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On Biased Technical Change: Was technological change in Japan electricity-saving?[*]

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Abstract

Since the Great East Japan Earthquake, electricity generation has declined in Japan, and electricity prices have allegedly increased. The literature on biased technical change suggests that such electricity supply constraints may induce a biased technical change. This paper explores the extent to which the technical change in Japanese industries is biased, using a system of translog cost share equations where electricity and non-electric energy are separately treated as inputs. Using Japanese industry data over the 1973-2008 period, our findings confirm that technical change has been energy-saving but not electricity-saving in many industries, and that it tends to be labor-saving and capital-using. As a result, factor prices are much more important than technical change as a determinant of electricity's cost share.

Keywords: Biased technical change, Cost function

JEL classification: O30, Q40

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1 Introduction

Since the Fukushima accident in the aftermath of the Great East Japan Earthquake on March 11, 2011, Japanese electricity generation has declined due to the suspension of operations at most nuclear power plants and due to the substitution of nuclear power with thermal (Figure 1). The electricity price allegedly has begun to rise for both industrial and residential use.[1] Such changes in electricity supply may give rise to a biased technical change: facing increasing electricity prices, firms may develop and adopt electricity–saving technologies. Theoretically, whether factor constraints are accompanied by a technical change that saves the use of constrained factors is ambiguous (e.g.Acemoglu (2002)). This paper explores the extent to which technical change has been biased in Japanese industries by estimating a system of translog cost share equations where electricity and other energy are separately treated as inputs.

Using the Japanese industry data over the 1973–2008 period, we find that technical change has been energy–saving but not electricity–saving in many industries and tends to be labor–saving and capital–using. Some industries, such as Wholesale and Retail and Rubber and Plastic, do indicate electricity–using technical change, but in general, factor prices are much more important than technical change as a determinant of electricity's cost share. We also confirm that production technology is in general neither constant returns to scale nor technical Hicks neutral.

The result about biased technical change in electricity suggests that it is unlikely that technical change will absorb the effect of increases in electricity price on the cost share of electricity. Other implications of the estimation are as follows. First, since the elasticity of cost with respect to output is way below one in most industries, enlarging production scale was an important source of TFP growth. Second, assuming production functions with constant returns to scale and Hicks neutral technology may not be appropriate, in particular in empirical work. Third, technical change in Japan's industries tends to be capital using

[1] In Japan, nine major electricity companies account for about 90% of total electricity supply. Each electricity company exclusively supplies within its designated territory. Dividing the nine major electricity companies' sales revenue from electricity by electricity demand yields an approximate electricity price index. This price index has risen since 2010 for seven of the nine major electricity companies (the data source is the profit–and–loss statement of the nine electricity companies).

and labor saving, which may imply that labor productivity improvement is due to capital accumulation or replacement.

Empirical cost functions have been explored for various purposes: for example, Berndt and Wood (1975) estimate energy demand, and Betts (1997) and Baltagi and Rich (2005) examine skill–biased technical change. Following these studies methodologically, the current paper examines biased technical change in Japanese industries, particularly focusing on electricity use. Fukunaga and Osada (2009) who estimate technical change in Japan with a particular attention toward energy use, is among the closest to our paper. However, we attempt to separate technical change in electricity and that in non–electricity energy while they are aggregated in Fukunaga and Osada (2009). In addition, our estimation allows non–constant returns to scale in production while they maintain the assumption that production technology is constant returns to scale. Our estimation suggests that production technology in general is not constant returns to scale.[2] In the due course of estimation, the paper also derives factor demand. Thus, this paper is related to the literature that explores electricity demand, such as Akiyama and Hosoe (2007) and Matsukawa, Madono, and Nakashima (1993) that gauge electricity demand elasticities in Japan.

The rest of the paper is organized as follows. The next section explains the empirical methodology. Section 3 describes the data. Section 4 reports the estimation results, and Section 5 concludes.

2 Conceptual Issues

The definition of biases in technical change is given by changes in the marginal rate of substitution between inputs for a given ratio of input use. Taking an example of a production function f with two primary inputs, if the marginal rate of substitution increases as the technology index z increases, technical change then is referred to as labor–biased:

$$\frac{\partial \frac{\partial f/\partial l}{\partial f/\partial k}}{\partial z} > 0, \tag{1}$$

[2]Fukunaga and Osada (2009) apply a variant of the Kalman filter estimator (e.g. Jin and Jorgenson (2010)) which allows flexibility in technical progress. However, mainly due to the limitation of observation, we take a simple linear trend for technology specification.

where where k represents capital input, l is labor input, and z is an index of technology. Profit maximization in the perfectly competitive factor markets implies that the marginal rate of substitution equals the wage–rental rate ratio. Thus, for a given wage–rental rate ratio, a labor–biased technical change leads to a rise in the labor–capital ratio, resulting in a rise in the relative expenditure share of labor. For this reason, a labor–biased technical change is interchangeably called a labor–using technical change. In the case of two primary inputs, it is immediate that increases in the expenditure share of labor for a given relative factor price exactly correspond to relative increases in the marginal product of labor. Since it is usually difficult to directly gauge changes in the marginal product of production factors, this one–to–one relationship between changes in the marginal product of a certain production factor and those in the expenditure share of that production factor is empirically useful.

Furthermore, tracing changes in the expenditure share of production factors is rather convenient in order to detect biases in technical change in the case of many (more than three) inputs. Since the summation of factor shares is unity by identity, there always exists at least one factor for which expenditure share declines, which implies that any production factor may have at least one production factor against which the marginal product relatively increases. Following Binswanger (1974), holding factor prices constant, if technical change increases (decreases) the expenditure share of a particular production factor, we say that the technical change is that production factor–using (production factor–saving).

In order to investigate biased technical change, it is necessary to estimate a production function or its corresponding cost function. However, the shape of the production function and the direction of technical change are *a priori* unknown. This is particularly true when we consider many production inputs. Accordingly, instead of imposing arbitrary assumptions on the cost function, I will specify the cost function in the translog form, which is a second–order approximation of a general cost function.

One drawback of using a flexible translog cost function is the fact that it only identifies a biased technical change (if any) as biased input usage as described above. Although estimating a flexible translog cost function may reveal a biased technical change such as a labor–saving change, it does not tell what technical change lets firms use more labor than earlier given the same factor prices. For example, a labor–augmenting technical change may or may not be labor–saving (see, e.g. Diamond, McFadden, and Rodriguez (1978)). This can be easily seen in a CES production function such that $y = [\gamma(\alpha l)^{(\sigma-1)/\sigma} + (1-\gamma)(\beta k)^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$. The marginal rate of substitution is given by

$$MRS = \frac{1-\gamma}{\gamma}\left[\frac{\alpha}{\beta}\right]^{\frac{\sigma-1}{\sigma}}\left[\frac{l}{k}\right]^{-\frac{1}{\sigma}}. \tag{2}$$

Therefore, a labor–augmenting technical change ($\alpha \uparrow$) is labor–saving only when $\sigma < 1$. This is because when σ is less than unity, an increase in the productivity of labor ($\alpha \uparrow$) increases the demand for capital more than the demand for labor, resulting in an excess demand for capital. Consequently, the marginal product of capital rises more than the marginal product of labor, which means that the technical change is capital–using and labor–saving.[3] In order to see whether this technical change will let firms use a particular production input more efficiently than before, it is necessary to add assumptions about technical change to the general translog cost function. In the next section, I will discuss the detail of the translog cost function used in estimation.

3 Empirical Strategy

Assuming cost minimization for a given factor price vector $\mathbf{w}$, let $c(\mathbf{w}, y, \mathbf{z})$ be the cost function where y represents real output and $\mathbf{z}$ a vector of the state of technology. For empirical specification, I employ a translog cost function with five inputs, capital (k), labor (l), electricity inputs (e), energy inputs excluding electricity (e_2), and material inputs (m). As is well–known, this functional form is sufficiently flexible, allowing for nonconstant returns to scale, nonlinear expansion paths, and biased technical change.

