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Abstract

Empirical studies report a marked dispersion in skill-premium changes across economies over the past few decades. Structural models in early studies successfully replicate the increases in skill premiums in many economies, while some other cases with a decline in the skill premium are yet to be explained. To this end, we develop a two-sector (i.e., manufacturing and non-manufacturing) general equilibrium model with skilled and unskilled labor, in which degrees of capital-skill complementarity differ across sectors. Based on the estimated structural parameters, we show that a decline in capital-skill complementarity in the non-manufacturing sector can provide a consistent explanation for the following aspects of the Japanese data at both the aggregate and industry levels: (i) a decline in the skill premium, (ii) widening of the sectoral wage gap due to a rise in manufacturing wages and decline in non-manufacturing wages, and (iii) an increase in the unskilled labor share in the non-manufacturing sector. We interpret that this change reflects compositional effects and uneven technology adoption of firms within non-manufacturing.

Keywords: Capital-skill Complementarity; Skill Premium; Two-sector DSGE Model; Bayesian Estimation.

JEL Classification: E22, E24, J31;

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1 Introduction

While the skill premium is generally thought to have been rising over time, a few economies have actually seen skill premiums decline over the past decade. Among others, this paper focuses on three notable aspects of the Japanese labor market at the industry level. First, the skill premium, defined as the ratio of the skilled wage to the unskilled wage, started to decline around the mid-1990s. Second, while the average manufacturing wage has kept rising, the non-manufacturing wage has declined significantly. Lastly, the input share of unskilled labor has increased over time in the non-manufacturing sector while holding relatively steady for manufacturers. These changes observed in the Japanese economy are in sharp contrast to what we have seen in most other economies. Understanding the main factors behind these differences is likely to have quite important policy implications for economic growth.

This paper studies a two-sector general equilibrium model with two types of labor, skilled and unskilled, and aims to account for the aforementioned three observations in a neoclassical framework. In particular, we introduce capital-skill complementarity, such that the production technology exhibits complementarity between skilled labor and physical capital stock as discussed in Krusell et al. (2000). Parameter values are crucial for the degree of capital-skill complementarity. We fit our two-sector DSGE model to quarterly sectoral data, using Bayesian methods to estimate the key structural parameters. We then use our model to perform a number of comparative statics exercises with a view to identifying the main driving force behind the aforementioned changes in the Japanese economy.

While the aggregate hourly wage started to decline in the mid-1990s, we observe stark differences in wages across the two sectors, i.e., manufacturing and non-manufacturing. More specifically, while the hourly wage in the manufacturing sector continues to rise over time, the hourly wage in the non-manufacturing sector has declined since the mid-1990s. As a result, the sectoral wage gap, measured by the relative wage, has widened by about 15 percentage points since the mid-1990s. Meanwhile, the skill premium, which has typically increased in other advanced economies as well as emerging nations, has decreased by about 8.4 percentage points on average. We need a two-sector setup in order to illustrate the divergence of sectoral wages and the decrease in the skill premium within the same framework. If sectoral wages had not diverged, it would be possible to conclude that the aggregate wage has merely been reflecting changes in productivity. Moreover, in one-sector models, the decline in the skill premium can be simply attributed to skill-biased technological changes.[1] These changes, however, cannot describe the difference in sectoral wages. Alternatively, Kawaguchi and Mori (2014) seek to offer some evidence for a labor-supply-side story to explain changes in the wage gap between college and high school graduates.[2] They point out that increasing relative supply of college graduates would lead to a decline in the skill

[1] There exists a vast literature on the skill-biased technological change. See, for example, Acemoglu (2002).
[2] The skill premium we will look at is different from the college premium they analyzed.

premium based on educational attainment. However, the aforementioned divergence of sectoral wages implies that structural changes on the labor supply side are unlikely to be the main reason for the skill premium having declined, because such changes would affect both manufacturing and non-manufacturing proportionally.

In this paper, we show that changes in capital-skill complementarity in the non-manufacturing sector can explain the stylized facts. Since we primarily focus on structural changes in the manufacturing and non-manufacturing sectors, the labor supply side in our model has a relatively simple structure. We just take the existence of the two types of labor as given and assume that households are indifferent between working for manufacturers or non-manufacturers. The two sectors hire both skilled and unskilled workers. Depending on the degree of capital-skill complementarity, firms choose a different mix of skilled and unskilled workers in terms of hiring.

Based on the estimated structural parameters, we find that a decline in the degree of capital-skill complementarity in the non-manufacturing sector can account for the observed decline in the skill premium. Specifically, lower capital-skill complementarity arising from a reduction in the elasticity of substitution between capital and unskilled labor in the non-manufacturing industry provides a consistent explanation for the observed changes in the skill premium and sectoral wages as well as the increased share of unskilled labor in the non-manufacturing sector.

We believe that the decline in capital-skill complementarity is consistent with what has been occurring in the Japanese economy since the mid-1990s. In our two-sector model, we can interpret a drop in the elasticity of substitution between capital and unskilled labor as a consequence of the ongoing expansion of the unskilled labor intensive services sector, which includes food services and nursing care. Even though we cannot address this compositional effect within the non-manufacturing sector in this model, the increasing importance of these industries relative to traditional non-manufacturing industries can be reflected in the lower elasticity of substitution between capital and unskilled labor.

The idea of capital-skill complementarity is not new. Griliches (1969) first hypothesizes that skill or education is more complementary with physical capital than unskilled labor. Recently, Krusell et al. (2000) revive the idea of capital-skill complementarity, using it to account for the observed increases in the skill premium in the US economy at the aggregate level. Although the increase in the skill premium has typically been attributed to unobserved skill-biased technological changes, they argue that capital-skill complementarity helps explain observed changes in the skill premium.[3] Our paper is related to Maliar and Maliar (2011), who construct a general equilibrium version of Krusell et al. (2000), together with additional driving forces. They derive restrictions that make the model consistent with bal-

[3] Polgreen and Silos (2008) re-examine findings of Krusell et al. (2000). They assure the existence of capital-skill complementarity. However, they also find that other results in Krusell et al. (2000) were sensitive to the data used.

anced growth. In contrast, our model focuses on the two-sector setup around a detrended steady state.

We estimate the degree of sectoral capital-skill complementarity within a framework of business-cycle models by using quarterly time series data. While most existing studies focus on the long-run implications of capital-skill complementarity, there are a few exceptions. Lindquist (2004) looks at a cyclical property of capital-skill complementarity. His finding suggests that capital-skill complementarity is an important factor in explaining the skill premium over the business cycle. In terms of aggregate production technology, however, Balleer and van Rens (2013) reach the opposite conclusion. They construct a quarterly skill premium series for the US economy using the Current Population Survey and then estimate responses of the economy to various technology shocks using a structural vector autoregression framework. In particular, they find that the skill premium responds negatively to investment-specific technology shocks. Their finding rejects the possibility of capital-skill complementarity and favors the existence of capital-skill substitutability in the aggregate production technology. Our own empirical analysis indicates that there is a significant difference in the degree of capital-skill complementarity between the manufacturing and non-manufacturing industries. In fact, our comparative statics exercises suggest that capital-skill complementarity vanishes for non-manufacturers in Japan. This heterogeneity of capital-skill complementarity might explain the conflicting results between Lindquist (2004) and Balleer and van Rens (2013).

Capital-skill complementarity is also increasingly important in the international trade literature. Parro (2013) develops a general equilibrium trade model with capital goods trade and capital-skill complementarity. In this setup, he shows that there are two possibilities that increase the skill premium. A technical change causes the relative price of capital to decline, which in turn increases the skill premium. This is true even in a closed economy. In addition, with capital goods trade, a decline in trade costs also reduces the price of capital goods, thereby catalyzing more trade in capital goods. As a result, the productivity of skilled labor and the skill premium both increase when capital-skill complementarity exists. This result has an important welfare implication for the Japanese economy: if capital-skill complementarity weakens, it will become more difficult for the Japanese economy to enjoy gains from trade (through cheaper capital goods with reduced transportation costs).

In terms of changes in sectoral allocation of labor, Ngai and Pissarides (2007) offer an alternative explanation. They show that as long as goods and services are complements, labor will flow into a sector with lower TFP growth. Marquis and Trehan (2010) apply this idea to explain sectoral dynamics in the US economy, finding that the elasticity of substitution between goods and services is zero or thereabout, and that labor thus flows from manufacturing to services. However, our estimation results suggest that the elasticity of substitution between goods and services is not close to zero, and is indeed significantly greater than unity.

Apart from the concept of capital-skill complementarity and two types of labor, this paper is related to Iacoviello et al. (2011), who use Baysian methods to construct and estimate a two-sector DSGE model. As with our own model, they make a clear distinction between goods and services. Their model features a detailed structure of inventories in order to capture the business cycle propagation mechanism. Two sectors (goods-producing and services-producing sectors) are differentiated by whether they hold inventories or not. This type of distinction is not included in our paper. Instead, the two sectors (i.e., goods and services) are different in our setup in terms of production technology, particularly with regard to the degree of capital-skill complementarity.

The rest of the paper is organized as follows. Section 2 presents the stylized facts that we would like to explain. Section 3 presents a two-sector neoclassical model with two types of labor. In Section 4, we use Bayesian methods to estimate model parameters that are important for explaining the stylized facts. We then use the estimated parameters to conduct a number of comparative statics exercises in Section 5. Section 6 concludes the paper.

2 Stylized Facts

Let us now present the stylized facts about the Japanese labor market that we would like to explain. We will focus on the following three facts.

Fact 1 The skill premium has started to decline (at least over the last two decades, 2.45 $\rightarrow$ 2.3).

Fact 2 While the average hourly wage in the manufacturing sector has been increasing over time, the non-manufacturing wage has been declining since the mid-1990s. As a result, the manufacturing to non-manufacturing wage ratio has increased quite sharply.

Fact 3 While the importance of part-time workers in the manufacturing industry has held steady, the percentage of total hours worked by part-time workers in the non-manufacturing industry has increased since the mid-1990s.

One important characteristic of the labor market is the distinction between skilled and unskilled workers. Let us now look at how the ratio of the skilled wage to the unskilled wage — the so-called "skill premium"— has evolved over time. Figure 1 shows the skill premiums for the manufacturing and non-manufacturing industries. Unlike in other economies, the skill premium has declined rather than rising over the past couple of decades. From 1993 to 2012, the manufacturing and non-manufacturing skill premiums declined by 6.6% and 7.4%, respectively. Alternatively, we can look at an education-based measure. Parro (2013) uses the college/high-school graduates wage ratio and finds that the skill premium in Japan declined by 3.4% from 1990 to 2005. This downward trend once again contrasts with other countries.

