar jobs. Our model misses this important channel. Instead, we are assuming that the demand for manual tasks directly increases due to the fall in price of computer capital, which is a relatively weaker channel. In order to overcome this difficulty, in Section 3.6, I will incorporate another sector (service sector) such as the one in Autor and Dorn (2013) that employs only the manual task. As it will be presented soon, having two goods in utility function, with appropriate choice of elasticity of substitution between them, generates a stronger demand channel for the manual jobs. As a result, we obtain the desired rise in share of manual tasks, while keeping the increase in relative wage of low skill occupations compared to middle skill occupations the same.

3.5.3.2 Wealth Distribution

Comparing the asset distributions, we can see that our model turned out to be quite successful in capturing the 'middle class squeeze'. As seen in Figure 3.6, there are more agents with negative wealth holdings after the exogenous shock to the price of computer capital and also the right tail of the wealth distribution is longer, while the erosion in the middle of wealth distribution is striking. This might be an indication of the likely role played by job and wage

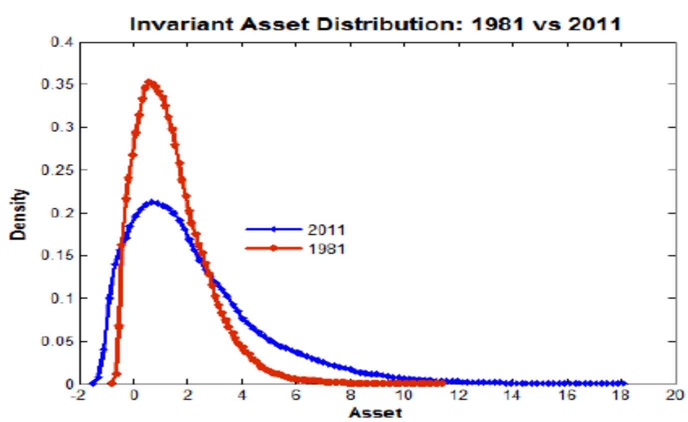
Figure 3.5: Job and Wage Polarization: Data vs Model





polarization triggered by the rapid decline in information capital prices on the increasing concentration of wealth in the hands of a smaller segment of the economy. Despite being the first study modeling the link between job/wage polarization and wealth inequality, this finding is quite promising and implies that this link deserves to be explored in more detail in future studies.

Figure 3.6: Invariant Asset Distribution in Model (1981 vs 2011)



3.5.3.3 Robustness

As mentioned earlier, the findings presented so far are sensitive to the choice of cost of education parameter φ. When we use public education instead of private nonprofit colleges to estimate a value for φ, more agents choose getting education in both steady states. Therefore, we are not able to match the wage ratios and employment shares in the data in absolute terms. Nonetheless, the direction of the changes in the employment shares and relative wages remain the same even with a low value for φ. Thus, the ability of the model to generate wage polarization and increase in the share of abstract occupations consistent with data and its inability to capture the rise in the share of manual occupations are robust to the choice of education parameter.

Findings concerning the employment share and relative wage of manual occupations are also sensitive to the choice of skill distribution. In our model, I assumed that skill distribution is exponential with parameter κ. Even though the model could generate the increase in relative wage of manual occupations, it failed to mimic the rise in the share of this group in employment. When we use Pareto distribution instead, this time we can generate a slight increase in the employment share of manual occupations. However, in this case, model fails to capture the rise in the relative wage of this group. Therefore we face the same problems mentioned earlier: skill distribution should be disciplined better and also there should be a stronger channel linking abstract and manual occupations, thereby generating a higher demand channel between computer price and manual occupations.

3.6 Extension to Two Sectors

As already discussed, our model with only one sector failed to generate the desired increase in share of manual tasks. We attributed this to the lack of a stronger and more realistic link between price of technology and demand for services. To overcome this, in this section, I incorporate a second sector into the baseline setup introduced in earlier sections. Following Autor and Dorn (2013), I assume that this second sector only employs low skill labor, who work in manual tasks, and produces service occupations. As long as consumption elasticity between the final good and service is sufficiently small, a rise in computer price will generate the desired flow of low skill labor from routine tasks to manual tasks.

