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How sectoral technical progress and factor substitution shaped Japan's structural transformation?

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Abstract

The paper quantitatively assesses the importance of supply-side drivers in the transition of the Japanese economy from low-skilled to high-skilled sectors and its implication for growth, labor demand and labor income shares. A sectoral supply-side system, estimated over the 1980-2012 period, reveals different rates of technical progress across production factors and sectors, but also heterogeneity in the sectoral elasticity of substitution between capital and labor. The fact that capital and labor are easily substitutable in low-skilled services but not in high-skilled services, coupled with the dominant role of capital-augmenting technical change in services is a key factor behind the relocation of labor towards high-skilled services, as well as behind the declining trend in the labor income share in low-skilled services.

Keywords: CES production function, biased technical change, labor demand, labor income share
JEL classification: O47, O33, J23

Non-technical summary

In Japan, the burst of the asset bubble in 1990 marked an abrupt shift in economic activity. Output growth moderated substantially in the 1990s and remained anemic during the 2000s. These two 'lost decades' coincided with the growing reliance of the economy on services. As the economy shifted towards the service sector, real value added and employment (total hours worked) increased in services and declined substantially in manufacturing. Along with this structural transformation towards services, the economy also transitioned from low-skilled to high-skilled intensive sectors both within manufacturing and services with high-skilled sectors accounting for an increasing share of total value added. During the process, the labor income share declined in low-skilled intensive services, increased in high-skilled intensive services and, to a lesser extent, in manufacturing. Motivated by these stylised facts, the goal of this paper is to document the sectoral transformation of the Japanese economy over the 1980-2012 period and to show that a multi-sectoral CES production system with differences in sectoral production functions explain these structural trends well.

I use annual data for 90 sub-sectors (industries) representative of Japan's private non-agricultural economy from the Japan Industrial Productivity Database. I split the industries within manufacturing and services depending on their intensity of using high-skilled labor into four sectors: (1) low-skilled and (2) high-skilled manufacturing, (3) low-skilled and (4) high-skilled services.

Similar to Herrendorf et al. (2015), the empirical approach simultaneously accounts for three supply-side determinants of structural transformation as identified by the literature: (i) sectoral differences in technical progress (ii) differences in the flexibility of factor substitutions across sectors and (iii) sectoral differences in factor proportions (i.e., labor or capital income share).

My results establish that there are substantial sectoral differences in the substitutability of capital and labor in the production process and that the average technical progress growth differs both across sectors and factors. I show that labor and capital are complements in manufacturing and in high-skilled services (the elasticity of substitution is lower than unity), while they are gross substitutes (elasticity of substitution is bigger than unity) in low-skilled services. In terms of efficiency gains, the results show that high-skilled sectors benefited on average by larger capital-augmenting technical change than low-skilled sectors.

My estimates of technical change coupled with the estimated elasticity of substitutions assure that the predictions for conditional labor demand match well the sectoral labor allocations observed in the data, with the CES specification outperforming predictions from standard sectoral Cobb-Douglas production functions. I highlight that differences in technical change and in the magnitude of elasticity of substitution are both quantitatively important drivers of the structural transformation of the Japanese economy and of the ensued changes in labor allocations, while factor proportions appear to be less relevant. I also find that differences in the magnitude of the elasticity of substitution are key to pin down the diverging trends in the relative factor income share across low-skilled and high-skilled services. Positive labor-augmenting technical change has freed up labor in low-skilled sectors and high-skilled manufacturing, while negative labor-augmenting technical change increased the demand for labor in high-skilled services. I show that in the presence of higher substitutability between capital and labor than in the Cobb-Douglas case, the low-skilled sector substituted more labor with capital than the other sectors, and this effect was quantitatively important.

From an empirical perspective, my paper provides estimates for unobserved elasticity of substitutions and factor-augmenting technical change at the sectoral level, which can be used to calibrate multi-sectoral growth models. It also provides a battery of robustness checks and discusses potential estimation issues that could arise in the estimation of the CES supply-side system for the Japanese economy.

From a policy perspective the paper shows that for an economy confronted with population ageing and a dual labor market, the transition to high-skilled services requires a strong focus on augmenting the existing human capital and minimising the labor market duality. That would help satisfy the demand for high-skilled labor, promote growth and avoid a concentration of income towards capital owners.

1 Introduction

In Japan, the burst of the asset bubble in 1990 marked an abrupt shift in economic activity. Output growth moderated substantially in the 1990s and remained anemic during the 2000s. These two 'lost decades' coincided with the growing reliance of the economy on services. As the economy shifted towards the service sector, real value added and employment (total hours worked) increased in services and declined substantially in manufacturing. Along with this structural transformation towards services, the economy also transitioned from low-skilled to high-skilled intensive sectors both within manufacturing and services with high-skilled sectors accounting for an increasing share of total value added. During this process, the labor income share declined in low-skilled intensive services, increased in high-skilled intensive services and, to a lesser extent, in manufacturing. Motivated by these stylised facts, the goal of this paper is to document the sectoral transformation of the Japanese economy over the 1980-2012 period and to show that a multi-sectoral CES production system with differences in sectoral production functions performs well in explaining these structural trends well. In addition, the paper quantitatively assesses the contribution of different drivers behind Japan's structural transformation – understood here as a a combination of changes encompassing shifts in sectoral real value added and sectoral labor input (total hours worked), jointly with changes in the relative shares of income received by factors of production across sectors.

I use annual data for 90 industries representative of Japan's private non-agricultural economy from the Japan Industrial Productivity Database and define four sub-sectors: (1) low-skilled and (2) high-skilled manufacturing and (3) low-skilled and (4) high-skilled services. In order to do that I split the industries within manufacturing and services depending on their intensity of using high-skilled occupations. I aggregate all variables of interest – real and nominal valued added, hours worked, capital stock, labor income share – across these sub-sectors. I depart from the traditional sectoral classification studied in the structural transformation literature (agriculture, manufacturing, services) for two reasons: (i) agriculture accounted only for a limited share of value added in Japan over the analysed period and (ii) services represent an important share of the economy and display significant heterogeneity, which calls for a more refined sectoral spilt in order to uncover underlying economic trends (see Jorgenson & Timmer (2011), and Duernecker et al. (2017)).[1]

Following Herrendorf et al. (2015) the empirical approach simultaneously accounts for the three supply-side determinants of structural transformation identified by the literature: (i) sectoral differences in technical progress (ii) differences in the flexibility of factor substitutions across sectors and (iii) sectoral differences in factor proportions (i.e., labor or capital income share). The first one, introduced by Baumol (1967) and more recently formalized by Ngai & Pissarides (2007) to allow for structural transformation along a balanced growth path, suggests that economic resources (labor in particular) are freed-up from sectors that exhibit fast productivity growth and are employed in the lower-productivity sectors. According to the second determinant proposed by Alvarez-Cuadrado et al. (2018) the more flexible sector (e.g., the one with higher elasticity of substitution between labor and capital) is better placed to substitute away from the production factor that becomes relatively more scarce, and consequently more expensive, inducing a reallocation of production factors across sectors and changes in their relative contribution to output. The third factor, proposed by Acemoglu & Guerrieri (2006), is that structural transformation occurs in the presence of technical progress because sectors use factors in different proportions (intensity).[2]

Studying the Japanese economy in the context of the supply-side determinants of structural transformation, this paper provides three main contributions to the literature. The first contribution is to document

[1] Jorgenson & Timmer (2011) provide evidence of structural transformation for the US, EU and Japan and document that since 1980 economies relied predominantly on services, which displayed significant heterogeneity in productivity. Duernecker et al. (2017) distinguish between low- and high- productivity industries within manufacturing and services and show that the growth slowdown in the US economy was due to structural transformation within services.

[2] In a two-sector growth model, the authors show that in the presence of technical progress, the rise in the aggregate capital to labor ratio leads to a faster growth in output for the capital-intensive sector and induces a reallocation of capital and labor away from that sector if the elasticity of substitution between the two sectors (two goods) is below unity. This is because the relative increase in output in the capital-intensive sector leads to a more than proportionate decline in the relative price of the goods produced in the capital-intensive sector, thus reducing the relative compensation of labor and capital in the capital-intensive sector.

the structural transformation of the Japanese economy from manufacturing to services by adding the extra layer of disentangling between low-skilled and high-skilled intensive sectors. This is shown to be a key factor for understanding developments of Japan's economic growth and labor income share. The second - and most important contribution - is to estimate a non-linear sectoral CES production system with factor-augmenting technical change with four sectors (low-skilled and high-skilled manufacturing and low-skilled and high-skilled services). I do this under different assumptions (e.g., exponential technical progress (TP), Box-Cox technical progress, different labor income shares, quality-adjusted factor inputs) to validate the results. The third contribution is to assess the drivers of labor allocations (changes in hours worked) and movements in relative labor income shares, using the sectoral estimates for unobserved technical progress and elasticity of substitution between capital and labor.

My results establish that there are substantial sectoral differences in the substitutability of capital and labor in the production process and that the average technical change differs substantially both across sectors and factors. In light of these results, and to better understand the growth process, the use of the more flexible CES production functions at the sectoral level rather then the commonly used Cobb-Douglas production functions [3] not only appears justified, but also desirable.

I show that labor and capital are complements in manufacturing and in high-skilled services (the elasticity of substitution is lower than unity), while they are gross substitutes (the elasticity of substitution is bigger than unity) in low-skilled services. This implies that labor-replacing automation (e.g., self-service checkouts, flexible robots) is likely to have been deployed at a faster rate in the low-skilled services compared to the other sectors as automation has moved from manufacturing to services and less complex occupations were easier to replace. In terms of efficiency gains, the results show that high-skilled sectors benefited on average by larger capital-augmenting technical change than low-skilled sectors. The faster accumulation of IT capital in high-skilled sectors is likely to have been responsible for the higher efficiency of capital as computers became cheaper and displayed an increasing performance over time. The non-intuitive, but robust finding of negative labor-augmenting technical change in the high-skilled services sector might reflect the sector's increasing reliance in production on older and non-regular (e.g., part-time) workers amid Japan's labor shortages. Several studies document that these workers are likely to be less productive either because they have limited opportunities for training and on-the-job learning either because they are less motivated given their overall poorer job prospects than younger cohorts and regular employers (see Fukao et al. (2006), Stucchi et al. (2011) and OECD (2018)).

Using estimates of technical change and elasticity of substitution I compute the optimal sectoral demand for labor (conditional on producing a given amount of output and given factor prices) and show that it mirrors well the sectoral labor allocations in the data and that the CES specification outperforms the prediction from standard sectoral Cobb-Douglas production function. I find that differences in technical change and in the magnitude of elasticity are both quantitatively important determinants of structural change, while factor proportions are less important.

Finally, the unified sectoral CES supply-system approach allows to document the decline in the labor income share (Neiman (2014)). I show that this decline was driven by developments in low-skilled services, while the labor income share increased in high-skilled service, suggesting that income inequality was generated within services. I show that differences in the elasticity of substitution are key to pin down diverging trends in the relative factors' income shares across low-skilled and high-skilled services. In low-skilled services, where the elasticity of substitution is estimated to be above-unity, net-capital augmenting technical change and capital deepening led to a decline in the relative income share of labor. In the spirit of Alvarez-Cuadrado et al. (2018) I provide a decomposition for the relative income share to highlight the key underlying factors governing its evolution across sectors.