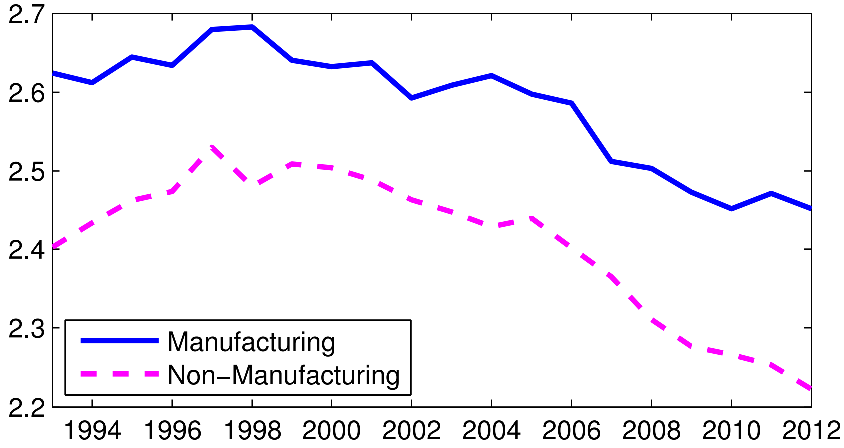


Figure 1: Skill Premium

Note: The skill premium is defined as the ratio of the nominal hourly wage paid to full-time workers to that of part-time workers. We take our data from the Monthly Labour Survey of the Ministry of Health, Labour, and Welfare, focusing on the figures for establishments with five or more employees. Non-manufacturing excludes agriculture, forestry, fishery, and public administration sectors.

For example, the skill premium in Germany increased by 14.4% over the same period. In the US, Parro (2013) finds that the skill premium as measured by the production/non-production workers wage ratio rose by 3.1% from 1990 to 2007. Moreover, he found that the skill premium declined in just eight of the 28 countries analyzed. It is typically argued that demand for skilled workers should increase in advanced economies as a consequence of trade with emerging economies and/or industrial off-shoring.[4] As such, it would be natural to expect the skill premium to rise over time. Since the literature has focused mostly on how to explain this upward trend, it is important to investigate why the skill premium has in fact declined (or at best held steady) in Japan and a number of other economies.

In this paper, we view full-time workers as skilled labor, and we use part-time workers, whose scheduled work hours are shorter than for full-time workers at the same business establishment, as a proxy for unskilled labor. Part-time workers are suitable for the notion of unskilled workers, because tasks performed by part-time workers are typically limited to less skill-intensive ones. This classification is also advantageous in our estimation, because we can have longer monthly data series for part-time workers. An alternative measure of the skill premium is the college/high-school wage ratio, which is sometimes called the college premium. However, we cannot obtain any sufficiently long time-series data with quarterly or higher frequency for the skill premium based on educational attainment. The college premium gives us qualitatively the same result as our measure based on full-time/part-time

[4]Since our model is a closed-economy model, we exclude a possible channel through international trade. The prediction from the Stolper-Samuelson theorem is a decline in the skill premium in countries where unskilled labor is abundant. It is difficult to say that Japan is a unskilled-labor-abundant country, relative to other countries. Thus, there is no harm in excluding the international trade channel.

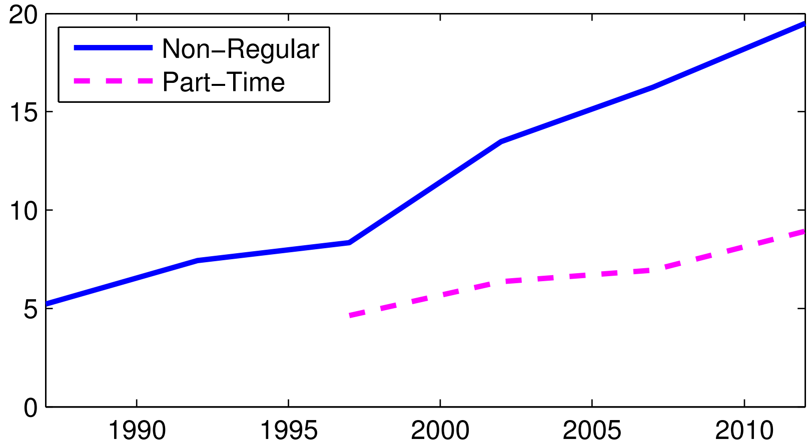


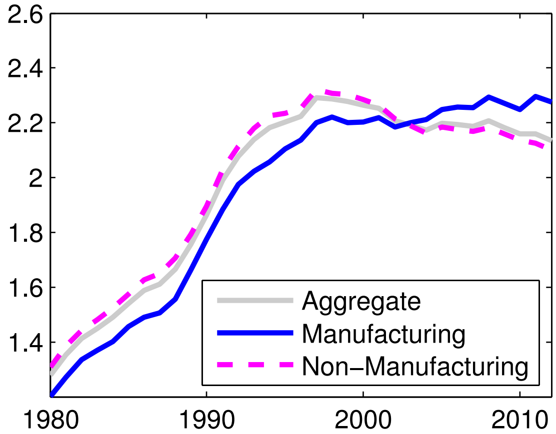
Figure 2: Fraction of Non-Regular/Part-Time Jobs in College-Graduate Employments (%)
Note: Data are taken from the Employment Status Survey conducted by the Statistics Bureau of Japan in 1987, 1992, 1997, 2002, 2007, and 2012. We calculate the fraction of non-regular workers among college-graduate employees (excluding executives) and that of part-time workers (including temporary workers). For 1987 and 1992, we do not know the number of executives, but based on the average fraction for other years we assume that 10% of total college-graduate employees are executives.

workers.

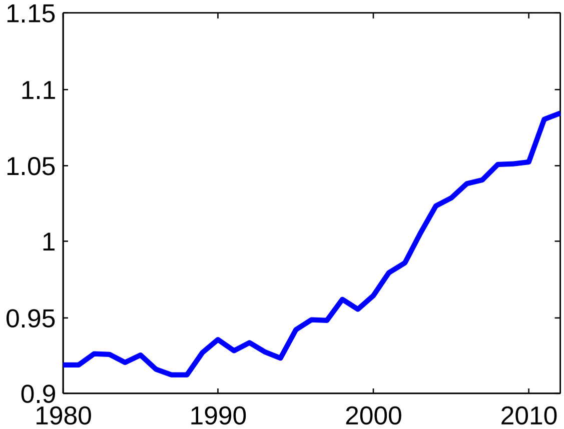
Figure 2 provides some justification for not using college/high-school graduates to classify skilled and unskilled workers. It shows the fraction of college-graduate workers who are classified as non-regular workers (solid line) or part-time (including temporary) workers (dashed line). It is clear that there is an increasing tendency for college graduates to work in less skill-intensive jobs. These non-regular or part-time jobs usually involve routine tasks and do not pay well. If we use college/high-school graduates as proxies for skilled/unskilled workers, we may overestimate the size of the skill premium. We acknowledge that regular workers include those who may not be skilled. However, we believe that treating part-time workers as a proxy for unskilled workers is more suitable in our context, particularly once data availability is taken into account.

Figure 3a shows the nominal hourly wage at the aggregate level together with the sectoral data.[5] Wages increased for both the manufacturing and the non-manufacturing sectors until the mid-1990s. More recently, however, while the manufacturing wage has kept rising (albeit at a somewhat slower pace), the non-manufacturing wage has started to decline. Since the non-manufacturing sector accounts for about 75% of all workers, this decline in the non-manufacturing wage has dragged down the aggregate hourly wage. This phenomenon is typically referred to as "wage deflation".

[5]See the note to Figure 3 for a description of the data and the definitions of the manufacturing and non-manufacturing industries.



(a) Nominal Wage (1,000 Yen)



(b) Manufacturing to Non-Manufacturing Wage Ratio

Figure 3: Nominal Wage Data

Note: We calculate the nominal hourly wage by dividing the total monthly wage bill (including overtime and bonuses) by the total hours worked in the month (including overtime hours). Where available, we use the data on establishments with five or more employees. Prior to 1989, however, we extrapolate from the data on establishments with 30 or more employees. Non-manufacturing does not include agriculture, forestry, fishing, and public administration. The data are obtained from the Monthly Labor Survey of the Ministry of Health, Labour and Welfare.

Figure 3b shows the ratio of the manufacturing wage to the non-manufacturing wage. It can be seen that this ratio was stable until the mid-1990s, but then started to rise sharply. If this wage deflation were accompanied by deflation of general prices, we would not observe the aforementioned divergence of sectoral wages. As such, it is very important to look at the sectoral data to understand the nature of aggregate wage deflation. The gap has in fact widened by about 15 percentage points over the past couple of decades or so.

Figure 4 shows the unskilled labor shares for the manufacturing and non-manufacturing sectors. Again, we use hours worked by part-time workers as a proxy for unskilled labor. While the share of unskilled workers has held relatively steady in the manufacturing sector, it has been increasing over time for non-manufacturers. Krusell et al. (2000) report that the labor input ratio of skilled to unskilled has been increasing in the US data since the 1960s. Meanwhile, the skill premium has increased drastically, especially from the 1980s to the 1990s. These two findings are the opposite of what we see in the Japanese economy.

In the next section, we will present a model that can explain these three stylized facts in the context of the Japanese economy.

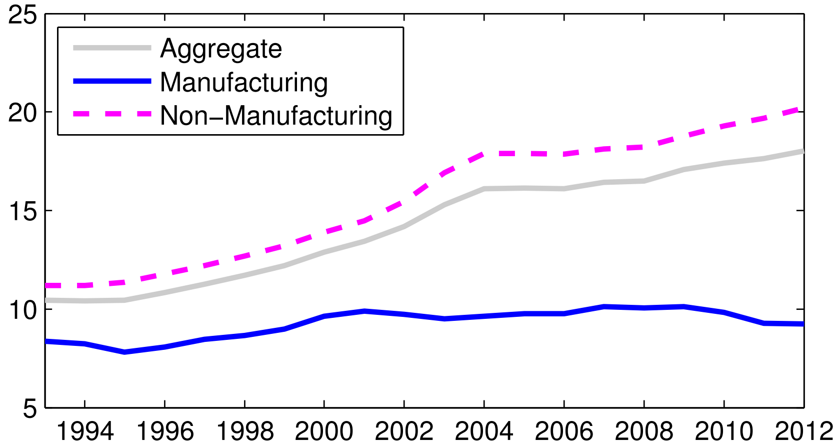


Figure 4: Fraction of Total Hours Worked by Part-time Workers (%)

Note: The data are taken from the Monthly Labour Survey of the Ministry of Health, Labour, and Welfare. We use the figures for establishments with five or more employees. Non-manufacturing excludes agriculture, forestry, fishing, and public administration. We divide the total hours worked by part-time workers by those worked by all (full-time and part-time) workers.

3 The Model

The economy consists of a infinitely-lived representative household and two sectors, manufacturing (sector m) and non-manufacturing (or services, sector n). There are two types of labor that the household supplies, skilled and unskilled labor. Output from the manufacturing sector will be consumed and invested. Capital stock is sector-specific and immobile between the two sectors.