[3]When σ equals unity, the CES production function is reduced to the Cobb-Douglas form. It is obvious from (2) that any factor augmenting technical change never causes a biased technical change. In the early days of the study of the aggregate production function, the U.S. production functions were rendered in Cobb-Douglas form since the estimated elasticity of substitution between capital and labor was not statistically different from unity (e.g. Berndt (1976)). This view was popular partly because the Cobb–Douglas production function fits well the macro economic empirical regularity of relatively stable factor shares accompanied by capital deepening. However, succeeding studies revealed that the elasticity of substitution between capital and labor is less than one (see, e.g. Yuhn (1991), Antras (2004), and others). In order to reproduce the empirical regularity under $\sigma < 1$, labor–augmenting technical progress is necessary. Acemoglu (2003) proposes an endogenous growth model in which a purely labor–augmenting technical change occurs and the share of labor in GDP is constant in the long run with a capital–augmenting technical change and a factor shares change occurring along the transition path.

The translog cost function expresses the natural logarithm of total cost ($\ln c$) as a function of the logarithm of factor prices ($\ln w_i$), the logarithm of real output ($\ln y$), the index of technology (z_t), and their cross terms as follows:

$$\begin{aligned}\ln c = \alpha_0 + \sum_i \alpha_i \ln w_i + \alpha_y \ln y + z_t \\ + \frac{1}{2}\sum_i \sum_j \gamma_{ij} \ln w_i \ln w_j + \frac{1}{2}\gamma_{yy}(\ln y)^2 \\ + \sum_i \gamma_{iy} \ln w_i \ln y + \sum_i \theta_i z_t \ln w_i + \theta_y z_t \ln y, \end{aligned} \quad (3)$$

where $i, j = k, l, e, e_2$, and m. It is assumed that the cost function of specification (3) is well behaved, and thus, it is homogenous with degree one in factor prices. Thus, along with the symmetry condition $\gamma_{ij} = \gamma_{ji}$, the following restrictions on parameters are imposed:

$$\sum_i \alpha_i = 1, \quad \sum_i \sum_j \gamma_{ij} = \sum_i \gamma_{ij} = \sum_j \gamma_{ij} = 0, \quad \sum_i \theta_i = 0,, \quad \sum_i \gamma_{iy} = 0. \quad (4)$$

Differentiating the log cost function in (3) with respect to $\ln w_i$ and using Shephard's lemma lead to the following simple expressions about the expenditure share of input in total cost $s_i = w_i x_i / c$, where x_i is the amount of factor input i:

$$s_i = \alpha_i + \sum_j \gamma_{ij} \ln w_j + \gamma_{iy} \ln y + \theta_i z_t. \quad (5)$$

These cost share equations and the log cost function will be simultaneously estimated. Due to the well–known cross equation restrictions, one of the share equations will be dropped from estimation (the share equation for materials input will be dropped without loss of generality).

Using estimated coefficients, the Allen partial elasticities of substitution (AES) between inputs i and j are obtained as follows:

$$\sigma_{ii} = \frac{\gamma_{ii} + s_i^2 - s_i}{s_i^2}, \quad \text{for all } i = j, \quad (6)$$

$$\sigma_{ij} = \frac{\gamma_{ij}}{s_i s_j} + 1, \quad \text{for all } i \neq j. \quad (7)$$

It is known that the price elasticity of factor demand is given by $\epsilon_i = s_i \sigma_{ii}$ and $\epsilon_{ij} = s_j \sigma_{ij}$.

One difficulty in estimating the system of (3) and (5) is that the form of z_t is unknown. A simple and traditional approach is to replace z_t with a linear time trend as Betts (1997) and others. Although more sophisticated methodologies, such as using a general index for the technology index (Baltagi and Griffin (1988)) and applying state space estimation (Jin and Jorgenson (2010)), are proposed, we here employ the simple time trend because of data limitation and because we wish to maintain flexibility about returns to scale.[4] Letting t be a time trend, the log cost function in (3) and the share equations in (5) are rewritten as

$$\begin{aligned}\ln c = \alpha_0 + \sum_i \alpha_i \ln w_i + \alpha_y \ln y + \theta t \\ + \frac{1}{2}\theta_{tt} t^2 + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln w_i \ln w_j + \frac{1}{2}\gamma_{yy}(\ln y)^2 \\ + \sum_i \gamma_{iy} \ln w_i \ln y + \sum_i \theta_i t \ln w_i + \theta_y t \ln y, \quad (8)\end{aligned}$$

and

$$s_i = \alpha_i + \sum_j \gamma_{ij} \ln w_j + \gamma_{iy} \ln y + \theta_i t, \quad (9)$$

respectively. Holding factor prices and real output, equation (8) leads to the rate of technical change such that

$$\dot{T} \equiv \frac{\partial \ln c}{\partial t} = \theta + \theta_{tt} t + \sum_i \theta_i \ln w_i + \theta_y \ln y, \quad (10)$$

which implies that technical change can be decomposed into three parts: effects due to Hicks neutral change ($\theta + \theta_{tt} t$), effects due to factor biased change ($\theta_i \ln w_i$), and effects due to scale–augmenting change ($\theta_y \ln y$). For example, if $\theta_i < 0$, the technical change shows factor i saving. If the estimates of θ_i and θ_y are zero, technical change is unbiased. Further, we can see whether production technology is constant returns to scale: if $\alpha_y = 1$ and $\gamma_{yy} = \gamma_{iy} = \theta_y = 0$, then the production technology is linear.

Inspection of our sample data set reveals that many variables are panel non–stationary. In particular, the hypothesis that the log of total cost ($\ln c$) is non–stationary cannot be rejected even after detrending. Thus, in stead of (8) and (9), I estimate the following

[4] The general index approach proposed by Baltagi and Griffin (1988) is very flexible for technical change, but greatly increases the coefficients to be estimated.

first–differenced equations:

$$
\begin{aligned}
\Delta \ln c = \beta + \sum_i \alpha_i \Delta \ln w_i + \alpha_y \Delta \ln y + \theta_{tt} t \\
+ \frac{1}{2} \sum_i \sum_j \gamma_{ij} \Delta \left(\ln w_i \ln w_j \right) + \frac{1}{2} \gamma_{yy} \Delta (\ln y)^2 \\
+ \sum_i \gamma_{iy} \Delta \left(\ln w_i \ln y \right) + \sum_i \theta_i \Delta \left(t \ln w_i \right) + \theta_y \Delta (t \ln y), \quad (11)
\end{aligned}
$$

and

$$
\Delta s_i = \theta_i + \sum_j \gamma_{ij} \Delta \ln w_j + \gamma_{iy} \Delta \ln y, \tag{12}
$$

where $\beta \equiv \theta - (1/2)\theta_{tt}$. The system of equations (11) and (12) is estimated by iterated seemingly unrelated regressions, while dropping one share equation from (12).[5]

4 Data

The sample data are taken from the Japan Industrial Productivity Database 2011 (JIP Database 2011) that comprises 108 industries in the agricultural, manufacturing, and services sectors, and covers the period from 1973 to 2008.[6] In order to maintain sufficient observations, I categorize the JIP industries into twelve manufacturing sectors and four non–manufacturing sectors. Several industries are omitted from the sample. First, governmental and non–profit sectors are excluded since they are not likely to follow cost minimization.[7] In addition, I exclude industries that seem inappropriate for including any industry group. Such industries are six agricultural industries, Mining, and some services industries. Finally, energy supply industries such as Petroleum products, Coal products, Electricity, Gas and heat supply are excluded because this paper focuses on the impact of technical change on industrial energy consumption.[8] The industry selection described above results

[5] We tested instrumental variables for the potential endogeneity problem in the estimation using seemingly exogenous variables such as the wage paid by the government and the oil price determined in foreign markets. Still, the main results hold.

[6] The JIP database is periodically maintained by the Research Institute of Economy, Trade and Industry (RIETI) and is publicly available at http://www.rieti.go.jp/en/database/JIP2011/index.html.

[7] The omitted non–profit sectors are Waterworks (64), Water supply for industrial use (65), Mail (79), Education (private and non-profit) (80), Medical (private) (82), Hygiene (private and non-profit) (83), and Other public services (84). (The figures in parentheses are the JIP industry codes.) Eleven more governmental sectors (from 98 to 108 in the JIP industry code) are also omitted.

[8] In addition, it is arguably likely that the electricity industry may not follow cost minimization due to regulation.

in the sample data containing 57 JIP industries. Industry classification in the sample data is given in detail in Appendix B.