The paper belongs to the rich literature on economic growth and structural transformation (see van Neuss (2019) for a recent summary of the literature). Narrowing down the scope, my work is closely connected to the strand of the literature estimating CES production functions with non-neutral technical change (Klump et al. (2012), León-Ledesma et al. (2015), Manu et al. (2022), Antras (2004), Chirinko & Mallick (2017), Mućk (2017), Herrendorf et al. (2015), Alvarez-Cuadrado et al. (2018), Young (2013)).

[3] Which postulate neutral technical progress and unity elasticity of substitution between capital and labor.

With few exceptions, most papers apply a CES supply-system to study the aggregate US economy.[4] My paper expands this literature by applying the approach within a coherent framework to Japan.

The studies above and the broader literature (see Knoblach & Stöckl (2020), for a survey) generally find that labor and capital are gross complements (below unity elasticity of substitution) either at aggregate level or at sectoral/industry level, and point to only limited above-unity estimates for the elasticity of substitution. Recently, Manu et al. (2022) elaborate on the importance of the elasticity of substitution as an engine for growth and highlight that an estimated above-unity elasticity played an important role in China's rapid economic expansion.[5] I show that in the low-skilled services sector in Japan, the elasticity of substitution is also consistently estimated above-unity, a finding which highlights the need to look at narrower sub-sectors in order to uncover deep parameters since aggregate sectoral data may mask important heterogeneity.[6]

By focusing on a different taxonomy, my work complements the existing structural transformation literature by providing quantitative metrics which help deepen our understanding about the relative importance of supply-side channels for labor allocation across sectors with different skill-intensity.

The paper is structured as follows. The next section provides a description of the data and shows stylised facts that document the evolution of sectoral value added, hours worked and factor income shares. Section 3 describes the methodology for the CES supply-system estimation and Section 4 discusses the estimation results. Section 5 explores the sectoral labor allocations while Section 6 delves into the drivers of relative factor income shares. Section 7 presents a battery of robustness tests. Section 8 concludes.

2 Data and stylised facts

2.1 Data

I use annual data provided by the Japan Industrial Productivity Database that spans over the 1973-2012 period.[7] I focus the analysis on the private non-agricultural economy (excluding public services and housing), which includes 90 industries, out of which 54 belong to the manufacturing sector (including construction[8]) and 36 belong to the service sector.[9]

I define four sub-sectors: (1) low-skilled and (2) high-skilled manufacturing and (3) low-skilled and (4) high-skilled services. In order to do that I first split the 90 industries within manufacturing and services depending on the intensity of using high-skilled occupations. The split is obtained by computing the share of employees working in high-skilled occupations as percent of total employees (e.g., working in all occupations) during the period 2008-2010. If the share of employees working in high-skilled occupations in a given industry belonging to manufacturing and services is higher than the average share of employees working in high-skilled occupations for the aggregate manufacturing or services, the respective industry is classified as high-skilled industry. The remaining ones are labeled low-skilled. As a benchmark I use the average share of employees in high-skilled occupations in manufacturing or services rather than the average share for the overall economy. This reflects the fact that the two sectors require a different set of occupations, with services displaying on average a more intensive use of high-skilled occupations. I consider managers and officials, professional and technical workers to be high-skilled occupations, while clerical and related workers, sales workers, service workers, production process workers and laborers to be low-skilled occupations. While it would be preferable to define the sectoral taxonomy of skills based on workers' tasks rather the workers' occupations, the relevant data on task classes is not available. After assigning individual industries to one of the two categories, I aggregate all variables of

[4] Herrendorf et al. (2015), Alvarez-Cuadrado et al. (2018), Young (2013) use sectoral or industry-data while Mućk (2017) provides aggregate CES production functions estimates for a sample of advanced economies, including Japan.

[5] At the sectoral level, Herrendorf et al. (2015) estimate an elasticity of substitution above unity for the agricultural sector.

[6] The estimated elasticity of substitution differ also between low-skilled and high-skilled manufacturing, but both elasticities are estimated to be below unity.

[7] The database covers 108 industries representative of Japan's economy as a whole. The source of the raw input data can be found at https://www.rieti.go.jp/en/database/JIP2015/index.html.

[8] The construction sector is assigned to manufacturing as in Herrendorf et al. (2015).

[9] Agriculture makes only a marginal contribution to growth while the measurement of value added in the public sector is problematic being often defined only as the sum of the labor costs.

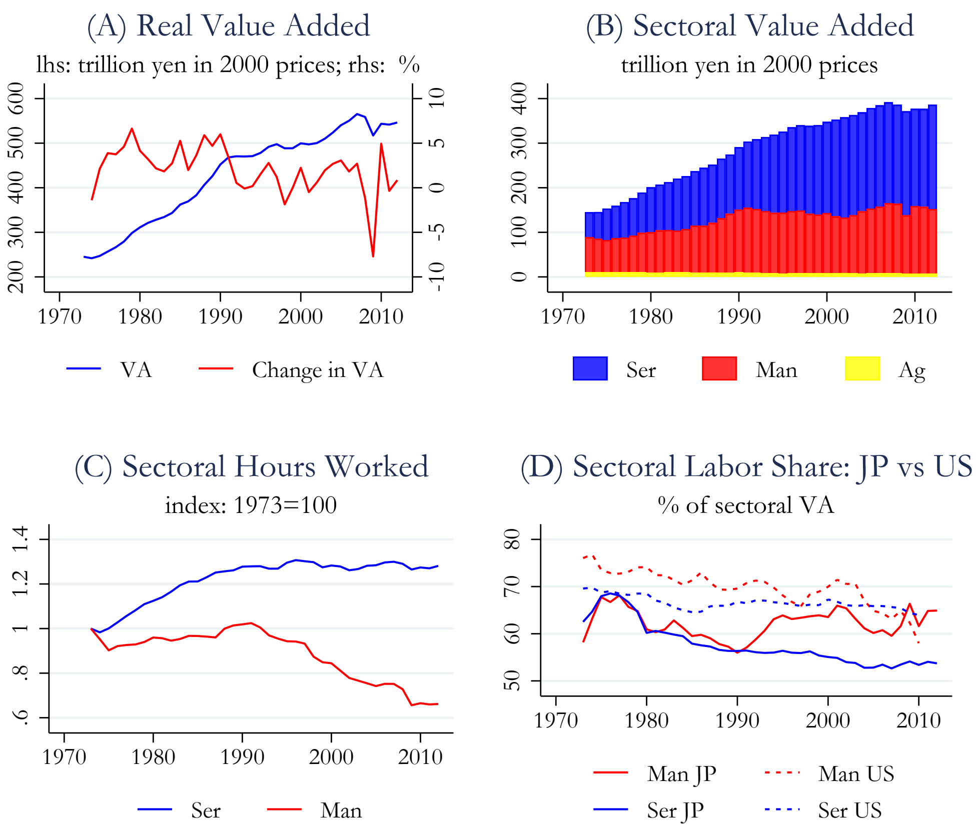
interest – real and nominal valued added, hours worked, capital stock, labor income share – across the four sub-sectors (see Appendix A).

The measure of output is gross value added in nominal and real prices. For the capital stock I use the real net capital stock, while the total number of hours worked represents a proxy of the labor input. To compute the labor income share I rely on the income approach, with gross value added computed as the sum of total compensation of employees (including mixed income), gross-operating surplus, consumption of fixed capital and taxes less subsidies. Thus, I calculate the labor income share by taking the ratio of the compensation of employees over nominal gross value added, excluding taxes and subsidies. According to Guerriero (2019), the latter is a more meaningful measure than total income, since taxes and subsidies do not represent any kind of return to labor or capital.

2.2 Stylised facts

Japan's 'lost decades' overlap with the period in which the country became highly reliant on services. Figure 1A and Figure 1B show that the low growth regime after 1990 coincided with a continued increase in the share of services in total value added, rising from close to 60% in early 1980 to 72% by 2015. Most of the remaining share is taken nowadays by manufacturing (26%).[10]

Figure 1: Output, hours worked and labor income shares



Note: Panel A and B show the evolution of real value added for the overall economy and for agriculture (Ag), manufacturing (Man) and services (Ser) in Japan. Panel C shows the evolution of total hours worked in services and manufacturing, indexed in 1973. Panel D shows the labor income share in Japan versus US in services and manufacturing, where the labor income share in Japan is computed by dividing the compensation of employees to nominal valued added in manufacturing (services). The data for the US comes from Herrendorf et al. (2015). For comparability purposes, the data for services in these charts refers to total services, including the public sector.

[10] In the post-war period only a marginal stake was attributed to agriculture (less than 2%).

As the economy shifted towards services, the number of hours worked in the services increased by about 36% between 1970 and 2012 (13% from 1980), while the numbers of hours worked in manufacturing declined substantially (Figure 1C). At the same time, the labor income share in services fell, contributing to the broad decline in the labor income share in the economy. In manufacturing, in contrast, the labor income share exhibited relatively more stable dynamics and even increased somewhat since 1980s. This contrasts with the experience of the US, where the decline in the labor income share was driven by the manufacturing sector (Figure 1D).[11]

By focusing on the private economy and distinguishing between low-skilled and high-skilled sectors I document the following stylised facts for the 1980-2012 period:

(i) The decline in real value added since the early 1990s was driven by dynamics within the low-skilled sectors, while the real value added produced in high-skilled sectors increased steadily throughout the period (Figures 2A). By 2012, the high-skilled manufacturing sector was producing almost an equal amount of real value added as the low-skilled manufacturing sector. In services, the high-skilled sector produced only 25% of value added produced by low-skilled sector, despite its steady growth over the years.

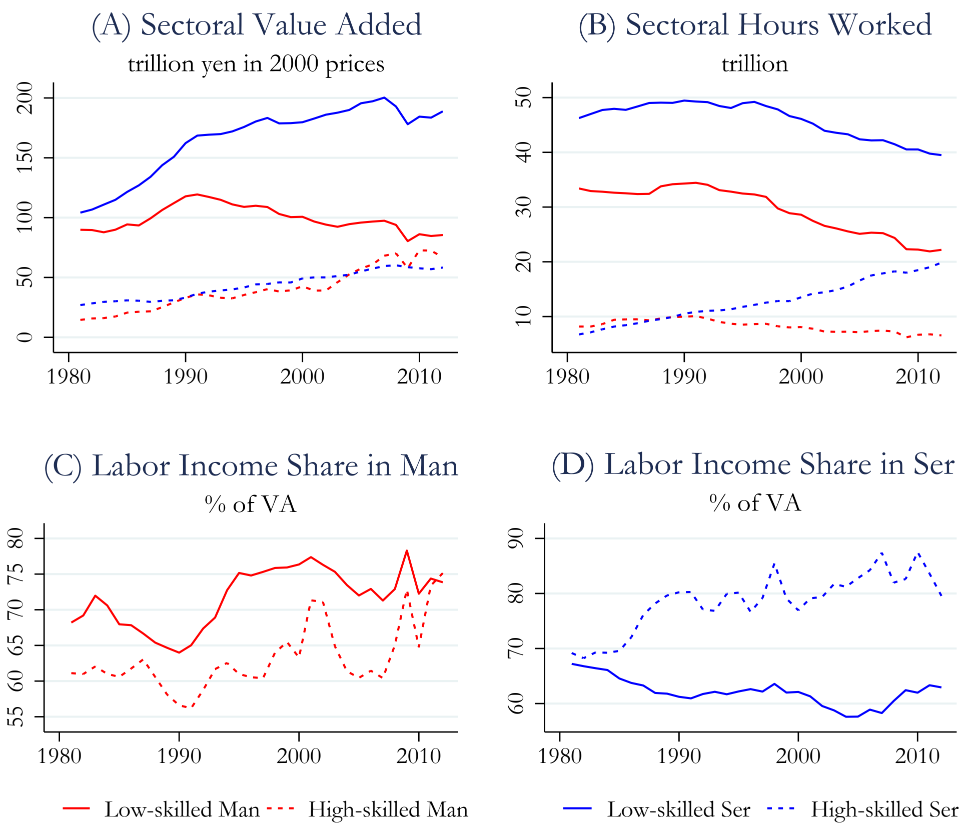
(ii) The labor input measured in total hours worked declined in low- and high-skilled manufacturing as well as in low-skilled services, while the labor input increased steadily in high-skilled services (Figure 2B).