3.1 Household

The representative household chooses consumption of goods ($C_{m,t}$) and services ($C_{n,t}$), labor supply of skilled (S_t) and unskilled (U_t), and investment in two sectors ($I_{m,t}$ and $I_{n,t}$) to maximize the discounted expected lifetime utility

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_t, H_t), \tag{1}$$

subject to the budget constraint and the law of motion for capital stock in each sector. Here β denotes the subjective discount factor. The budget constraint in real terms is given by

$$C_{m,t} + p_t C_{n,t} + I_{m,t} + I_{n,t} \leq r_{m,t} K_{m,t} + r_{n,t} K_{n,t} + w_{s,t} S_t + w_{u,t} U_t, \tag{2}$$

where $p_t \equiv P_{n,t}/P_{m,t}$, $r_{m,t} \equiv R_{m,t}/P_{m,t}$, $r_{n,t} \equiv R_{n,t}/P_{m,t}$, $w_{s,t} \equiv W_{s,t}/P_{m,t}$, $w_{u,t} \equiv W_{u,t}/P_{m,t}$. $P_{m,t}$ represents the manufacturing goods price and $P_{n,t}$ is the price for non-manufacturing goods.

$R_{m,t}$ and $R_{n,t}$ are the rental rates for capital stock. $W_{s,t}$ and $W_{u,t}$ denote nominal wages for skilled and unskilled labor, respectively. The law of motion for capital stock in each sector $j = m, n$ is subject to investment adjustment costs $\Phi(\cdot)$ and given by

$$K_{j,t+1} = I_{j,t}\left\{1 - \Phi\left(\frac{I_{j,t}}{I_{j,t-1}}\right)\right\} + (1-\delta)K_{j,t}. \tag{3}$$

Following Horvath (2000), we assume that the aggregate labor index takes the following form:

$$H_t = \left[(S_t)^{\frac{\theta+1}{\theta}} + (U_t)^{\frac{\theta+1}{\theta}}\right]^{\frac{\theta}{\theta+1}}, \tag{4}$$

where S_t and U_t represent skilled and unskilled labor, respectively. θ controls the elasticity of substitution between skilled and unskilled jobs. As $\theta \to \infty$, skilled and unskilled jobs become perfect substitutes. Thus, if the skilled job pays a higher wage, the household allocates all of its labor supply to that job. On the other hand, when $\theta \to 0$, there is no way to change the composition of the two types of jobs, so that skilled and unskilled jobs become perfect complements. In the somewhat more realistic case where $0 < \theta < \infty$, the household prefers to have diversity of labor. It is therefore possible for the household to supply both types of labor even when the nominal wages offered for skilled and unskilled labor are different. We believe that this assumption is reasonable. This is the most parsimonious way to introduce skilled and unskilled labor into the representative agent framework.[6] For example, Kondo and Naganuma (2014) find that skill difference is an important factor affecting inter-industry labor flows in Japan. This specification may be viewed as a parsimonious way of describing job polarization.

The composite consumption good C_t, which aggregates manufacturing goods and services, is defined similarly as

$$C_t = \left[\gamma\left(C_{m,t}\right)^{\frac{\kappa-1}{\kappa}} + (1-\gamma)\left(C_{n,t}\right)^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}, \tag{5}$$

where $\gamma \in [0, 1]$ is the share of the manufacturing good and κ is the elasticity of substitution between manufacturing goods and services. As $\kappa \to 1$, $C_t = C_{m,t}^{\gamma}C_{n,t}^{1-\gamma}$. As $\kappa \to \infty$, $C_t = \gamma C_{m,t} + (1-\gamma)C_{n,t}$.

For simplicity, we assume separability between aggregate consumption and labor. A parametric form of the household preferences is given by

$$u(C_t, H_t) = \log(C_t) - \varphi\frac{\eta}{1+\eta}H_t^{\frac{\eta+1}{\eta}}, \tag{6}$$

[6]Alternatively, we could introduce sector-specific skills, such as skilled and unskilled workers in manufacturing and those in non-manufacturing, and corresponding sector-specific skill-biased technology shocks. However, the ratio of skilled wages paid in manufacturing and non-manufacturing has been stable. The same applies to the unskilled wages. Thus, we believe that there is no harm in assuming that the labor market is not segmented across sectors.

where η is the Frisch elasticity of aggregate labor supply.

3.2 Firms

There are two types of firms in the economy, manufacturing (sector m) and non-manufacturing (sector n). A representative firm in each sector takes factor prices as given and maximizes its profits period by period.

We assume that production technology exhibits capital-skill complementarity as in Krusell et al. (2000). For each sector $j = m, n$, sectoral output $Y_{j,t}$ is produced from the following technology

$$Y_{j,t} = A_{j,t}\left[\mu_j(\psi_{u,t}U_{j,t})^{\sigma_j} + (1-\mu_j)\left\{\lambda_j(K_{j,t})^{\rho_j} + (1-\lambda_j)(\psi_{s,t}S_{j,t})^{\rho_j}\right\}^{\sigma_j/\rho_j}\right]^{1/\sigma_j}, \tag{7}$$

where $A_{j,t}$ represents sectoral productivity, and $\psi_{s,t}$ and $\psi_{u,t}$ measure quality of skilled and unskilled labor, respectively. μ_j and λ_j control the factor shares of unskilled labor and capital, respectively.

We assume exogenous processes that drive sectoral productivity, and skilled and unskilled labor efficiency as follows:

$$\log(A_{j,t}) = (1-\rho_{A_j})\log(A_j) + \rho_{A_j}\log(A_{j,t-1}) + \varepsilon_{j,t}, \tag{8}$$

$$\log(\psi_{l,t}) = (1-\rho_{\psi_l})\log(\psi_l) + \rho_{\psi_l}\log(\psi_{l,t-1}) + \eta_{l,t}, \tag{9}$$

where $\varepsilon_{j,t} \sim N(0, \sigma^2_{A_j})$ and $\eta_{l,t} \sim N(0, \sigma^2_{\psi_l})$ for $j = m, n$ and for $l = s, u$. Sectoral productivity and labor efficiency are assumed to be stationary with $|\rho_{A_j}| < 1$ for $j = m, n$ and $|\rho_{\psi_l}| < 1$ for $l = s, u$. This assumption rules out the possibility of differences in productivity growth rate driving sectoral shifts.

The elasticity of substitution between capital and unskilled labor, which measures how changes in the relative price affect relative input, is given by $\frac{1}{1-\sigma_j}$. Similarly, the elasticity of substitution between capital and skilled labor is $\frac{1}{1-\rho_j}$. As shown in Krusell et al. (2000), when $\sigma_j > \rho_j$, there is capital-skill complementarity, meaning that capital is more substitutable with unskilled labor than with skilled labor. We define $\alpha_j \equiv \sigma_j - \rho_j$, which can be used to measure the degree of capital-skill complementarity in sector j. When $\sigma_j \to 0$ and $\rho_j \to 0$, the typical Cobb-Douglas production function emerges as a special case:

$$Y_{j,t} = A_{j,t}(K_{j,t})^{(1-\mu_j)\lambda_j}(\psi_{s,t}S_{j,t})^{(1-\mu_j)(1-\lambda_j)}(\psi_{u,t}U_{j,t})^{\mu_j}. \tag{10}$$

3.3 The Rest of the Model

To clear labor markets for skilled and unskilled workers, the goods market, and the services market, we have the following market clearing conditions.

$$S_t = S_{m,t} + S_{n,t} \tag{11}$$

$$U_t = U_{m,t} + U_{n,t} \tag{12}$$

$$Y_{m,t} = C_{m,t} + I_{m,t} + I_{n,t} \tag{13}$$

$$Y_{n,t} = C_{n,t} \tag{14}$$

We construct the sectoral wage for $j = m, n$ as

$$w_{j,t} = (1 - \tau_{j,t})w_{s,t} + \tau_{j,t}w_{u,t}, \tag{15}$$

where $\tau_{j,t} = \frac{U_{j,t}}{S_{j,t}+U_{j,t}}$.

4 Estimation

We next fit our model to the data to estimate the key parameters that determine the size of capital-skill complementarity (σ's and ρ's), together with other structural parameters. To this end, we estimate the model structurally by using a Bayesian approach. In order to improve empirical fit, we will augment the model presented in Section 3 by introducing sector-specific investment-specific technology shocks and skill-specific wage markup shocks. All of these shocks are assumed to follow standard AR(1) processes. By fitting our model to the data, we can use the estimated structural parameters to gain insight into the true determinant of the observed changes in the Japanese economy (our three "stylized facts").

4.1 Data

In order to take advantage of our two-sector setup, we will utilize quarterly disaggregated data. We assume that output from the manufacturing sector is used for durable goods purchases, business fixed investment, and residential investment. Similarly, non-manufacturing output is used for non-durable goods and services. It is quite difficult to make a clear distinction between skilled and unskilled labor, especially at the quarterly frequency for sufficiently long time periods. We construct our own measures for hours worked for skilled and unskilled labor (with the latter proxied by part-time workers). Our Appendix explains the data construction process in detail. Our sample starts from 1975:Q1 and ends at 1995:Q4. Our objective is to configure our model parameters to provide a good representation of the Japanese economy before the change we observe in the 1990s. This motivates us to pick 1995:Q4, which roughly corresponds to the timing with which we start to observe the changes in the labor market depicted in Figure 3, as the end of our sample.

We use the following data to estimate our model: the growth rate of manufacturing output ($dy_{m,t}$), the growth rate of non-manufacturing output ($dy_{n,t}$), the growth rate of total hours worked by full-time workers (ds_t), the growth rate of total hours worked by part-time workers (du_t), the growth rate of the manufacturing wage ($dw_{m,t}$), the growth rate of the non-manufacturing wage ($dw_{n,t}$), and the inflation rate of the relative price between manufacturing and non-manufacturing (dp_t). The growth rates of output and hours worked are detrended by the growth rate of the population over 15 years of age.