All variables used in estimation are constructed from JIP 2011. Details of data construction are relegated to Appendix A. Here, I describe the general tendency of the data.[9]

- The price of capital tends to decline over the sample period with cyclical motions in both manufacturing and services sectors. In contrast, the wage rate exhibits a tendency to increase until the late 1990s. Since then, the wage rate has been rather stable in the manufacturing sector while it has even slightly decreased in the services sector (Figures 2 and 3).

- The prices of electricity and non–electricity energy rapidly increased from the mid–1970s to the early 1980s, and then, began declining (Figure 4). It gradually declined until the mid–2000s and slightly rose in the last few years of the sample. The energy price cyclically moved after a large drop in the late 1980s and started to increase rapidly around the beginning of the 2000s (Figure 5).

- Similar to electricity price, the price of materials in the manufacturing sector increased in the 1970s and tends to decline through the late 1980s and the 1990s (Figure 6). It started to rise around 2000. The price of materials in the services sector shows a more clear upward tendency through the whole sample period except for the 1990s.

- All input prices seem to depend on their own past prices in such time series. In fact, the augmented Dickey–Fuller (ADF) test cannot reject the null hypothesis for all input prices.[10]

- Although most expenditure shares seem rather stable, the capital share in manufacturing and the materials share in services exhibit upward trends while the labor share in services exhibits a downward trend (Figures 7 and 8). The ADF test reveals that

[9] The summary statistics of the sample data are shown in Table 10 in the appendix.

[10] Different specifications for lags are tested in the ADF test. In all cases, the null hypothesis of a unit root cannot be rejected. The ADF test is for the average input prices. I also perform a panel unit root test (the Levin–Lin–Chew test) for the twelve manufacturing sectors and the four services sectors. The prices of capital, labor, energy, and materials are non–stationary in most sectors while the electricity price is non–stationary in three out of sixteen sectors.

several input shares (labor and materials in the manufacturing sector and electricity and other energy in both sectors) are non–stationary.[11]

- Table 1 summarizes the average growth rate of input per worker. Both sectors exhibit a similar tendency: all inputs except energy are likely to increase. As is well known, long–run increases in the capital–labor ratio (capital deepening) accompanied with a stable labor share are a prediction of the standard growth theory. This holds in both a Cobb-Douglas production function and a labor–augmenting technical progress. In my sample, while the labor share is rather stable in the manufacturing sector, it tends to decline in the services sector. Thus, it is expected that given that the production function does not take a Cobb-Douglas form, labor–augmenting technical progress occurred at least in the manufacturing sector.

5 Empirical Results

5.1 Elasticities

Own–price elasticities and AES are reported in Tables 2 (manufacturing) and Table 3 (services). The own–price elasticities are negative and statistically significant with a few exceptions. Positive own–price elasticities are observed in capital (ϵ_k) for Construction, in electricity (ϵ_e) for Construction and Finance, and in other energy input (ϵ_{e_2}) for Machinery, Electrical products, Transportation equipment, and Finance. However, the elasticity in other energy input for Electrical products is not significantly different from zero.

The own–price elasticity of electricity ranges from -0.3 to -0.8 in the manufacturing sector while it ranges from -0.34 to 0.79 in the services sector. The preceding literature shows that it is between -1.26 and -0.552 (Akiyama and Hosoe (2007)) and -0.63 (Matsukawa, Madono, and Nakashima (1993)) for industrial and residential use, respectively, in Japan. Thus, most elasticities estimated here are in the reasonable range. Interestingly, the electricity demand in Chemicals, Nonmetallic mineral products, and Primary metals is much more elastic than that in Machinery, Electrical products, and Transportation equipment. This may reflect the difference in the reliance on self–supplied electricity.

[11]The ADF test suggests that real output and total cost in the manufacturing sector are also non–stationary.

As for the cross–substitution elasticities, capital and labor are substitutable in most industries. Only Chemicals and Primary metals show positive but insignificant elasticities. Capital and other energy inputs are substitutable in Chemicals, Nonmetallic mineral products, Primary metals, and Transportation. These industries show a similar tendency for capital and electricity substitution, along with Paper, Rubber and plastic, and Wholesale and retail. Only Food shows complementarity between capital and electricity. Material inputs are substitutable with other inputs in many industries.

Two energy inputs, electricity (e) and other energy inputs (e_2), shows complementarity in Food and beverage, Textiles and leather, Wood, Rubber and plastic, Machinery, Electrical products, Transportation equipment, and all services sectors. Only Chemicals and Primary metals significantly show that these two inputs are substitutable.

5.2 Technical Change

Key parameters are θ_i that capture the bias in technical change.[12] A positive (negative) coefficient of θ_i exhibits that the technical change is factor i–using (factor i–saving). A casual observation of Tables 4 and 5 provides an impression that technical change is not Hicks–neutral for almost all industries. Indeed, Wald tests, wherein the null hypothesis entails the condition of $\theta_i = 0$ for all $i = k, l, e.e_2, m$, statistically support the impression for all industries except for Construction. In short, technical change in general is biased.

There is an overall tendency that technical change is capital–using and labor–saving. Except for Construction, all industries have positive θ_k and negative θ_l. The tendency that most industries exhibit capital–using technical change is shared with Fukunaga and Osada (2009) that also examine biased technical change in Japanese industries.[13]

Turning to the two energy–related inputs, the estimates reveal that while no industry shows electricity–saving technical change, seven out of twelve manufacturing sectors and two out of four services sectors exhibit energy–saving technical change. Technical change

[12] We also tested the period of 1973–2000 since after 2000, the energy price rapidly rose. However, changing the sample period did not alter the main results.

[13] However, unlike this study, Fukunaga and Osada (2009) find that Electrical machinery and Transport and storage are capital saving. Other eight industries (Petroleum and coal products, Chemicals, Metals, Machinery, Transport equipment, Wholesale and retail, Construction, and Electricity, gas and water supply) are capital using. Their industry classification is different from ours. Further, their data source is different and the sample period covers 1973–2005.

in Food and beverage, Textiles and leather, Paper, Rubber and plastic, Machinery, and Wholesale and retail is electricity–using. As for the other industries, estimates of θ_e are not statistically significant. In contrast, Paper, Nonmetallic mineral products, Primary metals, Metal products, and Transportation exhibit energy–saving technical change. Its rate varies from 0.17 % (annual) in Primary metals to 0.03 % in Metal products. Machinery and Electrical products also show energy–saving technical change, but their values are quite small and near zero.

As for material inputs, only two industries have statistically significant estimates: Primary metals and Construction are material–using at the 5% level. For all other industries, θ_m are not statistically significant (Wood is material–using at the 10% level).

The parameter θ_y represents the scale–augmenting technical change. No manufacturing industry exhibits such effects at the 5% level while Finance shows a relatively large scale–augmenting technical change: 1.5 % annually.

Finally, θ and θ_{tt} present pure technical change (unbiased technical change). Only Textiles and leather, Nonmetallic mineral products, and Wholesale and retail show statistically significant pure technical progress (negative coefficients). Some other industries have negative coefficients (Wood, Chemicals, Primary metals, Machinery, Electrical products, Transportation equipment, Construction, and Transportation), but their standard errors are relatively large. Likewise, θ_{tt} is not statistically significant in many industries. Wholesale and retail has a statistically significant negative, which implies that pure technical progress tended to accelerate (slightly) in recent years.

One disadvantage of the first–difference estimator is that the first–difference estimator is less efficient than the level estimator. Needless to say, they are asymptotically indifferent, but our sample size is not very large. Indeed, once pooling all observations for the manufacturing sector, the first–difference estimator yields a negative coefficient of θ (-0.0032) which is statistically significant at the 5% level. However, the sample contains many non–stationary series, which may easily generate pseudo correlations.[14] Thus, we maintain the

[14] In fact, when I estimate equation (15) and its share equations, nine out of twelve manufacturing sectors show negative and statistically significant coefficients θ. However, these estimates are likely to suffer from serial correlations. Estimation based on an AR(1) model reduces the number of significant coefficients to six.

results of the first–difference estimator.