(iii) Heterogeneous development in value-added and labor input imply that labor productivity (defined as real value added per hour worked) exhibited different developments across sectors. Between 1980 and 2012, labor productivity more than tripled in low-skilled manufacturing (+240%) and rose substantially in high-skilled manufacturing (+170%) and low-skilled services (+160%), while it declined in high-skilled services (-30%). This reflected differences in sectoral capital deepening (the ratio of the capital stock to the total hours worked), but also, as I will show later, differences in technical progress both across sectors and factors.

(iv) Since 1980s, the labor income share declined in low-skilled services and increased in high-skilled services. In manufacturing, the labor income share increased somewhat, while displaying higher volatility than in the services (Figure 2 C and Figure 2D). These observed changes in sectoral labor income shares motivate the use of sectoral CES production function rather than a Cobb-Douglas production function which assumes constant labor income share.

[11] In terms of capital accumulation, both the capital-output ratio and the capital-labor ratio regained pace after 1990, with services displaying a larger intensity of capital relative to manufacturing (similar to the US economy).

Figure 2: Low-skilled and high-skilled sectors:
Value added, hours worked and labor income share



Note: The plots show developments in sectoral value added, sectoral hours worked and labor income share based on the defined taxonomy of skills. Services refer only to market services. The labor income share displayed in Panel C and Panel D refers to the ratio of the compensation of employees over nominal gross value added, excluding taxes and subsidies.

3 Methodology

3.1 Sectoral CES supply-system

To estimate sectoral production functions I apply the 'normalised' supply-system approach with cross-equation parameter constraints following the work of Klump et al. (2007*a*) and León-Ledesma et al. (2010). I use real value added production functions following the work of Herrendorf et al. (2015). That requires that real value-added and the intermediate goods (in aggregate) are separable in production (e.g., gross output can be represented by a Cobb-Douglas production function with two factors: real value added and an aggregator of intermediate goods) and that the share of intermediate goods is constant. In Japan, as in the United States, these shares are not strictly constant but they do not exhibit pronounced long-run trends (see Appendix B). Thus, the supply system consists of sectoral value-added CES production functions with biased technical change and the associated first order condition. The system is derived from the cost minimisation of a representative firm in each sector, assuming perfect competition in product and factor markets. Cost minimisation in the four sectors (low- and high-skilled sectors within manufacturing and services) results in a 12-equations system, 3 for each sector. The CES production function for each sector is explicitly normalised and takes the following form:

$$Y_t^j = f(\dot{}) = Y_0^j \left[\pi_0^j \left(\frac{\Gamma_t^{Kj} K_t^j}{\Gamma_0^{Kj} K_0^j} \right)^{\frac{\sigma^j - 1}{\sigma^j}} + \left(1 - \pi_0^j\right) \left(\frac{\Gamma_t^{Lj} L_t^j}{\Gamma_0^{Lj} L_0^j} \right)^{\frac{\sigma^j - 1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j - 1}} \tag{1}$$

where superscript j indicates sectors of the economy, low-skilled and high-skilled manufacturing and low-skilled and high-skilled services; subscripts 0 indicate the values of respective variables at the point of normalisation; the distribution parameter π_0^j reflects capital intensity in production for each sector at the point of normalisation and is given by $\frac{P_0^j Y_0^j - w_0^j L_0^j}{Y_0^j}$, where w_0^j denotes the real wage rate. Y_t^j, K_t^j and L_t^j refer to value added of sector j, capital stock in sector j and the number of hours worked in sector j, respectively. The terms Γ_t^{Kj} and $\Gamma_t^{Lj]}$ capture capital-augmenting and labor-augmenting technical progress.

The parameter σ^j is the elasticity of substitution between capital and labor in sector j. The substitution elasticity measures the percentage change in factors' proportions (K_t^j / L_t^j) given a unit change in the marginal rate of technical substitution (or in factor price ratio).[12] Equation 1 nests a Cobb-Douglas production function when $\sigma^j = 1$ (changes in factor proportions are matched by a proportionate change in relative factor prices, leaving income shares constant), a Leontief function when $\sigma^j = 0$ (fixed factor proportions), a linear production function when $\sigma \to \infty$ (factors are perfect substitutes). When $\sigma^j < 1$ factors of production are gross complements and when $\sigma^j > 1$ input factors of production are gross substitutes.

Solving for the first order conditions in each sector, the optimal labor and capital income shares are given by:

$$\frac{w_t^j \mathbf{L}_t^j}{\mathbf{P}_t^j Y_t^j} = \left(1 - \pi_0^j\right) \left(\frac{\Gamma_t^{Lj}}{\Gamma_0^{Lj}} \frac{L_t^j / L_0^j}{Y_t^j / Y_0^j} \right)^{\frac{\sigma^j - 1}{\sigma^j}} \tag{2}$$

$$\frac{r_t^j \mathbf{K}_t^j}{\mathbf{P}_t^j Y_t^j} = \left(\pi_0^j\right) \left(\frac{\Gamma_t^{Kj}}{\Gamma_0^{Kj}} \frac{K_t^j / K_0^j}{Y_t^j / Y_0^j} \right)^{\frac{\sigma^j - 1}{\sigma^j}} \tag{3}$$

3.2 Normalisation

The normalisation of the system is important in order for the parameters of the production function to have a direct economic interpretation. Without normalisation de La Grandville & Klump (2000) show that parameters are in fact dependent on the elasticity of substitution between capital and labor (σ), arbitrary and not robust (see León-Ledesma et al. (2010) for a detailed argumentation on the importance of normalisation). From an empirical perspective, the normalisation point can be defined based on the actual data, before estimating the supply-system. Klump et al. (2007*a*) and León-Ledesma et al. (2010) use for normalisation point geometric averages for output, labor and capital (trending variables) and the arithmetic averages for time and labor income share. However, Herrendorf et al. (2015) argue that using arithmetic averages for normalising the factor income shares implies that the normalised CES is an approximation of the actual CES, which may not be accurate far away from the point of approximation. They propose instead using geometric averages also for the factor income shares. In my estimation I use both alternatives and show that the empirical estimates are robust to the choice of normalising the labor income share. Nonetheless, the baseline estimation uses geometric averages for the normalisation of all variables.

3.3 Estimation

To estimate the parameter values of the supply system described by equations (1) to (3), I multiply each equation with an error term (which could exhibit cross-correlation across equations and sectors) and

[12] $\sigma = \frac{\partial \log(K/L)}{\partial \log(f_L^j / f_K^j)} \in [0, \infty)$ where f_K^j and f_L^j stand for the marginal product of capital and labor in sector j.

re-write the system in log form as follows:

$$\ln\left(\frac{Y_t^j}{Y_0^j}\right) = \frac{\sigma^j}{\sigma^j-1}\ln\left[\pi_0^j\left(\frac{\Gamma_t^{Kj}K_t^j}{\Gamma_0^{Kj}K_0^j}\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\pi_0^j\right)\left(\frac{\Gamma_t^{Lj}L_t^j}{\Gamma_0^{Lj}L_0^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}\right] + \ln(\xi^j) + \varepsilon_t^{Yj} \tag{4}$$

$$\ln\left(\frac{w_t^jL_t^j}{P_t^jY_t^j}\right) = \ln\left(1-\pi_0^j\right) + \left(\frac{\sigma^j-1}{\sigma^j}\right)\left[\ln\left(\frac{L_t^j/L_0^j}{Y_t^j/Y_0^j}\right) + \ln\left(\frac{\Gamma_t^{Lj}}{\Gamma_0^{Lj}}\right) + \ln(\xi^j)\right] + \varepsilon_t^{Lj} \tag{5}$$

$$\ln\left(\frac{Y_t^j - w_t^jL_t^j}{P_t^jY_t^j}\right) = \ln\left(\pi_0^j\right) + \left(\frac{\sigma^j-1}{\sigma^j}\right)\left[\ln\left(\frac{K_t^j/K_0^j}{Y_t^j/Y_0^j}\right) + \ln\left(\frac{\Gamma_t^{Kj}}{\Gamma_0^{Kj}}\right) + \ln(\xi^j)\right] + \varepsilon_t^{Kj} \tag{6}$$

As explained in Klump et al. (2007*b*) the additional parameter ξ is introduced because sample averages (arithmetic or geometric) need not exactly coincide with the implied fixed point of the underlying empirical CES function.
The baseline specification assumes that technical progress has an exponential form, where γ_i^j denotes technical change associated with factor i in sector j.[13]

$$\Gamma_t^{ij} = e^{\gamma_i^j*(t-t_0)} \tag{7}$$

I estimate the system using several non-linear system estimators – non-linear least squares (NLS), feasible generalised non-linear least squares (FGNLS) and iterative feasible generalised least squares (IFGNLS) – , accounting for cross-equation parameter restrictions as well as cross-correlated errors, over the period 1980-2012.[14]

4 Estimation results

Table 1 shows the parameter estimates together with 95% confidence intervals based on robust standard errors. Qualitatively all three non-linear estimators – NLS, FGNLS and IFGNLS – show similar results. Statistics diagnostics such as the log-likelihood and information criteria (Akaike and BIC) favor the IFGNLS[15] estimation (Column 3), which will represent the benchmark in the rest of the paper. Residuals diagnostics confirm that the system residuals are stationary, a necessary condition in the presence of unit-roots in the dependent variables (e.g., factor income shares and output). The results show that there are substantial differences in the easiness of factor substitution across sectors and that technologies have evolved at very different rates[16], both across factors and across sectors. I find that labor and capital are complements both in low-skilled and high-skilled manufacturing and in high-skilled services (estimated elasticity of substitution significantly below unity). Labor and capital are instead substitutes in the low-skilled services. The estimated above-unity elasticity of substitution in the low-skilled services suggests that labor-replacing automation (e.g., self-service checkouts, flexible robots) took place at a faster rate in the low-skilled services than in high-skilled ones as automation moved from production to services and relatively less complex occupations were easier to replace.

[13]The combination $\gamma_K^j = \gamma_L^j > 0$ denotes Hicks-neutral technical progress in sector j; $\gamma_K^j > 0$ and $\gamma_L^j = 0$ denotes Solow neutrality; $\gamma_K^j = 0$ and $\gamma_L^j > 0$ stands for Harrod neutrality and $\gamma_K^j \neq \gamma_L^j > 0$ indicates general factor-augmenting technical progress.