3.6.1 Amendments to the Baseline Model

The final good production technology is the same as before, except that I only allow use of four factors of production: L_a, L_r, K_c and K_s, rather than five. In other words, I rule out the use of manual task in goods production technology. Also, I will normalize ξ, the efficiency of high skill labor in abstract tasks, to 1, as we will rely on comparative advantages of each labor type in routine tasks to allocate labor in this version of the model. The final good production technology then becomes:

$$Y_g = K_s^{\alpha}\{\mu {L_r}^{\sigma} + (1-\mu)[\omega {L_a}^{\rho} + (1-\omega){K_c}^{\rho}]^{\sigma/\rho}\}^{(1-\alpha)/\sigma}$$

where Y_g is the final good produced. As in our one-sector model, abstract labor and computer capital will be relative complements, while abstract labor and routine labor will be relative substitutes with our calibration. The parameters governing the factor income shares will be re-calibrated below trying to match income shares, wage ratios and employment shares.

Final good is our numeriare good and hence its price is normalized to 1. The first order conditions of firm's profit maximizing problem are:

$$w_a = L_a^{\rho-1} K_s^{\alpha} \omega \left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}-1}(\alpha-1)\frac{\mu-1}{\left(L_r^{\sigma}\mu - \left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}}(\mu-1)\right)^{\frac{1}{\sigma}(\alpha-1)+1}}$$

$$w_r = L_r^{\sigma-1} K_s^{\alpha}\mu\frac{1-\alpha}{\left(L_r^{\sigma}\mu - \left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}}(\mu-1)\right)^{\frac{1}{\sigma}(\alpha-1)+1}}$$

$$r = K_s^{\alpha-1}\frac{\alpha}{\left(L_r^{\sigma}\mu - \left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}}(\mu-1)\right)^{\frac{1}{\sigma}(\alpha-1)}} - \delta$$

$$p_k = K_c^{\rho-1} K_s^{\alpha}\left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}-1}(\alpha-1)(\mu-1)\frac{1-\omega}{\left(L_r^{\sigma}\mu - \left(L_a^{\rho}\omega - K_c^{\rho}(\omega-1)\right)^{\frac{\sigma}{\rho}}(\mu-1)\right)^{\frac{1}{\sigma}(\alpha-1)+1}}$$

Note that L_r is the aggregate routine task labor in terms of efficiency units.

The service sector uses only manual labor and have a simple linear production function as follows:

$$Y_s = \alpha_s L_m$$

where Y_s is the total output of service sector and α_s is efficiency of manual labor, which will be normalized to 1.

The profit maximization of the service sector firm yields a simple condition:

$$p_s = w_m.$$

Computer capital production technology is same as before and price of computer capital is initially set equal to the price of final good.

As before, I am assuming that there is a continuum of mass one of both skilled (college educated) and unskilled labor. However, unlike Autor and Dorn (2013) and our baseline model, I allow skilled workers to work both in abstract and routine tasks but not in manual tasks. On the contrary, unskilled workers are not allowed to work in abstract tasks but can do both manual or routine jobs. Thus, efficiency endowment vectors are: $E_{S,i} = (1, \varpi_i, 0))$ and $E_{U,i} = (0, \eta_i, 1)$ where subscripts S and U represent skilled and unskilled, respectively. In our calibration, the average efficiency endowment in routine tasks will be lower for the skilled workers than that of unskilled workers. Therefore, unskilled labor will have a comparative advantage in routine tasks, as expected and thus, most of the skilled labor in routine tasks will leave that market after a significant decline in price of technology, leaving only the labor with very high relative efficiency in routine tasks.

Allowing the skilled labor to work in routine tasks as well is not unrealistic as it seems. As a matter of fact, CPS data between 1981 to 2011 reveal that on average 20% of college equivalent labor works in non-abstract tasks. This new set up will enable us to generate shifts in employment shares even in the absence of educational choice set up described in the baseline model. The main goal of this modification is to reduce the computation time substantially.

As before, skilled labor working in abstract tasks receive the same wage rate; w_a, since efficiency of a skilled labor in abstract tasks is the same across all agents. However, when a skilled labor works in routine task, she is paid based on her efficiency and thus receive $w_r \varpi_i$. The skilled labor faces a self selection problem: she chooses the highest paying task. To be more explicit, skilled worker chooses staying in abstract task if $w_r \varpi_i < w_a$ and will go and work in routine task otherwise. Similar to the problem of unskilled labor described earlier, this selection problem will generate a cutoff $\varpi^* = \frac{w_a}{w_r}$. Thus, an skilled labor will work in routine task only if her efficiency in routine tasks is very high. In other words, only the skilled labor with high comparative advantage in routine tasks will leave the abstract task market.