From equation (15), total factor productivity change ($T\dot{F}P$) defined as the negative of the change in average cost can be expressed by

$$T\dot{F}P = (1 - \epsilon_{cy})\frac{d\ln y}{dt} - \dot{T}, \tag{13}$$

where $\epsilon_{cy} \equiv \partial \ln c / \partial \ln y$ denotes the scale elasticity. In our specification, ϵ_{cy} is given by $\epsilon_{cy} = \alpha_y + \gamma_{yy} \ln y + \sum_i \gamma_{iy} \ln w_i + \theta_y t$.

Since our estimates of θ, θ_{tt}, and θ_y are insignificant in many industries, the major source of technical change is factor–biased technical change. Only Textiles and leather, Nonmetallic mineral products, and Wholesale and retail have negative and significant θ. In addition, the scale elasticity is way below one for all industries, and thus, the production technology is not constant returns to scale and scale economies play an important role in the determination of TFP. The estimates of α_y are significant at the 1 % level for all industries and vary from 0.251 (Finance) to 0.818 (Transport equipment). Figure 9 presents the decomposition of the average TFP growth in each decade.[15] The average TFP growth is decomposed to the contributions by scale economies and by technical change. The figure clarifies that scale economies play a major role in determining TFP growth.

5.3 Share Decomposition

From equation (12), it is straightforward to decompose changes in factor share into a technical change effect ($\theta_i \Delta t$), the effect of changes in factor prices ($\sum_j \gamma_{ij} \Delta \ln w_j$), and a scale effect ($\gamma_{iy} \Delta \ln y$). In order to see the relative importance of these three effects, we decompose share changes between 2000 and 2007 (seven years), as reported in Table 6 and 7. This period is interesting because during this time, the energy price rapidly increased, the capital price decreased, and the electricity price and labor wage were relatively stable.

Capital share declined in almost all industries during this period. The decomposition reveals that the primary reason of these decreases is the price effect, which mainly stems from relatively large declines in capital price. However, technical change is biased toward capital–using, which pushed up capital share and partially offset the price effect. Labor

[15] The bar labeled as 1970 presents the average over the 1974–1979 period. Other bars are similarly defined.

share declined in all industries. However, unlike capital, the technical change effect is negative (labor–saving), which contributes to the decreasing labor share.

With respect to electricity, ten out of sixteen industries observe cost share decreases. However, the technical change effect is positive in many industries. Moreover, our estimates of technical change parameters in electricity are positive (electricity–using) or insignificantly different from zero. In addition, the coefficient of the scale effect, γ_{iy}, is not statistically significant in many industries.[16] Thus, the price effect is important in electricity.

Energy share increases in all industries but one (Paper). In particular, Chemicals and Transportation services show high growth. As is expected, the primary reason of the share increases is the price effect. Unlike electricity, some industries exhibit energy–saving technical change (Paper, Rubber and plastic, Nonmetallic mineral products, Primary metals, Wholesale and retail, and Transportation). The technical change in these industries pushed down the cost share. However, the effect of technical change is much smaller than the price effect.

In summary, our estimation reveals several characteristics of technical change in the manufacturing and services sectors. They are as follows: (i) in general, production technology is increasing returns to scale; (ii) technical change is not Hicks neutral; (iii) technical change is biased toward capital–using and labor–saving; (iv) technical change also shows energy–saving to some degree and is electricity–using in some industries; (v) however, the size of technical change in electricity and energy are small relative to that in capital and labor. Several implications are derived from these results. First, since the elasticity of cost with respect to output (ϵ_{cy}) is way below unity for all industries, enlarging production scale was an important source of TFP growth. Second, technical change is also important, but unbiased technical change is rarely observed, which implies that assuming production functions with constant returns to scale and Hicks neutral technology may not be appropriate (particularly in empirical works). Third, technical change in Japan's industries clearly tends to be capital–using and labor–saving, which may imply improvements in labor productivity due to capital accumulation (or replacement).

[16] All estimates are available from the author on request.

6 Factor Augmentation

The estimation of the cost share equations clarifies that technical progress is energy–saving in nine industries and electricity–using in five industries. No industry shows electricity–saving technical change. However, as is discussed earlier, the estimation of the flexible translog cost function used here cannot tell which production factor technical change lets firms use inputs more effectively. By imposing some restrictions on the translog cost function, this section attempts to identify factor augmentation to clarify whether the technical change is electricity–augmenting. Fortunately, the examination of biased technical change thus far reveals that technical change is in general not neutral but factor biased. Accordingly, we now specify the cost function such that every technical change is factor–augmenting:

$$\ln c = \alpha_0 + \sum_i \alpha_i \ln R_i + \alpha_y \ln y + \frac{1}{2}\sum_i \sum_j \gamma_{ij} \ln R_i \ln R_j + \frac{1}{2}\gamma_{yy}(\ln y)^2 + \sum_i \gamma_{iy} \ln R_i \ln y, \quad (14)$$

where $R_i = e^{\phi_i t} w_i$. This specification of technical progress implies that factor i is augmented at a constant rate ϕ_i. As earlier, the system of the four cost share equations and the cost function is estimated after taking the first differences (see Appendix C for estimated equations).

The results of estimation are reported in Tables 8 and 9. The estimate of ϕ_i measures the rate of factor augmentation: negative ϕ_i means that factor i is augmented at the rate of ϕ_i per year. As for Paper and Transport equipment, the estimation does not seem successful since incredibly high and statistically significant coefficients are observed. Thus, we ignore the whole results for these two industries. Except for these, the estimation reveals that technical progress has been in general labor–augmenting except for Construction and Finance. The annual rate of labor–augmentation varies from 0.3% in Food and beverage to 3.4% in Electrical products. With respect to capital, there is no factor augmentation. The estimation of the factor–augmenting translog cost function endorses that labor–augmenting technical progress has prevailed. This result is consistent with the coexistence of relatively stable labor share and capital deepening.

Turning to electricity and other energy, no factor augmentation is observed for electricity. In contrast, Food and beverage, Rubber and plastic, Nonmetallic mineral products, Primary metals, Metal products, and Electrical products show energy augmenting technical progress in the manufacturing sector. The annual rate of augmentation is between 3.0% (Metal products) and 5.7% (Electrical equipment). In the services sector, Wholesale and retail and Finance record energy-augmenting technical progress, with the annual rate being 4.6% and 5.3%, respectively.

7 Concluding Remarks

This paper explores the extent to which technical change is biased in Japanese industries, using a system of the translog cost share equations where electricity and non–electricity energy are separately treated as inputs. Using the Japanese industry data over the 1973–2008 period, we find that (i) in general, production technology is not constant returns to scale; (ii) technical change is not Hicks neutral; (iii) technical change is biased toward capital-using and labor-saving; (iv) technical change also shows energy-saving to some degree and electricity-using in some industries; (v) however, the size of technical change in electricity and energy are small relative to that in capital and labor.

These findings suggest that production scale has been an important source of TFP growth in Japan. Further, technical change in Japanese industries is in general characterized by labor productivity improvement supported by capital accumulation (or replacement). We also find some evidence of electricity–using and energy–saving in many industries although the size of technical change herein is small relative to capital–using technical change or labor–saving technical change. The results suggest that absorbing the impact of increases in electricity price trough a technical change may not be easy.

There still remain issues that need further consideration. The limitation stemming from the simple specification about technical change alerts us to interpret the coefficients estimated. The sample size is not enough for some industries, which may result in any inefficiency or bias in the estimates. These issues are left for future research.

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Table 1: Average Growth of Input per Worker (1974–2008, %)

	Manufacturing	Services
Capital	3.62	3.55
Electricity	2.01	2.24
Energy (non–electricity)	−3.50	−1.84
Materials	1.42	2.09

Source: JIP 2011.
Note: All figures denote the growth rate of input per worker.