[14]The estimation via iterative generalised least squares does not converge if I start the sample with the first available observation in 1973. In Japan, the economy was hit by an important oil price shock and variables that enter the system show big jumps which is likely to affect the convergence. Other papers using similar data set resume their analysis starting 1980 (see Mućk (2017).

[15]Asymptotically equivalent to maximum likelihood.

[16]Estimated average factor-augmenting technical changes translate into different profiles of the level of technical progress (see Appendix). Capital-augmenting technical progress increases across the sample in all sectors, apart from in the low-skilled manufacturing. Labor-augmenting technical progress increases over the sample in high-skilled manufacturing and decreases in high-skilled services and it is very small in low-skilled manufacturing and services sectors.

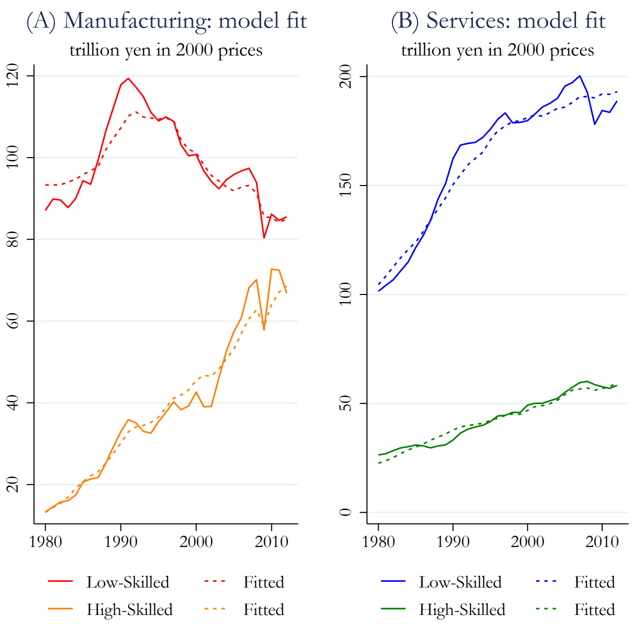
Table 1: Sectoral supply-system estimation (exponential TP)

	NLS	FGLS	IFGLS
	Low-skilled Manufacturing		
σ	0.541***	0.547***	0.525***
	0.469:0.613	*0.538:0.557*	*0.518:0.531*
γ_L	0.007***	0.006***	0.005*
	0.004:0.010	*0.004:0.008*	*0.004:0.006*
γ_K	-0.010***	-0.009***	-0.010***
	-0.014:-0.005	*-0.011:-0.007*	*-0.011:-0.008*
ξ	1.002***	1.002***	0.998***
	0.992:1.015	*0.997:1.006*	*0.998:1.007*
$\sigma = 1$	0.000	0.000	0.000
$\gamma_K = \gamma_L$	0.000	0.000	0.000
	High-skilled Manufacturing		
σ	0.904***	0.867***	0.774***
	0.805:1.003	*0.855:0.885*	*0.768:0.780*
γ_L	0.023	0.034***	0.044***
	-0.031:0.077	*0.027:0.041*	*0.039:0.049*
γ_K	0.077	0.055***	0.036***
	-0.017:0.171	*0.044:0.066*	*0.031:0.042*
ξ	0.991***	0.984	0.992***
	0.957:1.026	*0.970:0.998*	*0.978:1.005*
$\sigma = 1$	0.058	0.000	0.000
$\gamma_K = \gamma_L$	0.478	0.017	0.144
	Low-skilled Services		
σ	1.601***	1.445***	1.313***
	1.405:1.800	*1.434:1.455*	*1.304:1.323*
γ_L	0.018***	0.015***	0.010***
	0.015:0.020	*0.014:0.016*	*0.009:0.012*
γ_K	0.003	0.006***	0.014***
	-0.004:0.009	*0.003:0.010*	*0.011:0.017*
ξ	0.990***	0.990***	0.983***
	0.980:1.000	*0.983:0.996*	*0.977:0.988*
$\sigma = 1$	0.000	0.000	0.000
$\gamma_K = \gamma_L$	0.000	0.000	0.079
	High-skilled Services		
σ	0.781***	0.705***	0.613***
	0.678:0.886	*0.698:0.714*	*0.609:0.619*
γ_L	-0.025***	-0.020***	-0.016***
	-0.036:-0.014	*-0.023:-0.018*	*-0.018:-0.014*
γ_K	0.061**	0.046***	0.029***
	0.014:0.107	*0.040:0.051*	*0.026:0.032*
ξ	1.024	1.015***	1.010***
	0.997:1.052	*1.002:1.028*	*0.998:1.022*
$\sigma = 1$	0.000	0.000	0.000
$\gamma_K = \gamma_L$	0.003	0.000	0.000
ll	994.898	1027.78	1040.75
aic	-1957.8	-2023.56	-2049.49
bic	-1933.85	-1999.62	-2025.55

In terms of efficiency gains, the results show that high-skilled sectors benefited more than low-skilled sectors from larger capital-augmenting technical change. Over the 1980-2012 period, high-skilled manufacturing and high-skilled services display high and positive average capital-augmenting technical change

(4% and 3%).[17] Capital-augmenting technical change was on average smaller in low-skilled services (2%) and slightly negative in low-skilled manufacturing. The faster accumulation of IT capital in high-skilled sectors is likely to have boosted the efficiency of capital as computers became cheaper and more performant. Between 1980 and 2012 the IT capital share in total capital stock increased by about 20pp in high-skilled sectors, which compares with an increase of 10pp in low-skilled sectors. Average labor-augmenting technical change is found to be the highest in the high-skilled manufacturing sector (4.7%). The other sectors display more modest growth rates (0.3% in low-skilled manufacturing and 0.8% in low-skilled services) or even negative ones (e.g., high-skilled services sector at -2%). The non-intuitive, but robust finding of negative labor-augmenting technical change in high-skilled services might reflect the increasing reliance on elderly and non-regular employment given Japan's labor shortages.[18] The Japanese labor market is shaped by duality, a divide between regular and non-regular employees in terms of employment regulations and wages. Regular employees are hired directly by their employers, work full-time and have an open-ended contract. Non-regular workers include part-time workers, temporary workers, dispatched workers (from temporary labor agencies), entrusted employees, and contract employees. They suffer from lower job security and career prospects, are paid lower wages and receive significantly less social insurance. Since 1980, the Japanese economy has witnessed a steady increase in non-regular employment, and this was especially the case in the high-skilled services, where the share of part-time workers in total workers increased threefold to 30% in 2012.[19] Several studies document that such workers are likely to see their productivity eroding, in light of limited opportunities for training or on-the-job learning and in general poorer job prospects (see Fukao et al. (2006), Stucchi et al. (2011) and OECD (2018)).

Figure 3: Sectoral value added: model fit



Note: The solid lines show the real value added in levels; the dotted lines labeled 'fitted' show the model fit for the real value added.

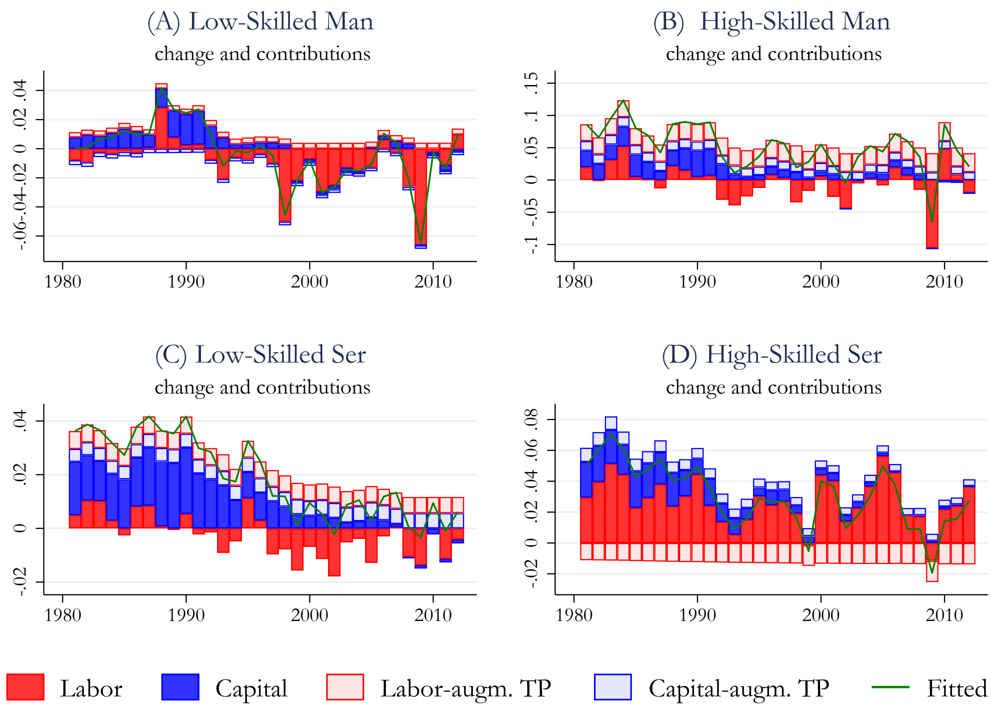
[17] Technical change is estimated at the point of normalisation which is equivalently the sample average point.

[18] Negative demographic trends meant that Japan experienced a fast decline in its productive population ratio and that the share of older cohorts in employment had increased. This phenomenon has affected different sectors in a different proportion. In 1980 the share of workers aged 55 and over in total workers has been the highest in high-skilled services sector (15.5%), followed by low-skilled services (12.2%) and it was the lowest for high-skilled manufacturing (8.3%). By 2012 the share of workers aged 55 and over increased close to 25% in high-skilled sectors and to 30% in low-skilled sectors.

[19] In low-skilled services sector the share of part-time workers doubled to reach 22% in 2012. While the share of part-time workers has increased also in the manufacturing sector, it remains significantly lower than in services (at 13.2% in high-skilled manufacturing and 16.3% in low-skilled manufacturing).

Figure 3 shows the model prediction for sectoral real value added. Panel A and B show that the model is able to capture underlying trends in the evolution of value added in all sectors. While it is always possible to improve the fit of the model by adding dummy variables, the purpose of this analysis is to investigate broader economic trends in the data rather than accommodating local changes.

Figure 4: Real valued added growth decomposition



Note: The fitted green line shows the fit for the sectoral real value added in annual changes from the estimated sectoral CES production function. The contributions to the annual growth are computed by constructing counterfactual scenarios for real value added where each factor and type of technical change is kept constant at a time. The contribution of each factor is then computed as the difference between the the fitted real value added and the relevant counterfactual.

Figure 4 decomposes the predicted change in value added in contributions of factor inputs and factor-augmenting technical progress. Apart from high-skilled services, all sectors registered a declining contribution of labor input, in particular after 1990. This negative trend relates to population ageing and a decline in working hours per worker.[20] The contribution of the capital stock to value added growth diminished in all sectors. After 1990s, firms' balance sheet impairments (Koo (2003)) and deflation are likely to have slowed down capital accumulation. However, the magnitude of the slowdown varies largely across sectors, with the value added growth of the low-skilled services, which relied strongly on capital accumulation prior to the 1990s, being most affected.

[20]There are two important elements regarding the decline in working hours per worker: (i) Japan's labor Standards Act was amended in 1987 and 'a 40 hour, five day week' was introduced leading to a gradual decline in working hours until the full implementation of the amendment in 1997 (see Hayashi & Prescott (2002)) (ii) the share of part-time workers increased, in particular in low-skill services, contributing to a further decline in the average working hours of employees.