The problem of unskilled labor is same as before. Unskilled labor supplies routine labor if her wage in routine task exceeds that in manual task: $w_r \eta_i \geq w_m$. This decision rule yields a cutoff efficiency level, $\eta^* = \frac{w_m}{w_r}$, above which unskilled agent supplies all of its labor to routine task.

As before, routine task efficiency units are assumed to be distributed with density $f(\eta_i)$, such that $\int_0^\infty f(\eta_i) d\eta_i = 1$. In addition to this, we now have a similar distribution for ϖ_i such that $\int_0^\infty g(\varpi_i) d\varpi_i = 1$. I will assume -and indeed our calibration will require- that $E(\eta_i) > E(\varpi_i)$, meaning that unskilled labor has comparative advantage in routine tasks over the skilled labor.

Following Autor and Dorn (2013), consumers have the following utility function defined over two goods: services and goods:

$$u = (\gamma c_s^\lambda + (1 - \gamma) c_g^\lambda)^{\frac{1}{\lambda}}$$

where λ and $\gamma < 1$. Here, elasticity of substitution in consumption between goods and services is $\frac{1}{1-\lambda}$. This elasticity plays a crucial role in shaping the employment shifts following the decline in price of technology. On the other hand, the parameter γ is a scaling factor that helps us to match the key facts targeted in our calibration.

One period budget constraints in this set up are as follows:

S :

$$c_{S,g} + p_s c_{S,s} + a'_S \leq (1+r)a_S + \max\{w_a, w_r \varpi_i\} z$$

U :

$$c_{U,g} + p_s c_{U,s} + a'_U \leq (1+r)a_U + \max\{w_r \eta_i, w_m\} z$$

where $c_{I,j} \geq 0$ and $a_I \geq \underline{a}$ for $I \in \{S, U\}$ representing skilled and unskilled labor and $j \in \{s, g\}$ representing goods and services. Letting C_g and C_s be the aggregate consumption of goods and services respectively, first order conditions of household problem yields:

$$(\frac{C_g}{C_s})^{1-\lambda} = \frac{1-\gamma}{\gamma} p_s \tag{3.9}$$

The market clearing conditions for goods and services are as follows:

$$Y_g = C_g + I_S + K_c$$

$$Y_s = C_s$$

Finally, the larbor market clears:

$$\begin{aligned} L_a &= \int_0^{\varpi^*} f(\varpi_i) d\varpi_i \\ L_r &= \int_{\varpi^*}^{\infty} \varpi_i f(\varpi_i) d\varpi_i + \int_{\eta^*}^{\infty} \eta_i f(\eta_i) d\eta_i \\ L_m &= \int_0^{\varpi^*} f(\eta_i) d\eta_i \end{aligned}$$

3.6.2 Calibration

Our calibration strategy is same as before. For the household side, we have the transition matrix and productivity endowments as in Aiyagari (1994) and discount factor β as in Huggett (1993). Elasticities of substitution between abstract and routine task and computer capital as well as the share of structural capital are taken from Krusell et al. (2000). Finally, I take the depreciation rate of structural capital from Greenwood et al. (1997) as in the baseline model.

To calibrate the elasticity of substitution between goods and services, I use consumption and price series for goods and services from the Bureau of Economic Analysis. For services, I take only personal care and clothing services item since it best represents the manual services in our model. However, results are robust to other choices of service items such as household maintenance services. I did not use the general service category since most of the subcategories under services such as financial, education and health services coincides with our abstract tasks in the model and hence are considered in goods. To calibrate the elasticity of substitution, I used equation 3.9 and regressed $\ln(\frac{C_g}{C_s})$ on a constant and $\ln(\frac{1}{p_s})$ and interpreted the coefficient of the explanatory variable, which is 0.6883068, as the elasticity of substitution between goods and services.[16] This implies $\lambda = -0.452843$.