Table 2: Own-Price and Cross Elasticities (Manufacturing)

Elasticity	Food and Beverage	Textiles and Leather	Wood	Paper	Rubber and Plastic	Chemicals
ϵ_k	-0.12	-0.31	-0.01^{+}	-0.30	-0.36	-0.37
ϵ_l	-0.25	-0.38	-0.38	-0.38	-0.37	-0.19
ϵ_e	-0.40	-0.52	-0.50	-0.75	-0.69	-0.80
ϵ_{e_2}	-0.38	-0.36	-0.19	-0.60	-0.20	-0.85
ϵ_m	-0.07	-0.18	-0.15	-0.19	-0.16	-0.14
σ_{kl}	0.18	0.66	0.46	0.66	0.65	0.39^{+}
σ_{ke}	-0.14	0.34^{+}	-0.08^{+}	0.68	0.64	0.79
σ_{ke_2}	-0.07^{+}	0.17^{+}	-0.63^{+}	0.49^{+}	0.07^{+}	0.91
σ_{km}	0.12^{+}	0.19	-0.18^{+}	0.14^{+}	0.30	0.34
σ_{le}	0.35^{+}	0.72	0.69	0.87	0.80	0.79
σ_{le_2}	-0.57^{+}	0.08^{+}	-0.21^{+}	0.45^{+}	-0.33^{+}	0.77
σ_{lm}	0.31	0.52	0.54	0.51	0.47	0.11^{+}
σ_{ee_2}	-9.55	-7.60	-10.63	-1.49^{+}	-5.66	0.61
σ_{em}	0.57	0.58	0.58	0.79	0.75	0.86
σ_{e_2m}	0.76	0.69	0.63	0.80	0.63	0.96

Elasticity	Nonmetallic Mineral Products	Primary Metals	Metal Products	Machinery	Electrical Products	Transportation Equipment
ϵ_k	-0.29	-0.36	-0.19	-0.33	-0.34	-0.32
ϵ_l	-0.38	-0.13	-0.38	-0.38	-0.37	-0.27
ϵ_e	-0.80	-0.80	-0.68	-0.42	-0.49	-0.30
ϵ_{e_2}	-0.83	-0.85	-0.47	0.25	0.17^{+}	0.48
ϵ_m	-0.21	-0.12	-0.17	-0.17	-0.15	-0.09
σ_{kl}	0.63	0.30^{+}	0.58	0.67	0.62	0.44
σ_{ke}	0.77	0.79	0.48^{+}	0.22^{+}	0.33^{+}	0.02^{+}
σ_{ke_2}	0.83	0.88	0.17^{+}	-0.55^{+}	-0.43^{+}	-0.91^{+}
σ_{km}	0.09^{+}	0.35	0.03^{+}	0.23	0.28	0.33
σ_{le}	0.90	0.77	0.81	0.64	0.65^{+}	0.29^{+}
σ_{le_2}	0.81	0.66	0.23^{+}	-0.84^{+}	-0.97^{+}	-2.59^{+}
σ_{lm}	0.46	0.05^{+}	0.52	0.52	0.48	0.33
σ_{ee_2}	0.43^{+}	0.51	-3.59^{+}	-19.94	-15.81	-29.16
σ_{em}	0.85	0.87	0.73	0.49	0.58	0.48
σ_{e_2m}	0.94	0.96	0.75	0.40^{+}	0.47^{+}	0.40^{+}

Notes: Elasticities without + are significant at least at the 5 % level. Cross–elasticities, σ_{ij}, are the Allen partial elasticities of substitutions.

Table 3: Own-Price and Cross Elasticities (Services)

Elasticity	Construction	Wholesale and Retail	Finance	Transportation
ϵ_k	0.48	-0.34	-0.27	-0.53
ϵ_l	-0.26	-0.21	-0.23	-0.26
ϵ_e	0.58	-0.34	0.79	-0.45
ϵ_{e_2}	-0.63	-0.60	1.36	-0.80
ϵ_m	-0.13	-0.14	-0.16	-0.13
σ_{kl}	0.68	0.91	0.89	0.95
σ_{ke}	2.85^+	1.30	1.94^+	1.10
σ_{ke_2}	0.12^+	0.63^+	-1.66^+	0.94
σ_{km}	-1.35	-0.48	-0.40	0.30
σ_{le}	-1.57	0.24^+	-1.27^+	0.16^+
σ_{le_2}	0.49	0.60	-1.67^+	0.79
σ_{lm}	0.42	0.32	0.39	0.00^+
σ_{ee_2}	-19.78	-8.31	-156.68	-2.04
σ_{em}	0.53^+	0.69	0.30^+	0.72
σ_{e_2m}	0.97	0.94	0.72	0.98

Notes: Elasticities without + are significant at least at the 5 % level. Cross–elasticities, σ_{ij}, are the Allen partial elasticities of substitutions.

Table 4: Technical Change Parameter Estimates (Manufacturing)

	Food and Beverage	Textiles and Leather	Wood	Paper	Rubber and Plastic	Chemicals
θ_k	0.00128**	0.00254**	0.00109**	0.00203**	0.00243**	0.00319**
	(0.000265)	(0.000573)	(0.000313)	(0.000368)	(0.000388)	(0.000413)
θ_l	$-$0.00148**	$-$0.00281**	$-$0.00110**	$-$0.00239**	$-$0.00272**	$-$0.00339**
	(0.000266)	(0.000571)	(0.000330)	(0.000428)	(0.000422)	(0.000423)
θ_e	0.000196**	0.000268**	1.19$e-$05	0.000364+	0.000286*	0.000204
	(5.68$e-$05)	(8.33$e-$05)	(8.17$e-$05)	(0.000186)	(0.000118)	(0.000235)
θ_{e_2}	$-$9.57$e-$05	$-$4.30$e-$05	1.00$e-$07	$-$0.000797*	$-$0.000292*	$-$0.000734
	(6.14$e-$05)	(0.000103)	(0.000103)	(0.000317)	(0.000113)	(0.000712)
θ_m	$-$0.00416	$-$0.00235	0.00558+	$-$0.00235	$-$0.00201	0.000302
	(0.00328)	(0.00600)	(0.00326)	(0.00371)	(0.00371)	(0.00268)
θ_y	$-$0.00666	0.0114^{+}	0.00602	$-$0.00137	$-$0.00385	0.000605
	(0.00535)	(0.00589)	(0.00443)	(0.00591)	(0.00751)	(0.00330)
θ	0.00308	$-$0.0143**	$-$0.00475	0.00170	0.000628	$-$0.000467
	(0.00296)	(0.00604)	(0.00432)	(0.00325)	(0.00390)	(0.00401)
θ_{tt}	$-$0.000103	$-$0.000294	$-$1.83$e-$06	3.57$e-$05	$-$0.000408	0.000494
	(0.000290)	(0.000441)	(0.000313)	(0.000333)	(0.000497)	(0.000364)
Obs.	175	70	70	105	70	245

	Nonmetallic Mineral Products	Primary Metals	Metal Products	Machinery	Electrical Products	Transportation Equipment
θ_k	0.00188**	0.00148**	0.00130**	0.00265**	0.00363**	0.000938*
	(0.000375)	(0.000537)	(0.000270)	(0.000460)	(0.000493)	(0.000474)
θ_l	$-$0.00214**	$-$0.00125^{+}	$-$0.00127**	$-$0.00285**	$-$0.00364**	$-$0.00100*
	(0.000424)	(0.000667)	(0.000291)	(0.000459)	(0.000491)	(0.000477)
θ_e	0.000254	$-$0.000229	$-$3.05$e-$05	0.000198*	1.46$e-$05	6.35$e-$05
	(0.000228)	(0.000500)	(0.000142)	(8.59$e-$05)	(9.61$e-$05)	(0.000101)
θ_{e_2}	$-$0.00127**	$-$0.00173**	$-$0.000338**	$-$7.91$e-$05*	$-$0.000110*	$-$7.74$e-$05
	(0.000341)	(0.000583)	(0.000111)	(3.59$e-$05)	(4.45$e-$05)	(5.13$e-$05)
θ_m	0.00142	0.00673∗	$-$0.00105	0.00132	$-$0.00171	0.00839
	(0.00395)	(0.00263)	(0.00197)	(0.00312)	(0.00288)	(0.00534)
θ_y	0.00128	$-$0.00527	$-$0.000136	0.00131	$-$0.00257	0.00247
	(0.00326)	(0.00435)	(0.00285)	(0.00321)	(0.00228)	(0.00926)
θ	$-$0.0105**	$-$0.00519	0.00350	$-$0.00262	$-$0.00550	$-$0.00450
	(0.00384)	(0.00541)	(0.00342)	(0.00370)	(0.00442)	(0.00425)
θ_{tt}	$-$1.21$e-$05	0.00105*	$-$0.000281	$-$0.000985*	$-$7.66$e-$05	$-$0.00109^{+}
	(0.000361)	(0.000474)	(0.000346)	(0.000408)	(0.000433)	(0.000604)
Obs.	140	105	105	140	315	70

Note: See Table 11 for a list of industry names in full and industry codes. Standard errors in parentheses. **, *, and + indicate significance at the 1%, 5%, and 10% levels, respectively.
Wald tests for Hicks–neutral technical change and constant returns to scale reject the null hypothesis in all industries.