We solve the log-linearized system of equations presented in Appendix B to get a state-space representation of the solution. It is then used to evaluate the log-likelihood function with the Kalman filter. Model variables that are expressed in terms of deviations from the steady state are linked to the data (all observable variables are demeaned) through the observation equation as follows.

$$dy_{m,t} = \hat{y}_{m,t} - \hat{y}_{m,t-1} \tag{16}$$

$$dy_{n,t} = \hat{y}_{n,t} - \hat{y}_{n,t-1} \tag{17}$$

$$ds_t = \hat{s}_t - \hat{s}_{t-1} \tag{18}$$

$$du_t = \hat{u}_t - \hat{u}_{t-1} \tag{19}$$

$$dw_{m,t} = \hat{w}_{m,t} - \hat{w}_{m,t-1} \tag{20}$$

$$dw_{n,t} = \hat{w}_{n,t} - \hat{w}_{n,t-1} \tag{21}$$

$$dp_t = \hat{p}_t - \hat{p}_{t-1} \tag{22}$$

4.2 Prior Distributions

As summarized in Table 1, we fix some parameter values and impose the steady-state ratios in the estimation in order to maintain consistency with reality. We set the discount factor (β) to be 0.995 and the depreciation rate (δ) to be 0.025. Based on the data, the manufacturing goods expenditure share (ω_m) is set to be 0.25. We assume that the steady-state skill premium $\frac{w_s}{w_u}$ is 2.45, which is consistent with the values seen in the early 1990s. We set the skilled-unskilled ratio in manufacturing ($\frac{S_m}{U_m}$) to be 13.85 and that in non-manufacturing ($\frac{S_n}{U_n}$) to be 7.06. These values are based on the average ratio of part-time workers to full-time workers over 1993–1995.[7] Since the average labor income shares in manufacturing and non-manufacturing from 1980 to 1995 are 54% and 46%, respectively, we set the capital cost share parameters $\alpha_{k_m} = 0.46$ and $\alpha_{k_n} = 0.54$. Finally, we assume the manufacturing share of skilled workers $\frac{S_m}{S_m+S_n}$ to be 0.36. Through the steady-state relationship, we can infer other steady-state ratios

[7] Again, we do not have good data on the ratio of skilled to unskilled workers at the sectoral level for the earlier period.

Table 1: List of Parameter Values Imposed

Discount factor	$\beta = 0.995$
Depreciation rate	$\delta = 0.025$
Goods expenditure share	$\omega_m = 0.25$
Skill premium	$\pi = 2.45$
Skilled-Unskilled ratio in sector m	$\frac{S_m}{U_m} = 13.85$
Skilled-Unskilled ratio in sector n	$\frac{S_n}{U_n} = 7.06$
Capital cost share in sector m	$\alpha_{k_m} = 1 - 0.54$
Capital cost share in sector n	$\alpha_{k_n} = 1 - 0.46$
Fraction of skilled in sector m	$f_s = \frac{S_m}{S_m+S_n} = 0.36$
Fraction of unskilled in sector m	$f_u = f_s \left(\frac{w_s}{w_u}\right)^{\theta} \left(\frac{S_m}{U_m}\right)^{-1}$
Share of skilled workers	$\omega_s = \frac{\pi^{\theta+1}}{\pi^{\theta+1}+1}$
Share of unskilled in sector m	$\omega_{u_m} = (1-\alpha_{k_m})\left(\frac{w_s}{w_u}\frac{S_m}{U_m}+1\right)^{-1}$
Share of unskilled in sector n	$\omega_{u_n} = (1-\alpha_{k_n})\left(\frac{w_s}{w_u}\frac{S_n}{U_n}+1\right)^{-1}$
Share of capital in sector m	$\omega_{k_m} = \frac{\alpha_{k_m}}{(1-\omega_{u_m})}$
Share of capital in sector n	$\omega_{k_n} = \frac{\alpha_{k_n}}{(1-\omega_{u_n})}$
Consumption share of goods	$\omega_c = (1-\omega_{i_m})\left(1+\frac{\delta\alpha_{k_n}}{r_n}\frac{(1-\omega_m)}{\omega_m}\right)^{-1}$
Investment share of goods in sector m	$\omega_{i_m} = \frac{\delta\alpha_{k_m}}{r_m}$

as summarized in Table 1.

Table 2 summarizes the model parameters to be estimated, together with the associated prior distributions. There are a couple of things we need to discuss. We use a Gamma distribution with mean 1.143 and standard deviation of 0.4 as the prior distribution for κ. This will give us its mode located at 1, which corresponds to Cobb-Douglas preferences over C_m and C_n. Prior probability of $\kappa < 1$ is 40%. We consider this to be a much more agnostic prior than that used in Iacoviello et al. (2011), for example. Whether the value of κ is greater or less than unity is crucial for whether or not the data support the story of Ngai and Pissarides (2007).

We assume that σ_j for $j = m, n$ is from a Beta distribution with mean and standard deviation of 0.2. Our underlying assumption is that the elasticity of substitution between capital and unskilled labor is greater than or equal to unity. We define $\alpha_j \equiv \sigma_j - \rho_j$, which controls the degree of capital-skill complementarity. We use a Gamma distribution with mean 0.5 and standard deviation 0.5 as the prior distribution for α_j. This reflects our prior belief that there exists capital-skill complementarity. We also allow for the possibility of no capital-skill complementarity since the support of α_j includes zero.

The remaining prior distributions are standard. The prior for the inverse Frisch labor supply elasticity is the same as in Sugo and Ueda (2008). It is Normally distributed and centered at 2 with standard deviation of 0.75. The prior for the investment cost parameter φ is a Gamma distribution with mean 4 and standard deviation of 1. This is a widely

Table 2: Prior Distributions

Parameter		Dist.	Prior Mean	Std Dev
κ	Elasticity of substitution between goods and services	G	1.143	0.4
$\frac{1}{\eta}$	Inverse Frisch labor supply elasticity	N	2	0.75
σ_m	Controlling the elasticity of substitution between K_m and U_m	B	0.2	0.2
σ_n	Controlling the elasticity of substitution between K_n and U_n	B	0.2	0.2
α_m	Controlling capital-skill complementarity in sector m	G	0.5	0.5
α_n	Controlling capital-skill complementarity in sector n	G	0.5	0.5
φ	Investment adjustment cost parameter	G	4	1
ρ_{a_m}	Persistence of TFP in sector m	B	0.75	0.1
ρ_{a_n}	Persistence of TFP in sector n	B	0.75	0.1
ρ_{ψ_s}	Persistence of skilled-specific shock	B	0.75	0.1
ρ_{ψ_u}	Persistence of unskilled-specific shock	B	0.75	0.1
ρ_{ξ_m}	Persistence of investment-specific shock in sector m	B	0.75	0.1
ρ_{ξ_n}	Persistence of investment-specific shock in sector n	B	0.75	0.1
ρ_{μ_s}	Persistence of wage markup shock for skilled	B	0.75	0.1
ρ_{μ_u}	Persistence of wage markup shock for unskilled	B	0.75	0.1
σ_{a_m}	Std Dev of TFP shock in sector m	IG	0.025	∞
σ_{a_n}	Std Dev of TFP shock in sector n	IG	0.025	∞
σ_{ψ_s}	Std Dev of skilled-specific shock	IG	0.025	∞
σ_{ψ_u}	Std Dev of unskilled-specific shock	IG	0.025	∞
σ_{ξ_m}	Std Dev of investment-specific shock in sector m	IG	0.025	∞
σ_{ξ_n}	Std Dev of investment-specific shock in sector n	IG	0.025	∞
σ_{μ_s}	Std Dev of wage markup shock for skilled	IG	0.025	∞
σ_{μ_u}	Std Dev of wage markup shock for unskilled	IG	0.025	∞

Note: N, B, G, IG, and U stand for Normal, Beta, Gamma, Inverse Gamma, and Uniform distributions, respectively.

used prior for the investment adjustment cost parameter. The prior distributions for the persistence parameters are all Beta distributions with mean 0.75 and standard deviation of 0.1. We assume that the priors for the standard deviations of the structural shocks are all Inverse Gamma distributions with mean 0.025. These choices are based on Iacoviello et al. (2011).

4.3 Results

Table 3 summarizes the posterior distributions of parameters estimated, which are generated from 300,000 Metropolis-Hastings draws (the first 30,000 draws are discarded as burn-in). We set the scaling parameter in the Metropolis-Hastings algorithm so that the average acceptance rate becomes about 30%. It is worth emphasizing a few things about our estimation results.

First, the elasticity of substitution between capital and unskilled labor differs substantially between manufacturing and non-manufacturing. The posterior mean of σ_m is significantly greater than zero and equal to 0.6254. The implied elasticity of substitution between capital

Table 3: Posterior Distributions

Parameter		Posterior Distribution Mean	90% Interval	
κ	Elasticity of substitution between goods and services	4.5705	3.7134	5.4186
$\frac{1}{\eta}$	Inverse Frisch labor supply elasticity	1.6710	1.1827	2.1474
σ_m	Controlling the elasticity of substitution between K_m and U_m	0.6254	0.5469	0.7011
σ_n	Controlling the elasticity of substitution between K_n and U_n	0.0025	0.0000	0.0065
α_m	Controlling capital-skill complementarity in sector m	4.5644	3.1990	5.8114
α_n	Controlling capital-skill complementarity in sector n	0.4034	0.2879	0.5127
φ	Investment adjustment cost parameter	1.7129	0.7033	2.7524
ρ_{a_m}	Persistence of TFP in sector m	0.6618	0.5192	0.8116
ρ_{a_n}	Persistence of TFP in sector n	0.9490	0.9203	0.9803
ρ_{ψ_s}	Persistence of skilled-specific shock	0.6645	0.5373	0.7920
ρ_{ψ_u}	Persistence of unskilled-specific shock	0.7717	0.6699	0.8778
ρ_{ξ_m}	Persistence of investment-specific shock in sector m	0.7558	0.5931	0.9222
ρ_{ξ_n}	Persistence of investment-specific shock in sector n	0.9226	0.8746	0.9756
ρ_{μ_s}	Persistence of wage markup shock for skilled	0.9444	0.9127	0.9785
ρ_{μ_u}	Persistence of wage markup shock for unskilled	0.8059	0.7191	0.8928
σ_{a_m}	Std Dev of TFP shock in sector m	4.5705	3.7134	5.4186
σ_{a_n}	Std Dev of TFP shock in sector n	1.6710	1.1827	2.1474
σ_{ψ_s}	Std Dev of skilled-specific shock	0.6254	0.5469	0.7011
σ_{ψ_u}	Std Dev of unskilled-specific shock	0.0025	0.0000	0.0065
σ_{ξ_m}	Std Dev of investment-specific shock in sector m	4.5644	3.1990	5.8114
σ_{ξ_n}	Std Dev of investment-specific shock in sector n	0.4034	0.2879	0.5127
σ_{μ_s}	Std Dev of wage markup shock for skilled	1.7129	0.7033	2.7524
σ_{μ_u}	Std Dev of wage markup shock for unskilled	0.6618	0.5192	0.8116
	Log Marginal Density	1548.90		

Note: Posterior distributions are generated from 300,000 Metropolis-Hastings draws. We discard the first 10% of draws as a burn-in period. We use the modified Harmonic mean estimator of Geweke (1999) to obtain the log marginal density.

and unskilled labor in manufacturing is 2.6696. This is much higher than the estimate in Krusell et al. (2000), which is obtained from the US aggregate data (1.67). On the other hand, the posterior mean of σ_n is quite small at just 0.0025. Moreover, the 90 percent probability interval contains zero. The implied elasticity of substitution is very close to unity (1.0025).