5 Sectoral labor allocations

In this section I analyse the optimal allocations of labor conditional on producing a given amount of output (Y) and given factor prices (i.e., wages or cost of labor (w) and user cost of capital (r)). To do so I use the estimated sectoral labor- and capital-augmenting technical change and sectoral elasticities of substitution between labor and capital. Solving the firms' problem under perfect competition for product and factor prices gives the optimal input combination which requires that the ratio of marginal products equals the ratio of factor prices. Accordingly, the optimal capital to labor ratio in each sector is given by:

$$\frac{\mathbf{K}_t^j}{\mathbf{L_t^j}} = \frac{1-\pi_0^j}{\pi_0^j}\left(\frac{\Gamma_t^{Kj}}{\Gamma_t^{Lj}}\right)^{\sigma^j-1}\left(\frac{w_t^j}{r_t^j}\right)^{\sigma^j}, \tag{8}$$

By substituting K_t^j from the optimal capital-labor ratio into the production function (equation (1)), conditional labor demand at the sectoral level can be expressed as:

$$L_t^j = \left(\pi_0^j\left(\frac{\pi_0^j}{1-\pi_0^j}\frac{\Gamma_t^{Kj}}{\Gamma_t^{Lj}}\frac{w_t^j}{r_t^j}\right)^{1-\sigma^j} + (1-\pi_0^j)\right)^{-\frac{\sigma^j}{1-\sigma^j}}\frac{Y_t^j}{\Gamma_t^{Lj}} \tag{9}$$

To assess the performance of CES production function and the importance of different elasticity of substitution I also compute the sectoral labor allocations using estimated sectoral Cobb-Douglas production function, explicitly normalised, with sector-specific labor income share.

$$Y_t^j = Y_0^j\,\frac{\alpha^j}{1-\alpha^j}\left(\frac{\Gamma_t^j K_t^j}{\Gamma_0^j K_0^j}\right)^{\alpha_j}\left(\frac{\Gamma_t^j L_t^j}{\Gamma_0^j L_0^j}\right)^{1-\alpha_j} \tag{10}$$

Accordingly, the labor demand can be expressed as:

$$L_t^j = \frac{\alpha^j}{1-\alpha^j}\left(\frac{K_0^j}{L_0^j}\frac{w_t^j}{r_t^j}\right)^{-\alpha^j}\frac{Y_t^j}{\Gamma_t^j}\frac{\Gamma_0^j}{Y_0^j} \tag{11}$$

I then use equation 9 to explore the three main mechanisms proposed by the literature for structural changes in sectoral labor inputs:

(i) **Sectoral differences in technical progress**: the second term Y_t^j/Γ_t^L in Equation 9 captures that sectors with higher level of labor-augmenting technical progress need less labor input to produce a given amount of output, and therefore when technical progress grows they release resources, which are then employed in lower-productivity sectors. Additionally, another channel operates via the first term of equation 9 as conditional labor demand varies with changes in relative factor-augmenting technical change, but the magnitude and the direction is conditional on the magnitude of the elasticity of substitution. For example, in the presence of net capital-augmenting technical change ($\Gamma_t^K > \Gamma_t^L$) and when capital and labor are complements ($\sigma < 1$), firms reduce the capital-labor ratio until the marginal products of factors are equal to factor prices and increase the capital-labor ratio when labor and capital are substitutes.

(ii) **Differences in flexibility of factor substitutions**: the more flexible sector is able to replace faster the factor that becomes scarcer (relatively more expensive).[21]

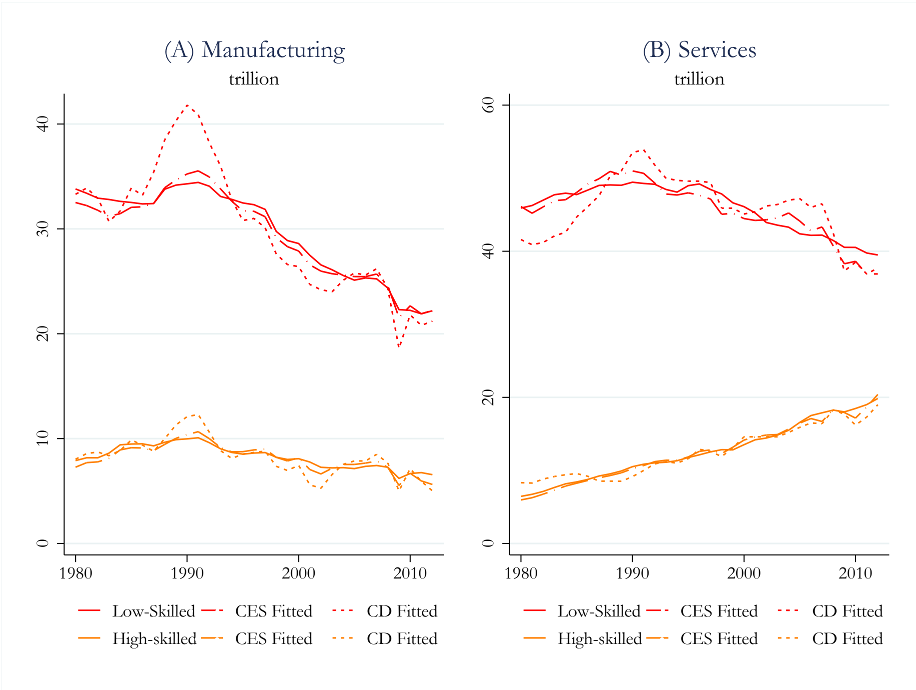
(iii) **Differences in factor income shares**: The importance of this channel for conditional labor demand is captured by the capital intensity parameter (π_0), since the response of labor demand to

[21] For example, when the aggregate capital-labor ratio increases and labor becomes more expensive relative to capital (as reflected in a lower ratio between the rental rate of capital and wages), the more flexible sector is able to absorb more capital and to release more labor vis-à-vis the less flexible sector. For two sectors that differ only in the elasticity of substitution, higher labor costs will lead to a stronger reduction in conditional labor demand in the more flexible sector.

changes in relative factor prices (w/r) or relative changes in factor-augmenting technical change depends on the magnitude of capital intensity.[22]

Figure 5 Panel A and B shows that the estimated conditional labor demand based on the CES specification mirrors well the sectoral labor allocation in the data and outperforms the prediction based on a standard sectoral Cobb-Douglas production function. On the drivers, I analyse first how **sectoral differ-**

Figure 5: Labor input: actual and model-fit



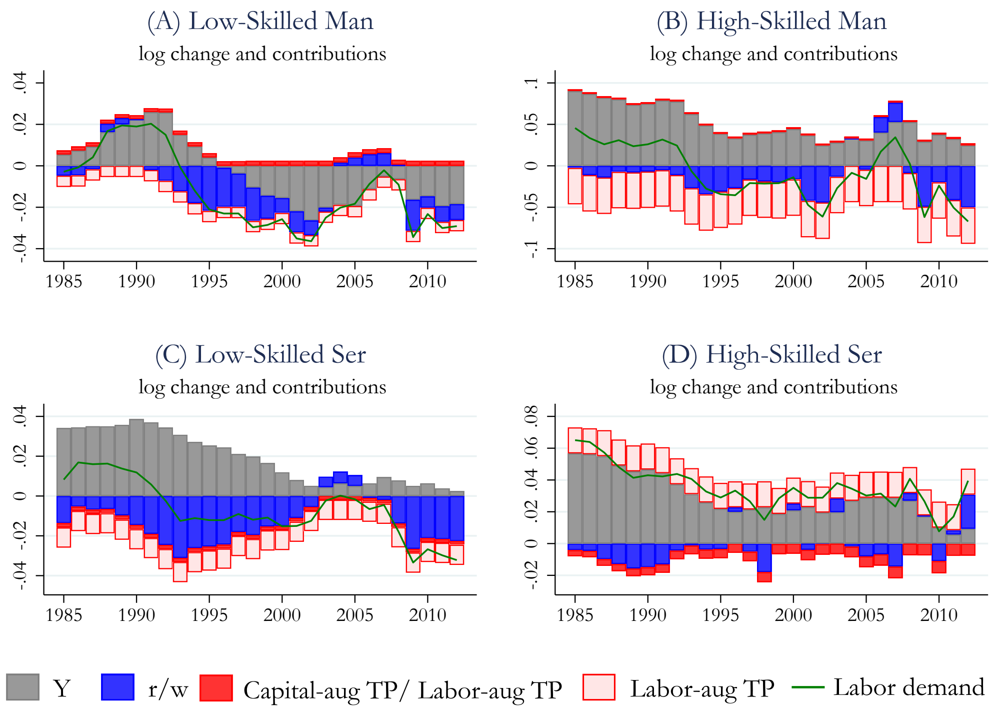
Note: The figure shows the observed number of hours worked versus the predicted levels from the conditional demand equation using the CES and CD specifications.

ences in technical progress shaped labor allocation. Figure 6 decomposes the change in predicted labor demand into the contribution from: labor-augmenting technical change (from the second term of equation 9), the ratio of capital-augmenting technical change to labor- augmenting technical change (from the first term of equation 9), the ratio of wages to the user cost of capital and the real value added. Positive labor-augmenting technical change freed-up labor in low-skilled services and high-skilled manufacturing (Panel B and Panel C), while more labor was needed to produce the same amount of output given the estimated decline in labor efficiency in high-skilled services (Panel D). However, in high-skilled services, this effect was dampened by net capital-augmenting technical change which lowers the capital-labor ratio, until relative marginal product of factors equals the relative factor prices.[23] Second, I quantify the relevance of **differences in the flexibility of factor substitutions** for changes in predicted labor demand (hours worked) by constructing counterfactual scenarios that embody different magnitudes for the elasticity of substitution while keeping everything else unchanged. Table 2 provides the sensitivity of changes in labor demand (hours worked) between the average of 2008-12 and the average of 1980-84 to different elasticity of substitutions (baseline +/- 0.5). If sectors would have displayed a higher flexibility in combining production factors, the substitution effect generated by relatively cheaper capital would have been stronger in all sectors leading to a smaller increase in labor demand in high-skilled services and more pronounced declines in labor demand in all the other sectors. Such effects are quantitatively important.

[22] An increase in the aggregate capital-labor ratio raises output more in sectors with higher capital intensity.

[23] The intuition is that an increase in capital-augmenting technical change means that less capital is needed to produce the same amount of output. If labor and capital are complements, firms would also decrease the amount of labor they hold until relative marginal products equal relative factor prices.

Figure 6: Conditional labor demand growth decomposition



Note: The green line shows the fit for the sectoral hours worked according to the conditional labor demand and estimated technology parameters, in changes over a 5-year moving average. The contributions are computed by constructing counterfactual scenarios for hours worked using the conditional demand equation, where each factor cost and type of technical change is kept constant at a time. The contribution of each factor is then computed as the difference between the the conditional demand prediction for sectoral hours worked and the relevant counterfactual.