Table 5: Technical Change Parameter Estimates (Services)

	Construction	Wholesale and Retail	Finance	Transportation
θ_k	0.000369	0.00218**	0.00424**	0.00576**
	(0.000248)	(0.000445)	(0.000734)	(0.000540)
θ_l	−0.000344	−0.00262**	−0.00417**	−0.00589**
	(0.000274)	(0.000463)	(0.000743)	(0.000524)
θ_e	$-2.50e{-}05$	0.000433**	$-6.76e{-}05$	0.000127
	($5.01e{-}05$)	(0.000139)	($6.73e{-}05$)	(0.000158)
θ_{e_2}	−0.000186	−0.000559**	$-5.51e{-}06$	−0.00114**
	(0.000218)	(0.000215)	($3.44e{-}05$)	(0.000423)
θ_m	0.0143*	0.00332	0.00986	−0.00363
	(0.00582)	(0.00492)	(0.00707)	(0.00508)
θ_y	0.00958*	−0.000308	−0.0145*	0.00958^{+}
	(0.00433)	(0.00607)	(0.00683)	(0.00519)
θ	−0.00539	−0.00794**	0.0134	−0.000440
	(0.00504)	(0.00235)	(0.00540)	(0.00353)
θ_{tt}	−0.00166**	−0.000659*	0.000281	−0.000923**
	(0.000414)	(0.000318)	(0.000544)	(0.000309)
Obs.	70	70	70	175

Notes: See Table 11 for a list of industry names in full and industry codes. Standard errors in parentheses. **, *, and + indicate significance at the 1%, 5%, and 10% levels, respectively.

Wald tests for Hicks–neutral technical change and constant returns to scale reject the null hypothesis in all industries except for construction. Construction cannot reject the null hypothesis of Hicks-neutrality at the 1% level but rejects at the 5% level.

Table 6: Cost Share Decomposition (2000–2007)

Capital	Change in share	Scale effect	Price effect	Technical change	Residual
Food & Beverage	−5.71	0.98	−7.78	0.90	0.19
Textiles & Leather	0.06	1.73	−4.23	1.78	0.77
Wood	−2.42	1.87	−3.38	0.76	−1.67
Paper	−4.19	0.78	−7.21	1.42	0.81
Rubber & Plastic	−3.81	−0.80	−5.81	1.70	1.09
Chemicals	−21.07	3.04	−41.47	2.23	15.14
Nonmetallic Mineral Products	−5.78	0.12	−13.66	1.32	6.44
Primary Metals	−21.32	−0.16	−21.19	1.04	−1.01
Metal Products	−6.63	1.85	−9.38	0.91	−0.01
Machinery	−7.15	−3.25	−6.76	1.86	1.01
Electrical Products	4.78	−8.36	−9.22	2.54	19.82
Transportation Equipment	−6.53	−1.63	−4.77	0.66	−0.79
Construction	−1.78	0.77	−3.00	0.26	0.20
Wholesale & Retail	−2.88	0.01	−4.49	1.53	0.07
Finance	−0.35	−1.21	−5.44	2.97	3.34
Transportation	−28.48	−2.33	−40.42	4.03	10.24

Labor	Change in share	Scale effect	Price effect	Technical change	Residual
Food & Beverage	−3.48	1.27	−6.87	−1.03	3.16
Textiles & Leather	−1.76	7.64	−1.87	−1.97	−5.56
Wood	−5.92	3.42	−4.06	−0.77	−4.51
Paper	−5.10	1.29	−2.76	−1.68	−1.96
Rubber & Plastic	−4.81	−0.59	−4.34	−1.90	2.03
Chemicals	−32.73	0.65	−4.43	−2.37	−26.58
Nonmetallic Mineral Products	−14.17	0.20	−5.39	−1.50	−7.49
Primary Metals	−14.28	−0.31	−20.69	−0.88	7.59
Metal Products	−17.36	3.41	−9.29	−0.89	−10.59
Machinery	−9.95	−2.37	2.05	−1.99	−7.63
Electrical Products	−4.79	−1.99	5.78	−2.55	−6.03
Transportation Equipment	−0.36	−3.03	0.62	−0.70	2.76
Construction	−5.93	2.61	−6.03	−0.24	−2.27
Wholesale & Retail	−4.67	0.28	1.71	−1.83	−4.83
Finance	−8.11	−2.41	6.12	−2.92	−8.90
Transportation	−13.22	−4.94	−3.27	−4.12	−0.88

Note: See Table 11 for a list of industry names in full and industry codes.

Table 7: Cost Share Decomposition (2000–2007)

Electricity	Change in share	Scale effect	Price effect	Technical change	Residual
Food & Beverage	0.80	0.01	−0.54	0.14	1.20
Textiles & Leather	0.40	−0.02	−0.61	0.19	0.84
Wood	0.12	0.11	−0.19	0.01	0.19
Paper	0.13	0.34	−0.69	0.25	0.22
Rubber & Plastic	−0.98	0.01	−0.52	0.20	−0.66
Chemicals	−9.39	0.10	−2.97	0.14	−6.66
Nonmetallic Mineral Products	−3.13	−0.01	−1.81	0.18	−1.48
Primary Metals	−2.42	−0.07	−1.07	−0.16	−1.12
Metal Products	−1.57	0.06	−1.43	−0.02	−0.18
Machinery	−0.25	0.06	−0.46	0.14	0.00
Electrical Products	−0.85	0.27	0.77	0.01	−1.90
Transportation Equipment	−0.15	−0.07	0.09	0.04	−0.22
Construction	−0.07	0.02	−0.16	−0.02	0.09
Wholesale & Retail	1.09	0.00	−0.07	0.30	0.86
Finance	−0.14	0.03	−0.05	−0.05	−0.07
Transportation	1.13	−0.26	0.12	0.09	1.19

Energy	Change in share	Scale effect	Price effect	Technical change	Residual
Food & Beverage	2.71	0.02	2.06	−0.07	0.69
Textiles & Leather	1.13	−0.06	1.01	−0.03	0.21
Wood	0.77	−0.11	0.76	0.00	0.13
Paper	−0.36	−0.45	4.05	−0.56	−3.40
Rubber & Plastic	0.00	0.00	0.89	−0.20	−0.70
Chemicals	39.49	−0.48	21.20	−0.51	19.28
Nonmetallic Mineral Products	7.43	−0.02	11.10	−0.89	−2.76
Primary Metals	2.86	−0.03	6.90	−1.21	−2.81
Metal Products	0.22	−0.07	1.37	−0.24	−0.85
Machinery	0.42	0.01	0.77	−0.06	−0.30
Electrical Products	1.65	−0.07	1.91	−0.08	−0.11
Transportation Equipment	0.31	−0.05	0.53	−0.05	−0.11
Construction	1.33	0.31	1.60	−0.13	−0.45
Wholesale & Retail	2.24	−0.02	2.00	−0.39	0.65
Finance	0.26	0.00	0.27	0.00	−0.01
Transportation	13.06	1.39	21.00	−0.80	−8.53

Note: See Table 11 for a list of industry names in full and industry codes.