Second, the degree of capital-skill complementarity is quite different between manufacturing and non-manufacturing. The posterior mean of α_m is 4.5644, suggesting that there exists capital-skill complementarity in manufacturing. This implies that the estimated value of ρ_m is -3.9390. The implied elasticity of substitution between capital and skilled labor in manufacturing is 0.2025, which is much smaller than the estimate in Krusell et al. (2000) of 0.67. The posterior mean of α_n is 0.4034, which is much smaller than that in manufacturing, suggesting that $\rho_n = -0.4009$. The implied elasticity of substitution between capital and skilled labor in non-manufacturing is 0.7138, which is higher than in manufacturing, and still lower than in the Cobb-Douglas case.

Third, the posterior mean of κ is 4.5705, which is significantly greater than unity. This implies that goods and services are not complements, suggesting that the data do not support the story of Ngai and Pissarides (2007).

The TFP shock in manufacturing is less persistent (0.6618) than that in non-manufacturing (0.9490). The same pattern applies to the persistence of investment specific shocks (0.7558 in manufacturing and 0.9226 in non-manufacturing). The skilled-specific shock is less persistent than the unskilled-specific technology shock (0.6645 versus 0.7717). The opposite is true for wage markup shocks. While the persistence of the wage markup shock for skilled is estimated to be 0.9444, that for unskilled is smaller at 0.8059.

5 Inspecting the Steady-State Skill Premium and Sectoral Wages

5.1 Steady-state Values and Comparative Statics

Based on the parameter estimates in Section 4, we perform comparative statics exercises in order to understand factors behind the observed changes in the Japanese labor market. Alternatively, we could estimate our model with data for 1996 onwards to see what changes in the model parameters can account for the stylized facts. However, we think that might not be an ideal way to explain changes in the labor market. First, it is possible that the Japanese labor market is still in transition to a new steady state, in which case using the transition period may give us somewhat misleading results. Second, it may be difficult to disentangle and identify the exact factor(s) accounting for the observed changes in the Japanese labor market because it is highly likely that the data contain many structural factors affecting the Japanese economy during this time period. For these reasons, we believe that it is better to take a comparative statics approach.

We want the model to capture the key observed features of the Japanese economy prior to the mid-1990s. We consider the size of the skill premium to be particularly important given that it characterizes the two different types of workers. Thus, we assume the steady-state skill premium (w_s/w_u) to be 2.45, which roughly corresponds to the average skill premium in the early 1990s. Together with the steady-state values of $\frac{U_m}{S_m}$, $\frac{U_n}{S_n}$, and $\frac{S_n}{S_m}$, the steady-state skill premium satisfies

$$\left(\frac{w_s}{w_u}\right)^{\theta} = \frac{S_m}{U_m} \frac{\left(1 + \frac{S_n}{S_m}\right)}{\left(1 + \frac{U_n/S_n}{U_m/S_m} \frac{S_n}{S_m}\right)}. \tag{23}$$

We will choose the value of θ, such that we can hit the target $w_s/w_u = 2.45$. Since we have imposed $\frac{U_m}{S_m}$, $\frac{U_n}{S_n}$, and $\frac{S_n}{S_m}$ in the estimation in the previous section, we can pin down the value of θ. The skill-premium-consistent value of θ is 2.3978. Using the posterior means, we can obtain the share parameters μ_m and μ_n, γ, and the productivity level of unskilled relative to skilled $b \equiv \frac{\psi_u}{\psi_s}$. To do this, we assume that the relative productivity level in non-manufacturing $\frac{A_n}{A_m}$ is unity, and we set $\lambda_m = \lambda_n = 0.4$.

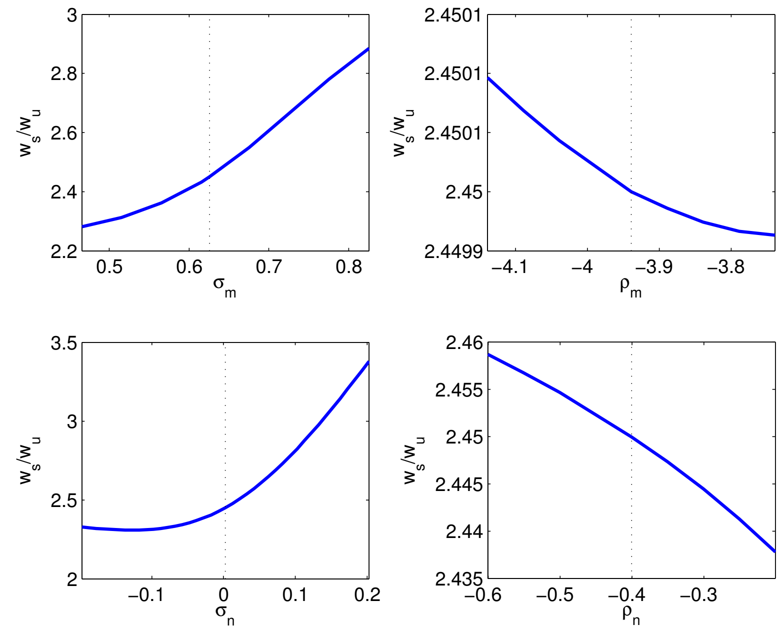


Figure 5: Changes in the Skill Premium

Note: The left panels depict changes in the skill premium (vertical axis) as σ_m and σ_n move. The right panels illustrate changes in the skill premium as we vary ρ_m and ρ_n. The dashed vertical line denotes the posterior mean of the corresponding parameter.

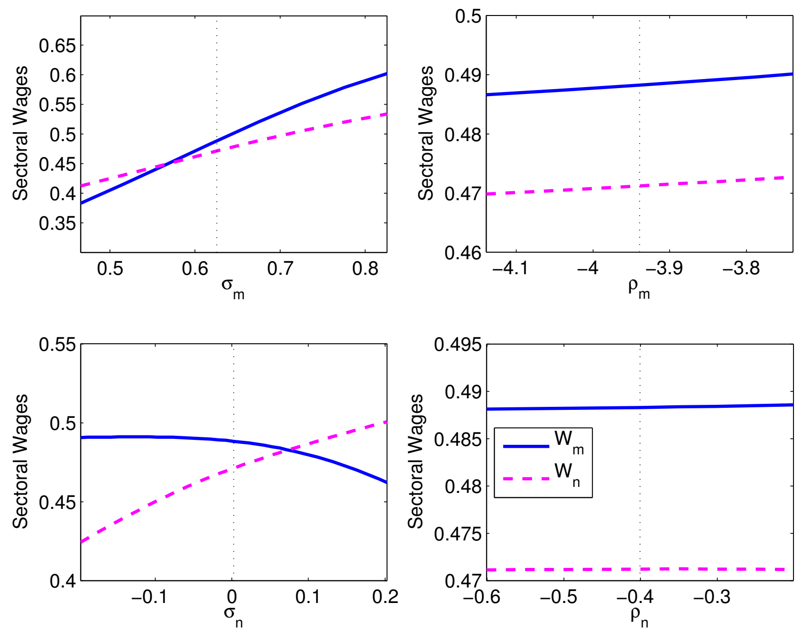


Figure 6: Changes in Sectoral Wages

Note: The left panels depict changes in sectoral wages (vertical axis) as σ_m and σ_n move. The right panels illustrate changes in sectoral wages as we vary ρ_m and ρ_n. The dashed vertical line denotes the posterior mean of the corresponding parameter.

Below we look at how the steady-state values change as we alter the values of σ_m, σ_n, ρ_m, and ρ_n, which are all relevant to the degree of capital-skill complementarity. An increase in σ means that the elasticity of substitution between capital and unskilled labor increases. Similarly, a rise in ρ translates into higher substitutability between capital and skilled labor.

Figure 5 depicts changes in the skill premium as we vary σ's and ρ's. The top left panel shows changes in the skill premium as σ_m moves and the bottom left figure corresponds to changing σ_n. The top right plot illustrates changes in the skill premium with different values of ρ_m and the bottom right figure depicts how the skill premium varies as ρ_n changes. The vertical dashed lines show the posterior mean of the corresponding parameter.

The skill premium becomes smaller as σ (σ_m or σ_n) decreases and/or as ρ (ρ_m or ρ_n) increases. In other words, reductions in the degree of capital-skill complementarity, $\sigma-\rho$, will dampen the skill premium. Why is this? With a lower degree of capital-skill complementarity, capital becomes more (less) substitutable with skilled (unskilled) labor than before. This means that firms require a smaller amount of skilled labor to utilize their capital. If the skill premium is unchanged, there is an excess supply of skilled labor. Accordingly, the skill premium decreases towards the level where there is no excess supply of skilled labor. Thus, any reduction in capital-skill complementarity (through one or any of σ_m, σ_n, ρ_m, and ρ_n) can lower the skill premium and is a candidate to explain the stylized facts mentioned in Section 2.[8]

Although changes in these parameters can explain the decline in the skill premium, inspecting Figure 6 reveals that changes in σ_m, ρ_m, and ρ_n cannot explain both changes in the skill premium and the sectoral wages presented in Section 2. Figure 6 illustrates changes in sectoral wages as we move σ's and ρ's. As σ_m decreases, or as ρ_m and ρ_n increase, both manufacturing and non-manufacturing wages move in the same direction. This is not consistent with the pattern observed in the data. Higher ρ's induce sectoral wages to increase. Reductions in σ_m would lower both manufacturing and services wages. Since the speed of reduction is slightly slower for the non-manufacturing wage, it could become higher than the manufacturing wage when the drop in σ_m is sufficiently large.

It is a decrease in σ_n that explains both the lower skill premium and the lower non-manufacturing wage. As σ_n decreases from the posterior mean, which is denoted by the vertical line in the figure, we can see that while the manufacturing wage increases slightly, the non-manufacturing wage declines considerably. This is consistent with what we have observed in the Japanese labor market since the mid-1990s.

Figure 7 compares changes in skilled and unskilled wages as we alter σ's and ρ's. These pictures indicate that skilled and unskilled wages move in the same direction as capital-skill complementarity in the manufacturing sector declines. On the other hand, the skilled wage drops and the unskilled wage rises as capital-skill complementarity in non-manufacturing

[8]In our model, lower capital-skill complementarity might increase the skill premium if unskilled labor accounts for a majority of the labor market. However, this may not be the case for Japan.