Finally, we used the same strategy as in the baseline to calibrate the remaining parameters: ω, μ, κ_1 and κ_2, where the last two are the parameters of exponential distribution governing the routine task efficiency distribution for unskilled and skilled labor, respectively. To calibrate these four parameters, along with the scaling parameter A, I target five facts from data and solve them along with the other steady state equations:

$$\begin{aligned} Share\_Manual &= 0.13 && (3.10) \\ Share\_Abstract &= 0.29 && (3.11) \\ \varpi^* &= \frac{w_A}{w_R} = 1.31 && (3.12) \\ \eta^* &= \frac{w_M}{w_R} = 0.71 && (3.13) \\ Capital\_Income\_Share &= 0.3 && (3.14) \end{aligned}$$

When these equations are solved for $p_k = 1$, we obtain the following parameters:

[16] When we take log of both sides, equation 3.9 becomes:

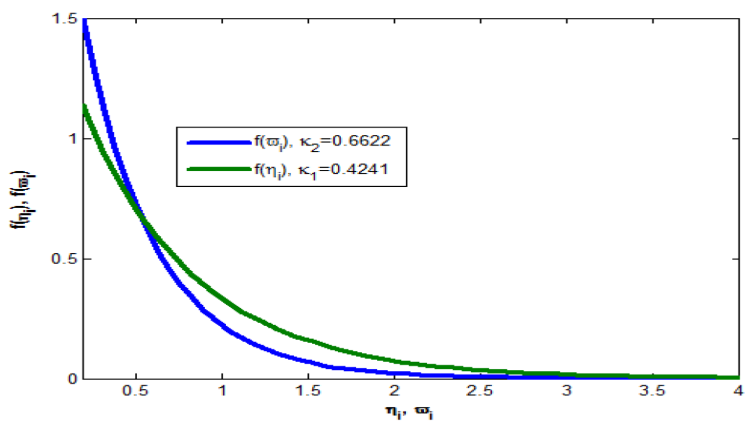
$$\begin{aligned} (1-\lambda)\ln(\frac{C_g}{C_s}) &= \ln(\frac{\gamma}{1-\gamma}) - \ln(\frac{1}{p_s}) \\ \ln(\frac{C_g}{C_s}) &= constant - \frac{1}{1-\lambda}\ln(\frac{1}{p_s}) \end{aligned}$$

Table 3.6: Calibrated Parameters of Two-Sectors Model

μ	Share of L_R in outer CES	0.4235
ω	Share of L_A in inner CES	0.4878
κ_1	Parameter of exponential distribution for unskilled labor	0.4241
κ_2	Parameter of exponential distribution for unskilled labor	0.6622

This parameterization ensures that unskilled labor has comparative advantage in routine task over the skilled labor since $E(\eta_i) > E(\omega_i)$. This is also depicted in Figure 3.7, which shows the distribution of efficiencies in routine task for two skill groups.

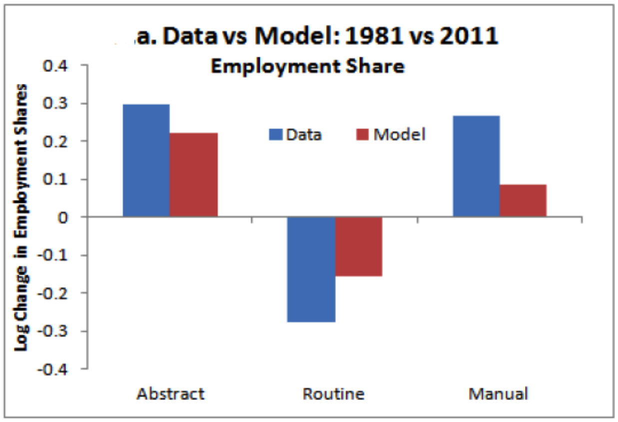
Figure 3.7: Efficiency Distribution in Routine Tasks: Skilled vs Unskilled

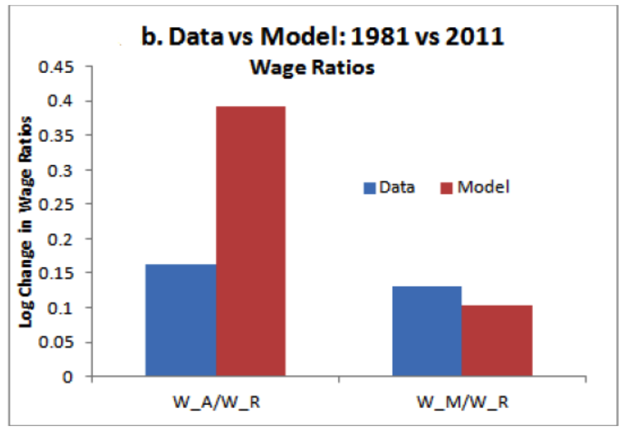


3.6.3 Comparison of Two Steady States

In this subsection, we follow the same strategy as in the baseline model and compare two steady states that only differ in price of computer technology. Figure 3.8 is a replication of Figure 3.5, using the two-sectors model instead of our baseline one-sector model. However, the findings presented in Figure 3.5 are general equilibrium results, while Figure 3.8 presents the solution to the partial equilibrium model for a given interest rate. Nevertheless, the change in interest rates do not play a significant role on employment and wage structure shifts. Solving the general equilibrium model only matters for obtaining the wealth distribution and the transition dynamics.