Table 8: The Joint Estimation of the Factor–Augmenting Translog Cost Function and Share Equations (Manufacturing)

	Food and Beverage	Textiles and Leather	Wood	Paper	Rubber and Plastic	Chemicals
ϕ_k	0.0217^{**}	0.0305^{*}	0.0154^{**}	0.616	0.0329^{**}	0.0309^{**}
ϕ_l	-0.00337	-0.0195^{**}	-0.0177^{**}	-1.390^{**}	-0.0161^{**}	-0.0144^{**}
ϕ_e	0.0161^{**}	0.0170^{*}	0.0117	11.11^{**}	0.0189^{**}	0.00468
ϕ_{e_2}	-0.0341^{**}	-0.0108	-0.00574	-11.33	-0.0479^{**}	-0.0186^{+}
ϕ_m	-0.00448	-0.000492	0.00337	0.993^{*}	0.000355	-0.000959
Obs.	175	70	70	105	70	245

	Nonmetallic Mineral Products	Primary Metals	Metal Products	Machinery	Electrical Products	Transportation Equipment
ϕ_k	0.0203^{**}	0.0233^{**}	0.0194^{**}	0.0343^{**}	0.0539^{**}	0.613^{**}
ϕ_l	-0.0184^{**}	-0.0107^{*}	-0.00727^{*}	-0.000940	-0.0347^{**}	-0.0924
ϕ_e	0.0170^{**}	0.00237	0.0134^{*}	0.0198^{**}	0.0262^{+}	8.537^{**}
ϕ_{e_2}	-0.0306^{**}	-0.0261^{*}	-0.0295^{**}	-0.0283^{+}	-0.0572^{**}	-9.851
ϕ_m	0.0134^{*}	0.00817^{+}	0.00308	-0.0262	0.0103	0.797^{**}
Obs.	140	105	105	140	315	70

Notes: See Table 11 for a list of industry names in full and industry codes. **, *, and + indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: The Joint Estimation of the Factor–Augmenting Translog Cost Function and Share Equations (Services)

	Construction	Wholesale and Retail	Finance	Transportation
ϕ_k	-1.557	0.00977^{+}	0.0830^{**}	0.481^{+}
ϕ_l	-1.908^{+}	-0.0141^{**}	0.0193	0.571^{+}
ϕ_e	9.503+	0.0454^{**}	-0.0221	-2.235^{+}
ϕ_{e_2}	-4.395^{+}	-0.0458^{**}	-0.0529^{**}	0.703
ϕ_m	-1.639	-0.0119^{**}	-0.0490	0.480^{+}
Obs.	70	70	70	175

Notes: See Table 11 for a list of industry names in full and industry codes. **, *, and + indicate significance at the 1%, 5%, and 10% levels, respectively.

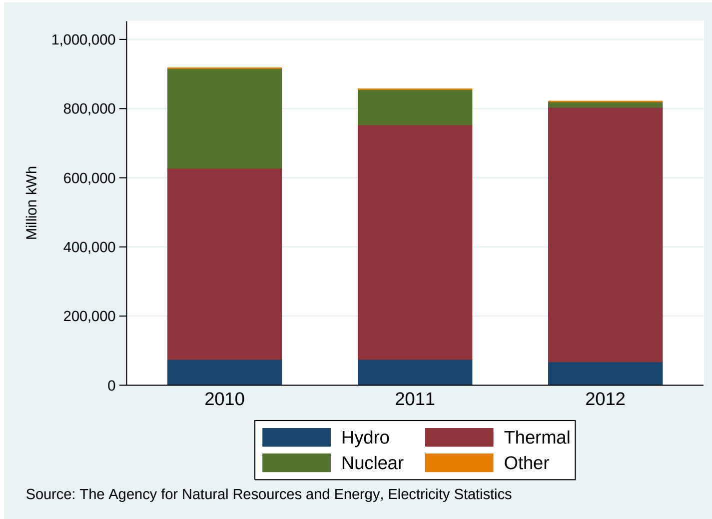

Figure 1: Electricity Generation

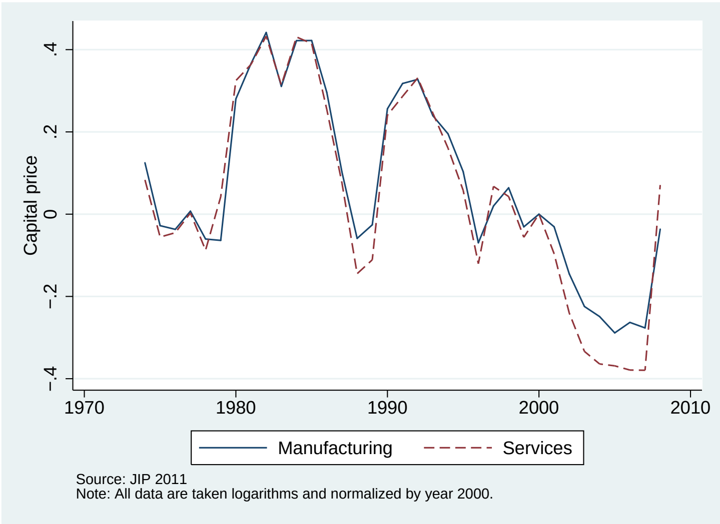

Figure 2: Capital Price

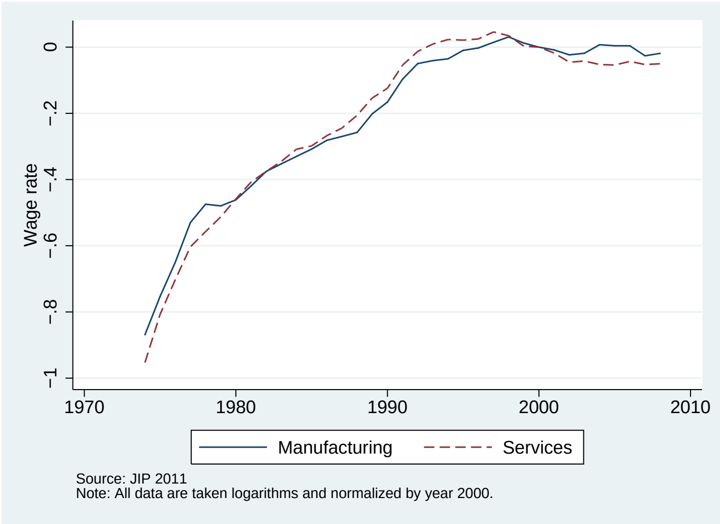

Figure 3: Wage Rate

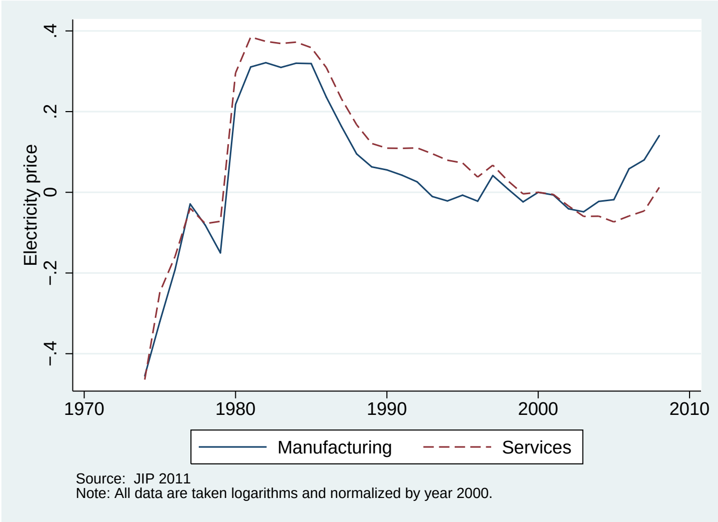

Figure 4: Electricity Price

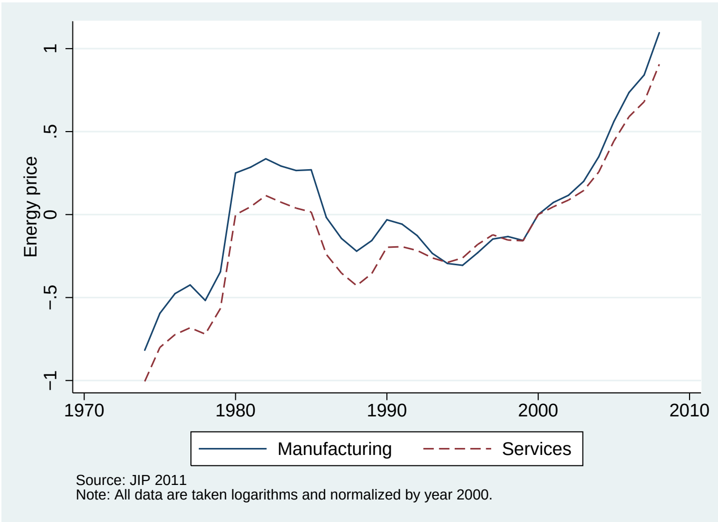

Figure 5: Energy Price (other than electricity)