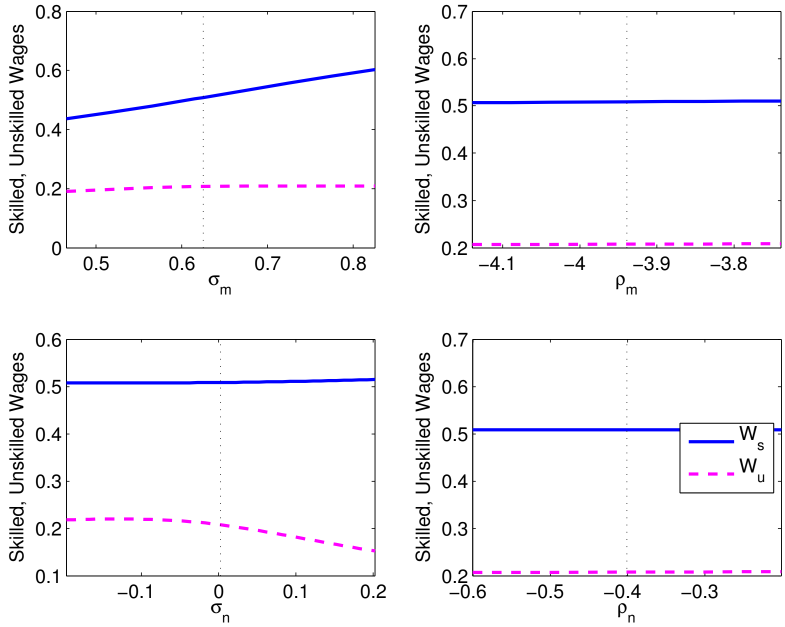


Figure 7: Changes in Skilled and Unskilled Wages

Note: The left panels depict changes in skilled and unskilled wages (vertical axis) as σ_m and σ_n move. The right panels illustrate changes in skilled and unskilled wages as we vary ρ_m and ρ_n. The dashed vertical line denotes the posterior mean of the corresponding parameter.

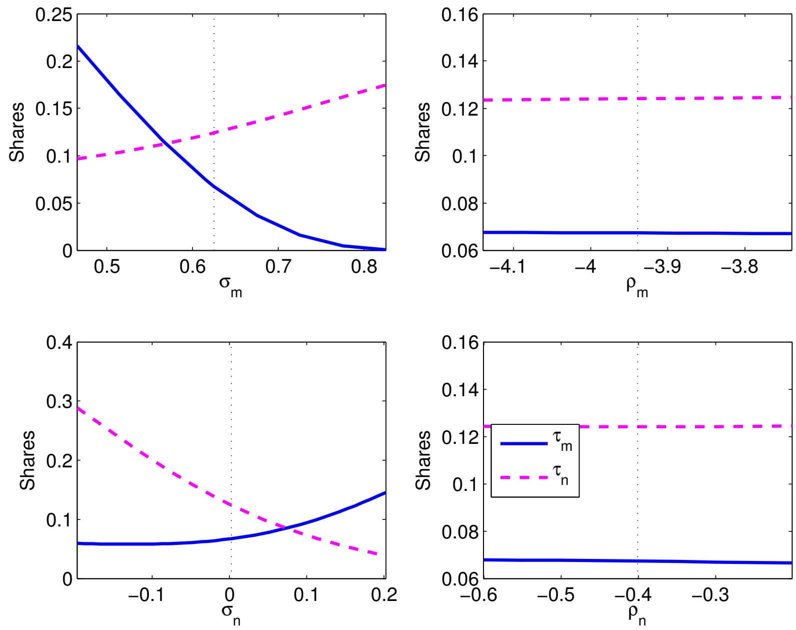


Figure 8: Changes in Unskilled Shares

Note: The left panels depict changes in the unskilled share (vertical axis) as we vary σ_m and σ_n. The right panels illustrate changes in the unskilled share as ρ_m and ρ_n move. The dashed vertical line denotes the posterior mean of the corresponding parameter.

decreases.

Figure 8 reveals why a reduction in σ_n leads to a decline in the non-manufacturing wage, while manufacturing wage slightly increases. The reduction of capital-skill complementarity through σ_n is associated with a large increase in the share of unskilled labor in the non-manufacturing sector. To elaborate on the importance of this factor, let us express changes in the sectoral wage (15) as

$$\begin{aligned} dw_j &= (1-\tau_j)dw_s + \tau_j dw_u + (w_u - w_s)d\tau_j \\ &= dw_s - \tau_j(dw_s - dw_u) + (w_u - w_s)d\tau_j \end{aligned} \tag{24}$$

for $j = m, n$. The second term in (24) represents changes in the skill premium, which are negative in the data. Thus, the contribution of changes in the skill premium becomes positive. Given the positive skill premium, the last term (changes in the unskilled labor share, $d\tau_j$) has a negative impact on sectoral wages. While the reduced capital-skill complementarity in non-manufacturing barely changes the unskilled share in manufacturing, it sharply increases the unskilled share in non-manufacturing. The contribution of the increased unskilled share in non-manufacturing dominates the positive effect that stems from the lower skill premium. As a result, the non-manufacturing wage declines. In contrast, the manufacturing wage does not change much due to the very small share of unskilled labor in manufacturing.

In terms of unskilled share, the opposite happens when σ_m decreases. The unskilled share in manufacturing rises and that in non-manufacturing declines slightly. The rise in the unskilled share and the reduction in the skilled wage together dampen the manufacturing wage. The drop in the skilled wage dominates other factors in non-manufacturing. As a result, declines in the non-manufacturing wage are slower than those in the manufacturing wage. Increases in ρ's barely affect the unskilled share in either manufacturing or non-manufacturing. Given the relatively small reduction in the skilled wage, the positive effect from changes in the skill premium dictates sectoral wages. As a result, we see both sectoral wages rise as ρ increases.

Among other parameter values, changes in the relative productivity of unskilled labor (b) are of particular interest. As shown in Figure 2, an increasing number of college graduates are now taking part-time jobs, which may mean more productive and capable unskilled workers are now available in the labor market. Figure 9 shows changes in the skill premium, skilled and unskilled wages, unskilled shares, and sectoral wages (from the top-left, clockwise) as we increase the relative productivity of unskilled (b). Although an increase in the productivity of unskilled labor relative to skilled can lower the skill premium, this induces a reduction in the manufacturing wage and a rise in the non-manufacturing wage, opposite to what we have seen in the data. This is because changes in the unskilled shares are moving in the opposite direction.

We can also explore other possibilities. However, changes in other parameter values

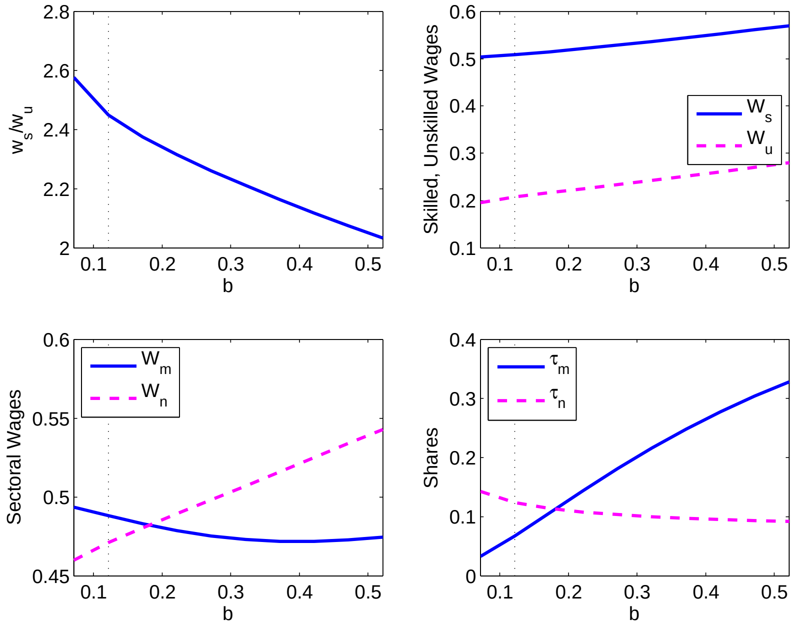


Figure 9: Effects of More Productive Unskilled Labor

Note: The top left plot depicts changes in the skill premium as b changes. The top right panel illustrates changes in the sectoral wages and the bottom left panel shows changes in skilled and unskilled wages as b varies. The bottom right graph shows the share of unskilled labor as a function of b. The dashed vertical line denotes the benchmark case.

do not alter the steady-state values, especially for the skill premium and sectoral wages, in a way that is consistent with the data. Changes in other parameter values can result in a reduction of the skill premium. For example, a drop in the weight for manufacturing goods (γ) lowers the skill premium. Also, an increase in the elasticity of substitution between skilled and unskilled labor supply (θ) reduces the skill premium. However, it turns out that these changes move the sectoral wages in the same direction and thus cannot account for the observed changes in sectoral wages in the data. This is primarily because these parameter changes do not generate meaningful changes in the unskilled shares.

To sum up, a reduction in σ_n (lower capital-skill complementarity in non-manufacturing) is the most likely single parameter change that can consistently explain the stylized facts outlined in Section 2, among the numerous possibilities we have considered. That is, while the manufacturing wage increases slightly, the non-manufacturing wage drops, and the skill premium declines. The value of σ_n that is consistent with the lower skill premium in the recent time periods, 2.3, is $\sigma_n = -0.14$.

5.2 Discussion

It is then natural to ask what specific change(s) in Japanese economy might explain the observed changes illustrated in Section 2. Even though our analysis above suggests that

Table 4: Actual Changes and Simulation Results

	Data	Case 1	Case 2	Case 3	Case 4
Percentage Changes in the Targets					
Skill Premium (W_s/W_u)	−8.61	−7.96	2.33	−11.44	−1.99
Sectoral Wage Gap (W_m/W_n)	14.74	6.03	−2.89	5.90	10.36
Manufacturing Unskilled Share (τ_m)	1.85	1.82	4.30	1.05	−0.33
Non-manufacturing Unskilled Share (τ_n)	9.17	11.53	−0.41	11.15	14.72
Changes in Parameter Values					
σ_n	n.a.	−0.19	0	−0.19	−0.19
θ	n.a.	−0.20	−0.20	0	−0.20
b	n.a.	0.05	0.05	0.05	0

Note: Observed changes in the targets are measured from 1995 to 2013. We evaluate the closeness between the data and the implied steady-state values by the sum of squared distances.

lower capital-skill complementarity in non-manufacturing is the main driving force behind the changes seen since the mid-1990s, it is important to assess the qualitative contributions of other factors. To this end, we will evaluate the impact of two other changes we have observed since the mid-1990s.

One is that working mothers with part-time jobs have increased markedly since the mid-1990s. In the context of our model, this is reflected as a reduction in θ, which means less substitutability between part-time and full-time worker supply. It used to be the case that most female workers in Japan would exit the labor force upon marriage or having children. However, there is now an increasing tendency to remain in the labor force with part-time jobs. Part-time jobs may be preferred to full-time jobs given that they offer a more flexible work schedule. As a result, working mothers would react less to changes in relative wages across the two types of jobs.

Another factor is an increase in the productivity of unskilled workers (i.e., an increase in b). This trend is evident from the fact that there is an increasing number of college graduates working in part-time (or non-regular) jobs as shown in Figure 2.

Table 4 summarizes the observed changes in the data and our simulation results. In particular, we pick parameter values such that percentage changes in the implied steady-state skill premium, sectoral wage gap, and unskilled shares in manufacturing and non-manufacturing become closer to those observed in reality. Case 1 corresponds to our preferred specification. Overall performance is quite good. It seems that there is a tradeoff between hitting the sectoral wage gap and the manufacturing unskilled share. The results reported for Cases 2 to 4, where changes in parameter value are muted one by one, tell us the quantitative importance of each parameter when others are held steady.