Table 2: Labor demand sensitivity to the elasticity of substitution

Elasticity of substitution				
	Baseline $\hat{\sigma}$	Scenario 1 $\hat{\sigma}+0.5$	Scenario 2 $\hat{\sigma}-0.5$	
Low-skilled manufacturing	0.525	1.025	0.025	
High-skilled manufacturing	0.77	1.27	0.27	
Low-skilled services	1.31	1.81	0.81	
High-skilled services	0.61	1.11	0.11	
Changes in labor demand: 2008-2012 vs 1980-1984				
	Baseline	Scenario 1	Scenario 2	Observed
Low-skilled manufacturing	-29.1 %	-36.5%	-10.4 %	-31.8 %
High-skilled manufacturing	-21.9 %	-40.5 %	8.3 %	-20.8 %
Low-skilled services	-17.3 %	-30.5 %	-1.2 %	-14.1 %
High-skilled services	170.9 %	103.5 %	367.7 %	158.9 %

Finally, I quantify the importance of **differences in factor income shares** for labor demand changes. Table 3 shows changes in predicted labor demand (hours worked) between the average of 2008-12 and the average of 1980-84 assuming that the capital intensity (e.g., the sample average of the capital income share) equals its observed value +/- 0.2pp. Compared with the baseline values, higher capital intensity leads to a faster decline in labor demand in high-skilled manufacturing, milder decline in labor demand in low-skilled services and less stronger increase in labor demand in high-skilled services. The largest variation is observed in the high-skilled services sector, which displays the lowest value of capital intensity in the actual data. However, quantitatively these effects appear less important than the previous two.

Table 3: Labor demand sensitivity to capital intensity

Capital intensity				
	Baseline π_0	Scenario 1 $\pi_0 + 0.2$	Scenario 2 $\pi_0 - 0.2$	
Low-skilled manufacturing	28%	48%	8%	
High-skilled manufacturing	36%	56%	16%	
Low-skilled services	38%	58%	18%	
High-skilled services	21%	41%	1%	
Changes in labor demand: 2008-2012 vs 1980-1984				
	Baseline	Scenario 1	Scenario 2	Observed
Low-skilled manufacturing	-29.1%	-30.1%	-29.9 %	-31.8%
High-skilled manufacturing	-21.9%	-26.3 %	18.5%	-20.8%
Low-skilled services	-17.3 %	-12.5 %	-20.6%	-14.1%
High-skilled services	170.9 %	145.5 %	164.0%	158.9%

6 Factors income shares

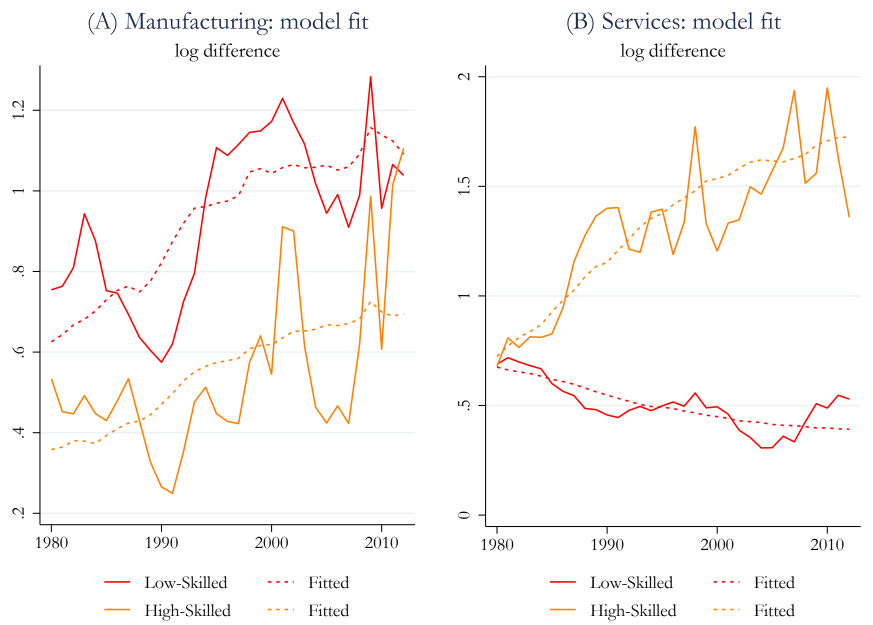
This section analyses the driving factors of relative factor income shares. Equation 12, obtained by dividing equation 4 to equation 3, shows that factor income shares depend on the capital deepening dynamics and on factor-augmenting technical progress (i.e., as captured by the ratio of capital-augmenting technical change to labor-augmenting technical change). The direction of the effect depends on the value of the elasticity of substitution between capital and labor. When input factors are gross complements an increase in capital deepening (K_t^j/L_t^j) reduces the ratio of capital compensation to labor compensation $(r_t^j K_t^j / w_t^j L_t^j)$ and lowers its relative marginal product f_K^j/f_L^j. Furthermore, assuming factors are gross complements, an increase in capital-augmenting technical progress relative to labor-augmenting technical progress $(\Gamma_t^{Kj}/\Gamma_t^{Lj})$ decreases its relative marginal product for given capital-labor allocation and the relative factor income shares.

$$\frac{r_t^j\,\mathbf{K}_t^j}{w_t^j\,\mathbf{L_t^j}} = \frac{\pi_0^j}{1-\pi_0^j}\left(\frac{\Gamma_t^{Kj}/\Gamma_0^{Kj}K_t^j/K_0^j}{\Gamma_t^{Lj}/\Gamma_0^{Lj}L_t^j/L_0^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}, \tag{12}$$

In the 'Stylised facts' sub-section I show that the aggregate labor income share is driven to a large extent by within sectoral shifts, with the labor income share decline concentrated in low-skilled services. Equation 12 can be used to shed further light on these facts. Figure 7 shows the model fit for the relative labor income share (e.g., the labor income share divided by the capital income share or equivalently the ratio of labor compensation to capital compensation). The model is able to capture well long-term trends in relative labor income shares both within manufacturing and services, while the unexplained variations are likely to reflect distortions from equilibrium conditions.

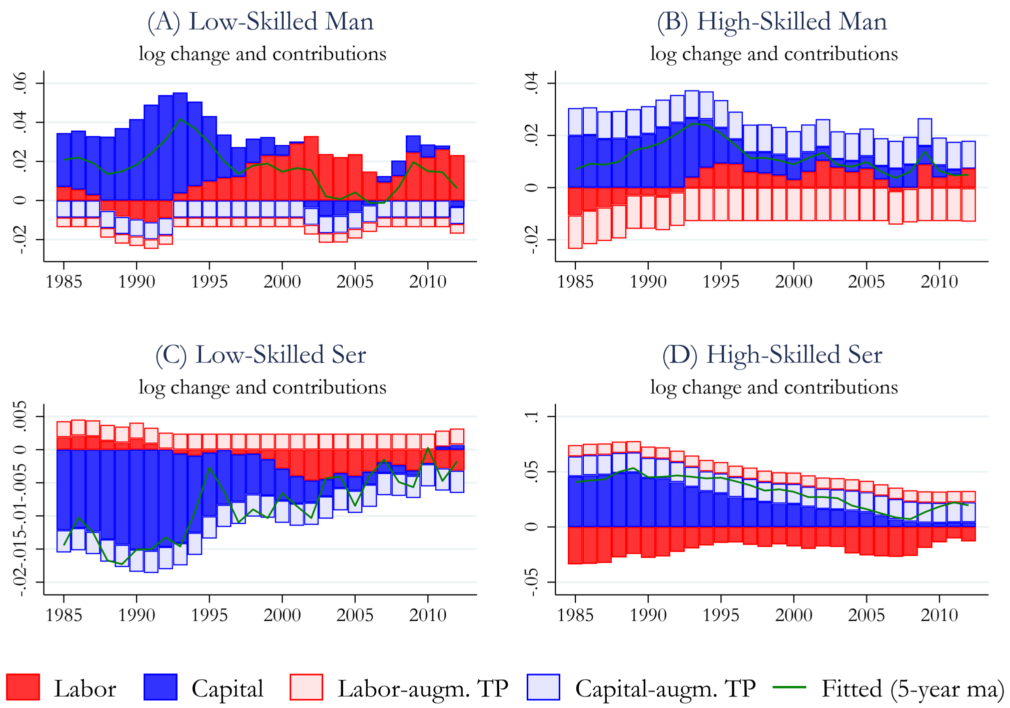
Figure 8 Panels A to D decompose the changes in relative labor income shares at the sectoral level in contributions from capital, labor and factor-augmenting technologies. Panel C shows that the decline in the relative labor income share in low-skilled services can be explained by two facts: technical progress has been net capital-augmenting (change in capital-augmenting technical progress > change in labor-augmenting technical progress) and above-unity elasticity of substitution between capital and labor. The latter implies that with increasing capital deepening, net capital-augmenting technical change has increased the relative marginal product of capital to labor and thus the relative factor prices. For the other sectors which display input factors complementary ($\sigma < 1$) the increase in the capital-labor ratio contributed to higher relative labor income shares. In terms of technical progress, the results show that positive capital-augmenting technical change increased the labor income share in high-skilled services, while positive-labor augmenting technical change contributed to the decline in the labor income share in low- and high-skilled manufacturing sectors.

Figure 7: Relative labor income share: model fit and its change decomposition



Note: The dotted lines labeled 'fitted' show the relative factor income shares according to equation 12, using the estimated technology parameters.

Figure 8: Relative labor income share change: a decomposition



Note: The green line shows the fit for the relative labor income share using eq. 12 and estimated technology parameters, in changes over a 5-year moving average. The contributions are computed by constructing counterfactual scenarios for the relative labor income share, where each factor and type of technical change is kept constant at a time. The contribution of each factor is then computed as the difference between the predicted relative labor income share and the relevant counterfactual.

7 Robustness

To check the validity of results, I re-estimate the supply-system parameters under a range of different conditions, including by: (i) filtering out transitory movements in observed variables, (ii) assuming a more flexible forms for technical progress, (iii) using an alternative definition for the labor income share, (iv) using arithmetic averages for computing the capital intensity at the normalisation point, (v) using quality adjusted measures for labor and capital inputs. Qualitatively, the tests confirm the main findings, but they also point to some uncertainty around the point estimates, which are somewhat sensitive to the modeling approach and data used in the estimation.

7.1 Filtering out transitory variations

The estimation of the parameters of the production function relies on the long-run relations among relevant variables, as reflected by the optimally conditions. Short-run cyclical movements, due to market frictions, will not be captured by the model and most likely they end-up in the system residuals. Recent work by Chirinko & Mallick (2017) argues that if the transitory variation in the data is not filtered out, estimates of the elasticity of substitution might suffer from a significant downward bias. To see how this might impact the estimation results, I use two different low-pass filters (Hodrik & Prescott (HP) and Baster & King (BK)) for all observable variables (value added, hours worked, capital stock and labor income share) in order to isolate the long-term trends, under the assumption that periodicities greater than eight years contain useful information for the parameter estimates. I then re-estimate the baseline supply-system using the long-term trends in the data, on the same sample (1980-2012) but also on a longer sample (1974-2012). Using the HP long-term trends for all variables overcomes the convergence issues encountered when using the iterative feasible generalized least square estimator over actual data, because the filter removes the large cyclical variations related to the oil crisis in 1973 and in 1977. Table 4 shows the results. Column 2 & 3 show the supply-side parameter estimates over the period 1980-2012.[24] Qualitatively results are very similar to the baseline; the elasticity of substitution in the low-skilled services sector is consistently estimated above unity and estimates are below unity for the other sectors. In terms of the point estimate, there is some evidence that including business cycle frequency in the data causes a downward bias in the estimated elasticity of substitution. This is the case in the high-skilled manufacturing sector and the low-skilled services sector, where using the variables' long-term trends results in higher elasticity of substitution, suggesting that these sectors are somewhat more flexible in combining labor and capital. The evidence is confirmed by using a longer sample (column 5). When using the BK filtered data over the complete sample the estimation displays implausible results, in particular for technical progress in the low-skilled manufacturing (column 4). Across the estimation using the filtered data, information criteria and the log-likelihood favor the use of the HP filter (column 3 & 5).