Figure 3.8: Job and Wage Polarization: Data vs Two-Sectors Model





The modified model is promising in the sense that when it is reasonably well calibrated, it is able to capture both the employment and labor shifts in the labor markets. Unlike one-sector model, which generates a counterfactual decrease in the share of manual service jobs; two-sectors model is able to convert this counterfactual movement to an increase. Despite the correct directions of structural shifts, the increase generated in the share of manual jobs remains relatively modest compared to what is observed in data. Furthermore, the rise in the relative wage of abstract tasks are overstated in the model. Yet, the relative increase in wage of manual tasks is quite consistent with data. To sum it up, by switching to the two-sectors model, the model's success to predict the relative wage trends remained the same, while the failure of the model in terms of generating the shifts in employment structure has been fixed to a great extent. There is still much room for potential improvement in results with a more sound calibration.

3.7 Conclusion

U.S. wage inequality has been rising in the past three decades. A recently growing literature has linked increased wage inequality with the recent job and wage polarization processes that have been observed in many developed countries in the same period. Meanwhile, both the supply of skilled labor and college premium has been increasing, implying that the rise in the demand for skill, which is evident from job polarization, has been dominating the effect of increase in supply.

Even though job and wage polarization might be explained by various factors such as globalization and offshoring, a great bulk of the literature focuses on routinization hypothesis as the main trigger of this employment and relative wage shifts. In short, routinization hypothesis suggests that due to the rapid decline in the price of computer capital, routine tasks are replaced by this particular type of capital in production, while inducing a higher demand for abstract and manual tasks. This results in an increase in employment shares and relative wages of both high and low skill occupations compared to middle skill ones.

In this paper, I tested the predictions of routinization hypothesis in an incomplete markets environment with heterogeneous agents. To do so, I combined various elements from standard models of both SBTC and job polarization literatures in a Bewley (1977) type economy. Having incomplete markets enabled us to analyze the saving behavior of the agents under the presence of job polarization and establish the link between job polarization literature and wealth inequality. Furthermore, it allowed us to introduce a simple mechanism of education choice, thereby making the supply of skilled labor endogenous. That way, we were able to generate increase in supply and employment share of high skill labor following a rapid decline in computer price, unlike most of the standard models in job polarization, which usually lack any market imperfections and fail to generate the desired increase in the employment share of skilled labor.

To test the routinization hypothesis and analyze the implications of job and wage polarization on wealth accumulation, I first built and calibrated a heterogenous agents DSGE model with incomplete markets and job and wage polarization ingredients, that matched different aspects of U.S. wage and employment data for 1981. Later, I fed the model with the price of computer capital for the year 2011 and solved the model again, while keeping the parameters the same as in 1981. Comparing two periods, which only differed in terms of price of computer capital, our model showed that routinization hypothesis alone accounts for a great part of increase in employment share of high skill occupations and their relative wages, as well as the increase in the supply of labor with a college equivalent degree. The model has also been successful in explaining the erosion of wealth in the middle of wealth distribution, while increasing share of asset holdings at the two extremes, thereby indicating the role that might have been played by job and wage polarization on the recently discussed phenomenon of middle class squeeze.

Despite its success in capturing most of the changes in labor markets and asset holdings, the model failed to generate a growth in the share of low skill occupations. On the contrary, it even resulted in a decline in the employment share of this group. As discussed extensively in earlier sections, this might be the result of choice of distribution of routine task efficiency and hence might be overcome to some extent by disciplining this distribution from data. Furthermore, another channel that would increase the demand for service (low skill) occupations as computer prices decline should be introduced. This could be achieved by introducing another sector, that uses only manual tasks and produces a service that would be demanded more as there are more high skill occupations with a relatively higher wages Autor and Dorn (2013).

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