As demonstrated in Section 5.1, a reduction in σ_n plays a crucial role in explaining the observed changes in the data. As evident in Case 2, if σ_n is not lowered, the skill premium,

Table 5: Changes in Non-manufacturing Industries (percentage points)

	High Group	Middle Group	Low Group
Changes in Employment Share from 1997 to 2012	6.1	−0.0	−6.1
Changes in Part-time Ratio from 1997 to 2012	5.1	4.0	2.4

Note: We classify non-manufacturing industries into three groups (high, middle, and low) by part-time ratio (ratio of part-time to total workers) in 2012. The high group includes retail trade, accommodations, eating and drinking services, living-related and personal services, and social insurance and social welfare. The low group includes electricity, gas, heat supply and water, information and communications, transport and postal activities, wholesale trade, finance and insurance, and education, learning support. The middle group consists of all other non-manufacturing industries. The employment share for each group is the number of workers in the group divided by total workers. Data in this table are taken from the Statistics Bureau's Employment Status Survey.

sectoral wage gap, and unskilled share in non-manufacturing move in the opposite direction. As equation (24) indicates, rapid growth in part-time non-manufacturing jobs (i.e., an increase in the unskilled share denoted by τ_n) is the key to a consistent interpretation. As noted in Section 2, the skill premium in Japan declined by 8.6 percent from 1995 to 2013 while the sectoral wage gap (W_m/W_n) widened over the same period.

We can see the role of lower θ from Case 3 reported in Table 4. Less substitutability between skilled and unskilled jobs helps to account for the increase in the unskilled share in manufacturing. Similarly, the rise in b (productivity of unskilled relative to skilled) plays a role in increasing the unskilled share in manufacturing. While lower θ increases the skill premium, higher b yields a lower skill premium.

What does the lower σ_n mean in the real world? A closer look at the expansion of Japan's service sector provides a clue as to how one might interpret lower capital-skill complementarity in the non-manufacturing sector. Table 5 compares changes in employment shares and part-time ratios within non-manufacturing industries, indicating that the fastest growing service industries tend to be more dependent on part-time workers. Prime examples include social welfare and nursing, the restaurant business, and retail, all of which are highly labor intensive and relatively low paid jobs. Conversely, full-time-worker dependent service industries tend to grow more slowly, which can result in lower σ_n. Even though it is not easy to identify factors affecting the employment share of each industry within the current framework, we can make a case that employment shares within the non-manufacturing sector have notably changed as a consequence of uneven growth speeds, with the resulting sectoral labor reallocation reflected in the change in the parameter value (σ_n) that characterizes the production technology of the non-manufacturing sector as a whole.

Table 5 also shows a faster increase in the part-time ratio for part-time-worker dependent industries, suggesting that the non-manufacturing sector as a whole turns to be more unskilled-labor-intensive. This may reflect their efforts to minimize labor costs since the mid-1990s. Moreover, these industries might prefer to employ part-time workers because they are more flexible than full-time workers in terms of working hours. For example, in recent years, more restaurants and supermarkets have extended opening hours until midnight by utilizing part-time workers at night. Declines in σ_n might also reflect this change. On the flipside, with less capital-intensive technology, capital-skill complementarity can lose its importance. This interpretation suggests that the entire non-manufacturing sector has, over time, applied a less capital-skill complementary technology on average.

Although the current paper has paid particular attention to the declining skill premium in Japan, one implication from this study is that lower capital-skill complementarity in other countries may be able to explain declines in their skill premiums. There are several possible explanations for the reduction in the skill premium. However, the role played by lower capital-skill complementarity becomes more important and relevant if a global factor, such as the cheaper relative price of capital goods interacting with lower trade costs, is operating and positively affecting the skill premium, as discussed in Parro (2013). However, this hypothesis is left as an important question for future research.

6 Conclusion

While many studies document and offer explanations for rises in the skill premium across economies, less attention has been paid to declines in the skill premium observed in some countries over the past few decades. This paper documents changes in the Japanese labor market at both aggregate and industry levels. We observe a decline in the skill premium, a widening of the sectoral wage gap, and an increase in the unskilled share in non-manufacturing.

In order to provide a consistent explanation for the above-mentioned changes, we build a two-sector neoclassical general equilibrium model with two types of labor (skilled and unskilled), in which production technology features capital-skill complementarity. The two sectors can differ in terms of the degree of capital-skill complementarity. We use Bayesian methods to fit our model to the Japanese data. We find evidence of sectoral heterogeneity in capital-skill complementarity. Based on the estimated structural parameters, we show that the decline in capital-skill complementarity — reflecting the decline in the elasticity of substitution between capital and unskilled labor in non-manufacturing — can account for the observed changes in the Japanese data.

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Appendix

A Steady-State Relationship

To simplify the presentation below, let us define for $j = m, n$ in the steady state

$$Z_j \equiv \mu_j \left(\frac{\psi_u U_j}{\psi_s S_j}\right)^{\sigma_j} + (1-\mu_j)\left\{\lambda_j \left(\frac{K_j}{\psi_s S_j}\right)^{\rho_j} + (1-\lambda_j)\right\}^{\frac{\sigma_j}{\rho_j}}. \tag{25}$$

Given the steady-state value of $r = \frac{1}{\beta} - (1-\delta)$ and other parameter values, together with the definitions of Z_m and Z_n in (25), the following non-linear system of 12 equations characterizes the steady state of this economy.

$$\begin{aligned}
\frac{Y_m}{\psi_s S_m} &= A_m (Z_m)^{\frac{1}{\sigma_m}} \\
\frac{Y_n}{\psi_s S_n} &= A_n (Z_n)^{\frac{1}{\sigma_n}} \\
\frac{C_m}{\psi_s S_m} &= \frac{Y_m}{\psi_s S_m} - \delta \frac{K_m}{\psi_s S_m} - \delta \frac{K_n}{\psi_s S_n}\frac{S_n}{S_m} \\
\frac{C_n}{\psi_s S_n} &= \frac{Y_n}{\psi_s S_n} \\
p\left(\frac{C_n}{\psi_s S_n}\right)^{\frac{1}{\kappa}} &= \frac{(1-\gamma)}{\gamma}\left(\frac{C_m}{\psi_s S_m}\frac{S_m}{S_n}\right)^{\frac{1}{\kappa}} \\
\left(\frac{w_s}{w_u}\right)^{\theta} &= \frac{S_m}{U_m}\frac{\left(1+\frac{S_n}{S_m}\right)}{\left(1+\frac{U_n/S_n}{U_m/S_m}\frac{S_n}{S_m}\right)} \\
r &= (1-\mu_m)\lambda_m A_m \left(\frac{K_m}{\psi_s S_m}\right)^{\rho_m - 1} (Z_m)^{\frac{1-\sigma_m}{\sigma_m}} \left\{\lambda_m \left(\frac{K_m}{\psi_s S_m}\right)^{\rho_m} + (1-\lambda_m)\right\}^{\frac{\sigma_m-\rho_m}{\rho_m}} \\
\frac{r}{p} &= (1-\mu_n)\lambda_n A_n \left(\frac{K_n}{\psi_s S_n}\right)^{\rho_n - 1} (Z_n)^{\frac{1-\sigma_n}{\sigma_n}} \left\{\lambda_n \left(\frac{K_n}{\psi_s S_n}\right)^{\rho_n} + (1-\lambda_n)\right\}^{\frac{\sigma_n-\rho_n}{\rho_n}} \\
w_s &= (1-\mu_m)(1-\lambda_m)(A_m)^{\sigma_m}\left(\frac{Y_m}{\psi_s S_m}\right)^{1-\sigma_m}\left\{\lambda_m \left(\frac{K_m}{\psi_s S_m}\right)^{\rho_m} + (1-\lambda_m)\right\}^{\frac{\sigma_m-\rho_m}{\rho_m}} \\
\frac{w_s}{p} &= (1-\mu_n)(1-\lambda_n)(A_n)^{\sigma_n}\left(\frac{Y_n}{\psi_s S_n}\right)^{1-\sigma_n}\left\{\lambda_n \left(\frac{K_n}{\psi_s S_n}\right)^{\rho_n} + (1-\lambda_n)\right\}^{\frac{\sigma_n-\rho_n}{\rho_n}} \\
w_u &= \mu_m (A_m)^{\sigma_m}\left(\frac{Y_m}{\psi_s S_m}\right)^{1-\sigma_m}\left(\frac{\psi_u U_m}{\psi_s S_m}\right)^{\sigma_m - 1}\psi_u \\
\frac{w_u}{p} &= \mu_n (A_n)^{\sigma_n}\left(\frac{Y_n}{\psi_s S_n}\right)^{1-\sigma_n}\left(\frac{\psi_u U_n}{\psi_s S_n}\right)^{\sigma_n - 1}\psi_u
\end{aligned}$$

This system describes the steady-state relationship among the following 12 variables:

$$\frac{Y_m}{S_m}, \frac{Y_n}{S_n}, \frac{C_m}{S_m}, \frac{C_n}{S_n}, \frac{K_m}{S_m}, \frac{K_n}{S_n}, \frac{U_m}{S_m}, \frac{U_n}{S_n}, \frac{S_n}{S_m}, p, w_s, w_u.$$

B Log-Linearized System

The log-linearized system of equations used in the estimation in Section 4 is as follows.