[24]The Baster & King filter uses a smoother of three years for annual data, meaning that the number of observation is 27 compared with 33 in the baseline regression.

Table 4: Sectoral supply-system estimation (Low-Pass Filter)

	1980-2012			**1974-2012**	
	Baseline	BK	HP	BK	HP
		Low-skilled Manufacturing			
σ	**0.525*****	0.605***	0.619***	0.999***	0.730***
γ_L	**0.005****	0.002***	0 .008***	1.113	0.003***
γ_K	**-0.010*****	-0.001***	-0.006***	-2.812	0.006***
ξ	**0.998*****	1.004***	1.006***	1.013***	0.994***
		High-skilled Manufacturing			
σ	**0.774*****	0.803***	0.904***	0.769***	0.974*
γ_L	**0.044*****	0.043***	0.038***	0.079***	0.047*
γ_K	**0.036*****	0.038***	0.044***	-0.009***	0.044***
ξ	**0.992*****	1.090***	1.080***	1.004***	0.958***
		Low-skilled Services			
σ	**1.313*****	1.417***	1.517***	3.330***	1.688***
γ_L	**0.010*****	0.015***	0.017**	0.190***	0.014***
γ_K	**0.014*****	0.007***	0.013	0.014***	0.012***
ξ	**0.983*****	1.002***	1.055***	0.973***	0.988***
		High-skilled Services			
σ	**0.613*****	0.765***	0.683***	0.656***	0.817***
γ_L	**-0.016*****	-0.022***	-0.022***	-0.019***	-0.022***
γ_K	**0.029*****	0.057***	0.033***	0.020***	0.060***
ξ	**1.010*****	0.995	1.002**	1.054***	1.004***
ll	**1040.75**	928.03	1503.81	991.670	1463.37
aic	**-2049.49**	-1824.06	-2975.61	-1951.40	-2894.75
bic	**-2025.55**	-1803.33	-2951.67	-1927.45	-2868.13

7.2 Time-varying technical progress

The shift in the macroeconomic conditions in Japan, especially after the 1990 recession, could signal that technical change has not been constant over time. To allow for some variation in technical progress, I relax the conventional estimation constraint of exponential technical progress by assuming technical change follows a Box-Cox transformation as in Klump et al. (2007*a*). The exact functional form of sectoral augmenting technical progress is defined as:

$$\ln\left(\frac{\Gamma_t^{ij}}{\Gamma_0^{ij}}\right) = \frac{t_0\gamma_i^j}{\lambda_i^j}\left[\left(\frac{t}{t_0}\right)^{\lambda_i^j} - 1\right] \tag{13}$$

The curvature parameter λ_i^j determines the shape of technical progress; $\lambda_i^j = 1$ yields the (textbook) linear specification; $\lambda_i^j = 0$ a log-linear specification and $\lambda_i^j < 0$ a hyperbolic implying that the level of technology is bounded above. When γ_i^j is different from 0, deviations of λ_i^j from unity implies either a smoothly accelerating or decelerating technical change over the sample period. This is a reasonable relaxation of conventional estimation constraints, especially, in the context of the structural transformation in Japan, where sectors are likely to have registered different technical change across time. Table 5 shows the estimation results using again the three estimators. Qualitatively the baseline results are confirmed. Across estimators, IFGLS (column 3) appears to perform better in terms of likelihood and information criteria, but it delivers unreasonably large technical change estimates in the high-skilled services. Instead, the FGLS estimator (column 2) performs almost as well as IFGLS in terms of likelihood and information criteria, but in addition it delivers reasonable parameters estimates, including for the parameter ξ which is estimated closer to its expected value of around unity in the high-skilled manufacturing sector. I will focus therefore on these results. Compared with the baseline regression, these estimates allow to understand better the evolution of technical progress as the estimated values for the curvature parameter depart in some cases significantly from unity. There are two main differences compared to the baseline specification: (i) in high-skilled services, labor-augmenting technical progress registered a pronounced deceleration in the first part of the sample and (ii) in high-skilled manufacturing, capital-augmenting technical progress shows a pronounced acceleration towards the end of sample.

Table 5: Sectoral supply-system estimation (Box-Cox TP)

	Low-skilled Manufacturing			**High-skilled Manufacturing**		
	NLS	FGLS	IFGLS	NLS	FGLS	IFGLS
σ	0.450***	0.486***	0.405***	0.876***	0.876***	0.672***
γ_L	0.007***	0.006***	0.005***	0.027*	0.036***	0.041***
λ_L	0.137	0.023	-0.299***	0.444	0.652***	0.667***
γ_K	-0.014***	-0.013***	-0.013***	0.064***	0.046***	0.029***
λ_K	1.192***	1.110***	0.618***	2.230***	2.580***	3.280***
ξ	1.020***	1.020***	1.000***	0.950***	0.934***	0.908***
	Low-skilled Services			**High-skilled Services**		
σ	1.560***	1.250***	1.392***	0.948***	0.797***	0.931***
γ_L	0.016***	0.009***	0.013***	-0.106**	-0.025***	-0.080***
λ_L	0.699***	0.878***	0.941***	0.369***	0.158***	0.173***
γ_K	0.003	0.015	0.009***	0.384*	0.073***	0.278***
λ_K	-0.213	0.195	0.096***	0.771***	0.715***	0.597***
ξ	1.010***	1.010***	0.993***	0.989***	0.976***	0.976***

Likelihood & information criteria

	NLS	FGNLS	IFGNLS
ll	1028.68	1074.24	1090.54
aic	-2009.36	-2100.48	-2133.09
bic	-1973.44	-2064.57	-2097.17

7.3 Other robustness tests

I do three additional tests by checking how the results change when: **[1]** the labor income share is defined as compensation of employees over total value added including taxes and subsidies **[2]** the capital intensity at the normalisation point is computed using arithmetic averages instead of geometric ones and **[3]** the labor and capital inputs are adjusted for changes in quality. Table 6 shows the results using the IFGLS estimator. Qualitatively all tests broadly confirm our baseline results. To recall, in the baseline specification the labor income share is the ratio of the total compensation of employees and mixed income over total value-added excluding taxes and subsidies. Column 1 shows results of an estimation where total value-added income, including taxes and subsides, is used as done in many applications. In terms of the elasticity of substitution, the estimates show a higher elasticity of substitution for low-skilled manufacturing, while results are broadly unchanged for the other sectors. In terms of technical progress, these results suggest somewhat higher technical change in high-skilled manufacturing and somewhat lower in high-skilled services. Column 2 shows the results using arithmetic averages for computing the factor income shares at the normalisation point. There are only mild discrepancies compared to the baseline results featuring geometric averages. Column 3 uses quality-adjusted labor and capital input series. The reason for this is that the number of hours worked or the stock of capital does not necessary represent the best measure for the flow of labor/capital services because it ignores the differences in the quality of services provided by different workers/different capital assets. I address this issue by using quality-adjusted labor input and capital service inputs, available in the Japan Industrial Productivity Database. Following Gollop & Jorgenson (1980), the labor input is computed by weighting the hours worked by different categories of workers by their labor compensation share in total sectoral labor compensation. Following Jorgenson & Griliches (1967), the capital services input is computed by weighting different types of capital assets by the value of the respective asset in the total asset value, assuming that the marginal productivity of capital by asset type equals the cost of capital by asset type. In this case, the elasticity of substitution would be somewhat higher for all sectors, except for low-skilled services, where the elasticity would be estimated somewhat lower, but still significantly above unity. At the same time, this estimation reinforces the finding that technical change was predominantly capital-augmenting since it estimates somewhat higher average growth in capital-augmenting technical progress and lower one in labor-augmenting technical change across sectors.

Table 6: Sectoral supply-system estimation (Other tests)

	Baseline	[1]	[2]	[3]
	Low-skilled Manufacturing			
σ	**0.525*****	0.704***	0.650***	0.676***
γ_L	**0.005****	0.005***	0 .003***	-0.004***
γ_K	**-0.010*****	-0.011***	-0.001	-0.003**
ξ	**0.998*****	0.993***	1.002***	0.999***
	High-skilled Manufacturing			
σ	**0.774*****	0.735***	0.785***	0.891**
γ_L	**0.044*****	0.056***	0.047***	0.021***
γ_K	**0.036*****	0.017***	0.031***	0.051***
ξ	**0.992*****	0.990***	0.988***	0.0997***
	Low-skilled Services			
σ	**1.313*****	1.300***	1.268***	1.197***
γ_L	**0.010*****	0.003***	0.008**	-0.001
γ_K	**0.014*****	0.022***	0.019	0.019***
ξ	**0.983*****	0.976**	0.985***	0.988***
	High-skilled Services			
σ	**0.613*****	0.590***	0.686***	0.670***
γ_L	**-0.016*****	-0.011***	-0.020***	-0.030***
γ_K	**0.029*****	0.006***	0.039***	0.031**
ξ	**1.010*****	1.019	1.010**	1.030***
ll	**1040.75**	1164.3	1040.43	1026.81
aic	**-2049.49**	-2296.6	-2048.85	-2021.62
bic	**-2025.55**	-2272.66	-2024.91	-1997.67

8 Conclusion

In this paper I quantitatively assess the importance of supply-side drivers in the transition of the Japanese economy from low-skilled sectors to high-skilled sectors and their implication for sectoral value-added growth, labor demand and labor income shares. The novelty of this paper is the estimation of a normalised CES supply system with factor-augmenting technical progress across sectors with different skill-intensity. This approach enables a much more granular understanding of developments in the Japanese economy over the period 1980-2012.

Results indicate that there are substantial sectoral differences in the substitutability of capital and labor in the production process and that the average technical growth differs both across sectors and factors. In terms of efficiency gains, results show that relative to low-skilled sectors, high-skilled ones benefited from higher capital-augmenting technical change. My estimates of technical change coupled with the estimated elasticity of substitutions assure that the predictions for conditional labor demand match well the sectoral labor allocations observed in the data, with the CES specification outperforming predictions from standard sectoral Cobb-Douglas production functions. I highlight that differences in technical change and in the magnitude of elasticity of substitution are both quantitatively important drivers of the structural transformation of the Japanese economy and of the ensued changes in labor allocations, while factor proportions appear to be less relevant. I also find that differences in the magnitude of the elasticity of substitution are key to pin down the diverging trends in the relative factor income share across low-skilled and high-skilled services.

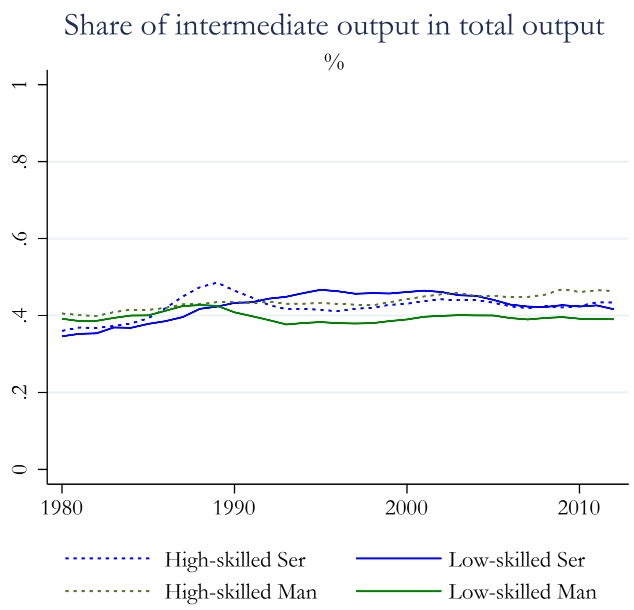
From an empirical perspective, my paper provides estimates for unobserved elasticity of substitutions and factor-augmenting technical change at the sectoral level, which can be used to calibrate multi-sectoral growth models. It also provides a battery of robustness checks and discusses potential estimation issues that could arise in the estimation of the CES supply-side system for the Japanese economy.

From a policy perspective the paper shows that for an economy confronted with population ageing and a dual labor market, the transition to high-skilled services requires a strong focus on augmenting the existing human capital and minimising the labor market duality. That would help satisfy the demand for high-skilled labor, promote growth and avoid a concentration of income towards capital owners.

A Sectoral taxonomy of skills

Manufacturing		Services	
Low-skilled	High-skilled	Low-skilled	High-skilled
Livestock products	Tobacco	Waterworks	Research (private)
Seafood products	Basic inorganic chemicals	Water supply for industrial use	Medical (private)
Flour and grain mill products	Basic organic chemicals	Electricity	Advertising
Miscellaneous foods and related products	Organic chemicals	Gas, heat supply	Other services for businesses
Prepared animal foods and organic fertilizers	Chemical fibers	Waste disposal	Broadcasting
Beverages	Miscellaneous chemical products	Wholesale	Information services & internet-based services
Textile products	Pharmaceutical products	Retail	Publishing
Lumber and wood products	General industry machinery	Finance	Video picture, sound information, character information production and distribution
Furniture and fixtures	Special industry machinery	Insurance	
Pulp, paper, and coated and glazed paper	Miscellaneous machinery	Real estate	
Paper products	Office and service industry machines	Housing	
Printing, plate making for printing and bookbinding	Electrical generating, transmission, distribution and industrial apparatus	Railway	
Leather and leather products	Household electric appliances	Road transportation	
Rubber products	Electronic data processing machines, computer equipment and accessories	Water transportation	
Chemical fertilizers	Communication equipment	Air transportation	
Petroleum products	Electronic equipment and electric measuring instruments	Other transportation and packing	
Coal products	Semiconductor devices and integrated circuit	Telegraph and telephone	
Glass and its products	Electronic parts	Mail	
Cement and its products	Miscellaneous electrical machinery equipmen	Rental of office equipment and goods	
Pottery	Motor vehicles	Automobile maintenance services	
Miscellaneous ceramic, stone and clay products	Motor vehicle parts and accessories	Entertainment	
Pig iron and crude steel	Other transportation equipment	Eating and drinking places	
Miscellaneous iron and steel	Precision machinery & equipment	Accommodation	
Smelting and refining of non-ferrous metals		Laundry, beauty and bath services	
Non-ferrous metal products			
Fabricated constructional and architectural metal products			
Miscellaneous fabricated metal products			
Plastic products			
Miscellaneous manufacturing industries			
Construction			
Civil engineering			

B Intermediate inputs across sectors



C Technical progress

Figure 9: Technical progress

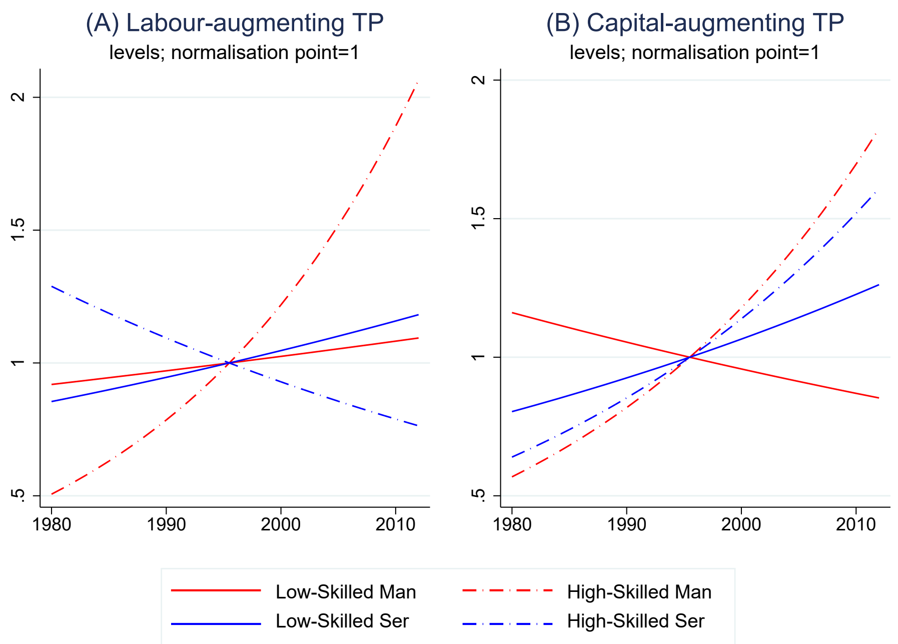
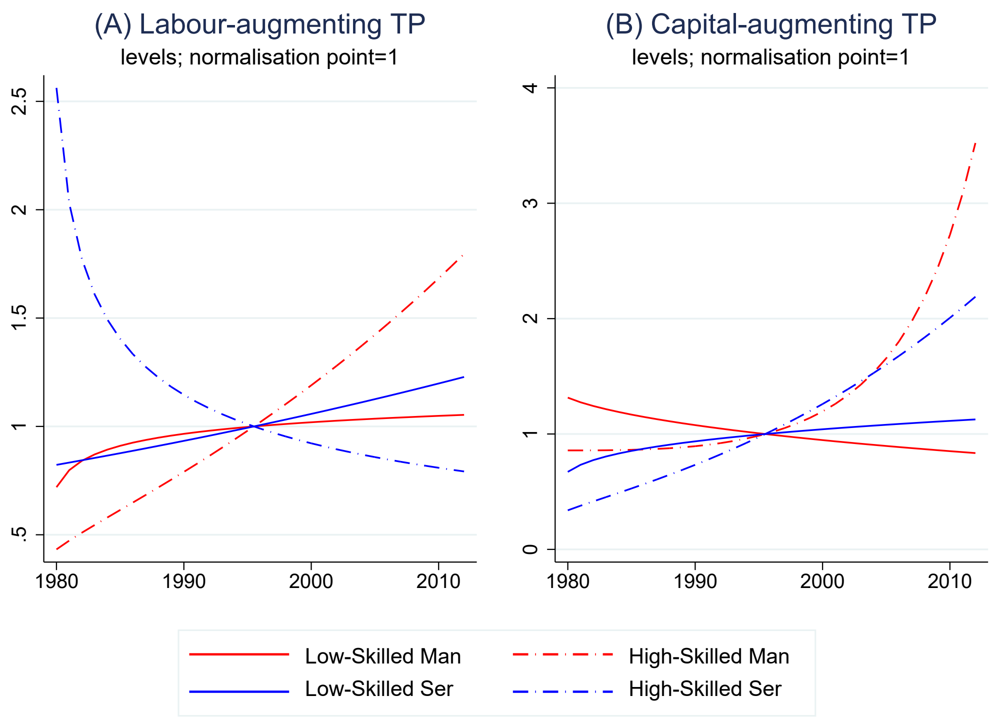


Figure 10: Technical progress - Box- Cox transformation



D Relative prices across sectors

This section assesses how well my model captures changes relative output prices. Relative price changes are an important mechanism for structural transformation. Ngai & Pissarides (2007) shows that changes in sectors' relative employment can be expressed as a function of the substitution elasticity between final goods and either differences in technical progress between sectors or changes in sectoral relative prices. I investigate changes in implied sectoral output prices of high-skilled and low-skilled services and high-skilled manufacturing relative to low-skilled manufacturing. Starting from the fact that real wages per unit of value added equal the marginal product of labor, the price of value added in sector j can be expressed as the ratio between observed nominal wages (W_t^j) and the marginal product of labor MPL_t^j.

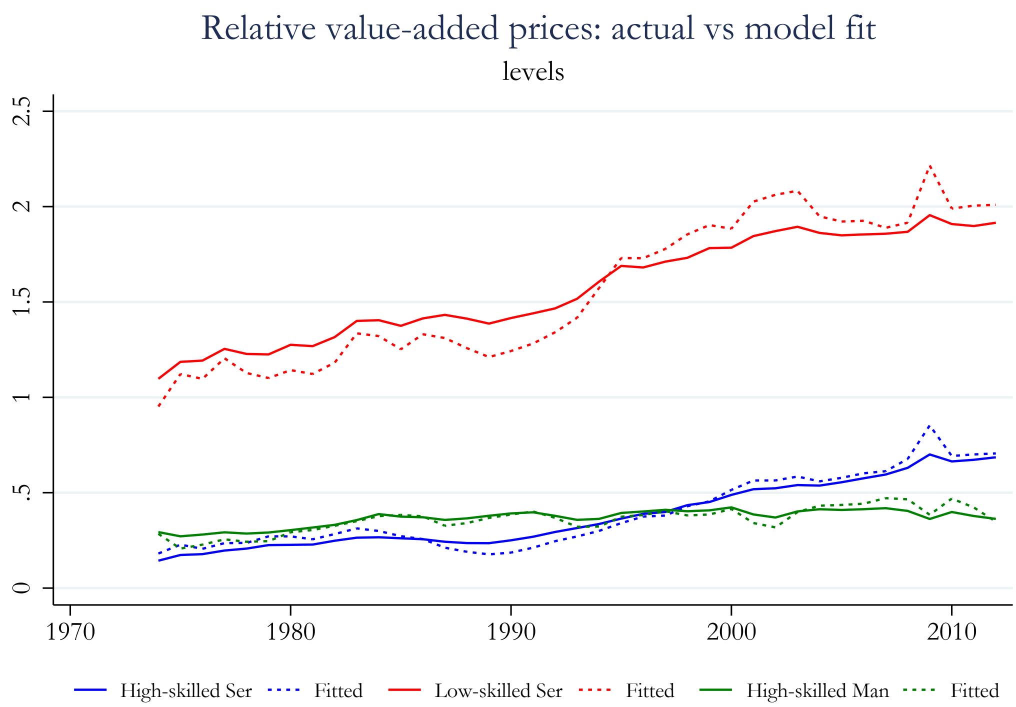
$$P_t^j = W_t^j / MPL_t^j \tag{14}$$

Dividing equation 11 by the price of value added in the low-skilled manufacturing sector, leads to the the following expression for relative prices:

$$\frac{\mathbf{P}_t^j}{\mathbf{P}_\mathbf{t}^\mathbf{lsM}} = \frac{W_t^j MPL_t^{lsM}}{W_t^{lsM} MPL_t^j} \tag{15}$$

I compute the implied relative value-added prices by using the model values for the marginal product of labor conditional on the observed factor prices.
Figure 10 shows the relative prices. The model is able to capture the changes in relative prices.

Figure 11: Relative prices



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