$$\begin{aligned}
\hat{c}_t &= \omega_m \hat{c}_{m,t} + (1-\omega_m)\hat{c}_{n,t} \\
\hat{\Lambda}_t &= -\frac{1}{\kappa}\hat{c}_{m,t} + \left(\frac{1}{\kappa} - 1\right)\hat{c}_t \\
\hat{\Lambda}_t + \hat{p}_t &= -\frac{1}{\kappa}\hat{c}_{n,t} + \left(\frac{1}{\kappa} - 1\right)\hat{c}_t \\
\hat{h}_t &= \omega_s \hat{s}_t + (1-\omega_s)\hat{u}_t \\
\hat{\Lambda}_t + \hat{w}_{s,t} &= \frac{1}{\theta}\hat{s}_t + \left(\frac{1}{\eta} - \frac{1}{\theta}\right)\hat{h}_t + \hat{m}_{s,t} \\
\hat{\Lambda}_t + \hat{w}_{u,t} &= \frac{1}{\theta}\hat{u}_t + \left(\frac{1}{\eta} - \frac{1}{\theta}\right)\hat{h}_t + \hat{m}_{u,t} \\
\hat{\Lambda}_t &= \hat{\Psi}_{m,t} + \hat{\xi}_{m,t} + \varphi\left\{\hat{i}_{m,t-1} - (1+\beta)\hat{i}_{m,t} + \beta\mathbb{E}_t[\hat{i}_{m,t+1}]\right\} \\
\hat{\Lambda}_t &= \hat{\Psi}_{n,t} + \hat{\xi}_{n,t} + \varphi\left\{\hat{i}_{n,t-1} - (1+\beta)\hat{i}_{n,t} + \beta\mathbb{E}_t[\hat{i}_{n,t+1}]\right\} \\
\hat{\Psi}_{m,t} &= \beta\mathbb{E}_t\left[r\hat{\Lambda}_{t+1} + r\hat{r}_{m,t+1} + (1-\delta)\hat{\Psi}_{m,t+1}\right] \\
\hat{\Psi}_{n,t} &= \beta\mathbb{E}_t\left[r\hat{\Lambda}_{t+1} + r\hat{r}_{n,t+1} + (1-\delta)\hat{\Psi}_{n,t+1}\right] \\
\hat{x}_{m,t} &= (\sigma_m - \rho_m)\left\{\omega_{k_m}\hat{k}_{m,t} + (1-\omega_{k_m})(\hat{\psi}_{s,t} + \hat{s}_{m,t})\right\} \\
\hat{x}_{n,t} &= (\sigma_n - \rho_n)\left\{\omega_{k_n}\hat{k}_{n,t} + (1-\omega_{k_n})(\hat{\psi}_{s,t} + \hat{s}_{n,t})\right\} \\
\hat{r}_{m,t} &= (1-\sigma_m)\hat{y}_{m,t} + \sigma_m\hat{a}_{m,t} + (\rho_m - 1)\hat{k}_{m,t} + \hat{x}_{m,t} \\
\hat{r}_{n,t} - \hat{p}_t &= (1-\sigma_n)\hat{y}_{n,t} + \sigma_n\hat{a}_{n,t} + (\rho_n - 1)\hat{k}_{n,t} + \hat{x}_{n,t} \\
\hat{w}_{s,t} &= (1-\sigma_m)\hat{y}_{m,t} + \sigma_m\hat{a}_{m,t} + \rho_m\hat{\psi}_{s,t} + (\rho_m - 1)\hat{s}_{m,t} + \hat{x}_{m,t} \\
\hat{w}_{s,t} - \hat{p}_t &= (1-\sigma_n)\hat{y}_{n,t} + \sigma_n\hat{a}_{n,t} + \rho_n\hat{\psi}_{s,t} + (\rho_n - 1)\hat{s}_{n,t} + \hat{x}_{n,t} \\
\hat{w}_{u,t} &= (1-\sigma_m)\hat{y}_{m,t} + \sigma_m\hat{a}_{m,t} + \sigma_m\hat{\psi}_{u,t} + (\sigma_m - 1)\hat{u}_{m,t} \\
\hat{w}_{u,t} - \hat{p}_t &= (1-\sigma_n)\hat{y}_{n,t} + \sigma_n\hat{a}_{n,t} + \sigma_n\hat{\psi}_{u,t} + (\sigma_n - 1)\hat{u}_{n,t} \\
\hat{y}_{m,t} &= \hat{a}_{m,t} + \omega_{u_m}(\hat{u}_{m,t} + \hat{\psi}_{u,t}) + (1-\omega_{u_m})\hat{x}_{m,t} \\
\hat{y}_{n,t} &= \hat{a}_{n,t} + \omega_{u_n}(\hat{u}_{n,t} + \hat{\psi}_{u,t}) + (1-\omega_{u_n})\hat{x}_{n,t} \\
\hat{k}_{m,t+1} &= \delta\hat{i}_{m,t} + (1-\delta)\hat{k}_{m,t} \\
\hat{k}_{n,t+1} &= \delta\hat{i}_{n,t} + (1-\delta)\hat{k}_{n,t}
\end{aligned}$$

$$
\begin{aligned}
\hat{s}_t &= f_s\hat{s}_{m,t} + (1-f_s)\hat{s}_{n,t} \\
\hat{u}_t &= f_u\hat{u}_{m,t} + (1-f_u)\hat{u}_{n,t} \\
\hat{y}_{m,t} &= \omega_c\hat{c}_{m,t} + \omega_i\hat{i}_{m,t} + (1-\omega_c-\omega_i)\hat{i}_{n,t} \\
\hat{y}_{n,t} &= \hat{c}_{n,t} \\
\hat{a}_{m,t} &= \rho_{a_l}\hat{a}_{m,t-1} + \varepsilon_{a_m,t} \\
\hat{a}_{n,t} &= \rho_{a_n}\hat{a}_{n,t-1} + \varepsilon_{a_n,t} \\
\hat{\psi}_{s,t} &= \rho_{\psi_s}\hat{\psi}_{s,t-1} + \varepsilon_{\psi_s,t} \\
\hat{\psi}_{u,t} &= \rho_{\psi_u}\hat{\psi}_{u,t-1} + \varepsilon_{\psi_u,t} \\
\hat{\xi}_{l,t} &= \rho_{\xi_l}\hat{\xi}_{l,t-1} + \varepsilon_{\xi_l,t} \\
\hat{\xi}_{n,t} &= \rho_{\xi_n}\hat{\xi}_{n,t-1} + \varepsilon_{\xi_n,t} \\
\hat{m}_{s,t} &= \rho_{m_s}\hat{m}_{s,t-1} + \varepsilon_{m_s,t} \\
\hat{m}_{u,t} &= \rho_{m_u}\hat{m}_{u,t-1} + \varepsilon_{m_u,t} \\
\hat{w}_{m,t} &= \eta_{\chi_m}\hat{\chi}_{m,t} + \eta_{w_{sm}}\hat{w}_{s,t} + \eta_{w_{u,1}}\hat{w}_{u,t} \\
\hat{w}_{n,t} &= \eta_{\chi_n}\hat{\chi}_{n,t} + \eta_{w_{sn}}\hat{w}_{s,t} + \eta_{w_{u,2}}\hat{w}_{u,t} \\
\hat{\chi}_{m,t} &= \eta_{u_m}\hat{u}_{m,t} + \eta_{s_m}\hat{s}_{m,t} \\
\hat{\chi}_{n,t} &= \eta_{u_n}\hat{u}_{n,t} + \eta_{s_n}\hat{s}_{n,t}
\end{aligned}
$$

where

$$
\begin{aligned}
\omega_m &= \frac{\gamma(C_m)^{\frac{\kappa-1}{\kappa}}}{\gamma(C_m)^{\frac{\kappa-1}{\kappa}} + (1-\gamma)(C_n)^{\frac{\kappa-1}{\kappa}}} = \frac{C_m}{C_m + pC_n} & \omega_s &= \frac{(S)^{\frac{\theta+1}{\theta}}}{(S)^{\frac{\theta+1}{\theta}} + (U)^{\frac{\theta+1}{\theta}}} & \varphi &= \Phi''(1) \\
\omega_{k_m} &= \frac{\lambda_m(K_m)^{\rho_m}}{\lambda_m(K_m)^{\rho_m} + (1-\lambda_m)(\psi_s S_m)^{\rho_m}} & \omega_{k_n} &= \frac{\lambda_n(K_n)^{\rho_n}}{\lambda_n(K_n)^{\rho_n} + (1-\lambda_n)(\psi_s S_n)^{\rho_n}} \\
\omega_{u_m} &= \frac{\mu_m(\psi_u U_m)^{\sigma_m}}{\mu_m(\psi_u U_m)^{\sigma_m} + (1-\mu_m)(X_m)^{\frac{\sigma_m}{(\sigma_m-\rho_m)}}} & \omega_{u_n} &= \frac{\mu_n(\psi_u U_n)^{\sigma_n}}{\mu_n(\psi_u U_n)^{\sigma_n} + (1-\mu_n)(X_n)^{\frac{\sigma_n}{(\sigma_n-\rho_n)}}} \\
f_s &= \frac{S_m}{S} & f_u &= \frac{U_m}{U} \\
\omega_c &= \frac{C_m}{Y_m} & \omega_i &= \frac{I_m}{Y_m} \\
\eta_{\chi_m} &= \frac{1-\pi}{\frac{S_m}{U_m}\pi + 1} & \eta_{\chi_n} &= \frac{1-\pi}{\frac{S_n}{U_n}\pi + 1} \\
\eta_{w_{sm}} &= \left(1 + \frac{1}{\frac{S_m}{U_m}\pi}\right)^{-1} & \eta_{w_{sn}} &= \left(1 + \frac{1}{\frac{S_n}{U_n}\pi}\right)^{-1} \\
\eta_{w_{um}} &= \left(1 + \frac{S_m}{U_m}\pi\right)^{-1} & \eta_{w_{un}} &= \left(1 + \frac{S_n}{U_n}\pi\right)^{-1}
\end{aligned}
$$

C Data Construction

Since there are no quarterly output and price data at the sectoral level, we assume that semi-durable and durable goods, and investment goods for residential and business fixed investment are produced by the manufacturing industry (Y_m). Also, we assume that non-durable goods and services are produced by the non-manufacturing industry (Y_n). We construct price indices for each output accordingly (P_m and P_n). The relative price (p) is defined as P_n/P_m. We obtain GDP components and corresponding price indices from the Cabinet Office's National Accounts.

Population (15 years old and over) consists of labor force and non-labor force (excluding people with unknown labor status), which are taken from the Labour Force Survey (LFS) by the Statistics Bureau of the Ministry of Internal Affairs and Communications. This is used to convert quantity variables in per capita term.

We construct the sectoral hourly wage (W_m and W_n) by dividing the nominal wage bill per worker by total hours worked per worker for each industry. Until 1989, we use data from establishments with 30 or more employees. From 1990 onwards, we use data from establishments with 5 or more employees. These data are taken from the Monthly Labour Survey (MLS) by the Ministry of Health, Labour and Wealth.

Part-time workers are defined as those who work fewer hours than regular (full-time) workers per day or per week. From 1990, we use the numbers of full-time (L_s) and part-time (L_u) workers reported in the MLS. However, there are no official statistics until 1989. We extrapolate the number reported in the MLS by using the data from the LFS. We categorize employees who work at least 35 hours per week as full-time workers and those working shorter hours as part-time workers.

We construct the average hours worked per full-time worker by using the following relationship:

$$h = \frac{h_s L_s + h_u L_u}{L_s + L_u} = h_s \left(\frac{L_s}{L_s + L_u} + \zeta \frac{L_u}{L_s + L_u} \right),$$

where h is the average hours worked per worker, h_s and h_u are the average hours worked per full-time and per part-time worker, L_s and L_u denote the numbers of full-time and part-time workers, and $\zeta = \frac{h_u}{h_s}$. To measure h, we use the MLS. From 1990, we use data from establishments with five or more employees. Until 1989, we use data from establishments with 30 or more employees. ζ is taken from the MLS from 1990 (establishments with five or more employees). Until 1989, we use the Basic Survey on Wage Structure by utilizing linear interpolation. Given h, L_s, L_u, and ζ, we construct h_s and then calculate $h_u = \zeta h_s$. Finally, we construct by $S = h_s L_s$ and $U = h_u L_u$.