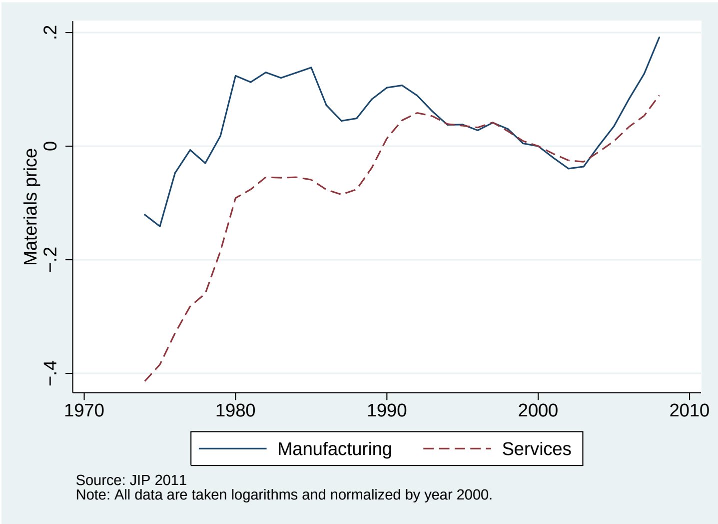

Figure 6: Materials Price

Figure 7: Manufacturing

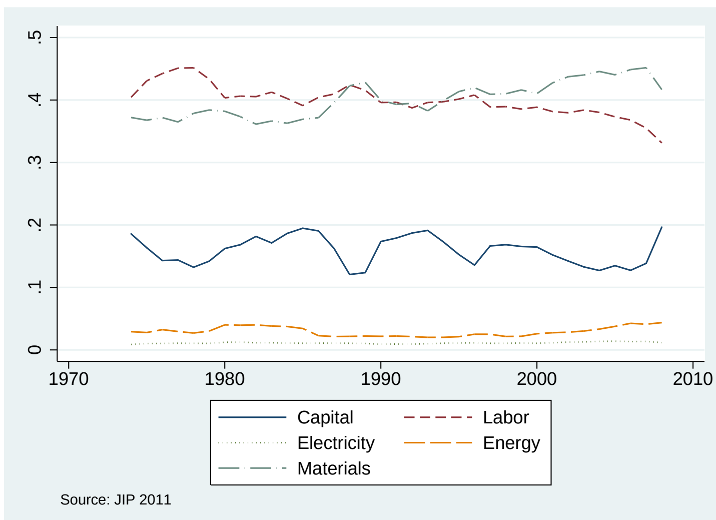

Figure 8: Services

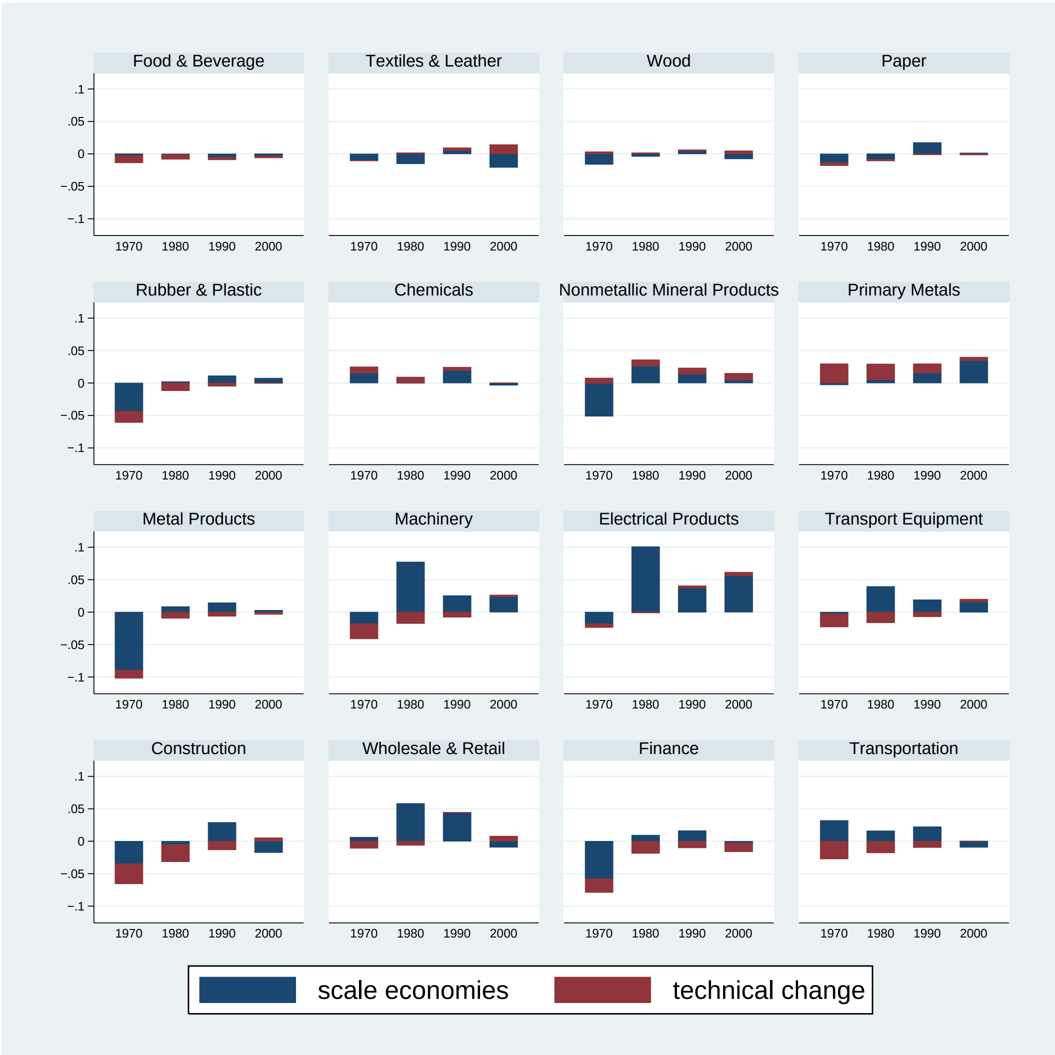

Figure 9: TFP Growth Decompotition

A Data Construction

The variables used in estimation are constructed as follows:

Real output (y) Real output by sectors is obtained from real gross output (million yen in year 2000 prices) in the growth accounting tables of JIP 2011.

User cost of capital (w_k) User cost of capital is computed by dividing nominal capital services (nominal rental price $\times$ real net capital stock, million yen) by capital service input (divisia index, 2000=1). An alternative measure of the user cost of capital is obtained by dividing nominal capital services (nominal rental price $\times$ real net capital stock, million yen) with real net capital stock (million yen in year 2000 prices).

Wage rate (w_l) JIP 2011 includes nominal labor cost by sectors. The wage rate by sectors is obtained by dividing nominal labor cost by labor input index (divisia index, 2000=1).

Electricity price (w_e) Electricity price is constructed using the input-output table in JIP 2011. The input-output table reports nominal purchases from the electricity sector (JIP code 62) by sectors. JIP 2011 also reports the real values for these purchases. Electricity price by sectors is computed by dividing the nominal purchases by the corresponding real values.

Energy price excluding electricity (w_{e_2}) Energy inputs excluding electricity are composed of each sector's purchases from Petroleum products (JIP code 30), Coal products (JIP code 31), and Gas and heat supply (JIP 63). I constructed divisia indices for real inputs using the weights of purchasing shares for each energy input. Then, dividing nominal purchase by the real input index leads to the input price of energy excluding electricity.

Price of other materials (w_m) Expenditure on other material inputs is computed using real and nominal intermediate input in the input-output table in JIP 2011. After subtracting, all energy related expenditure from intermediate input purchases, I reconstruct a divisia index of real intermediate input.

Total cost of production (c) Total production cost is obtained by summing nominal labor cost, nominal capital services, and nominal intermediate inputs (including the energy supply sectors, such as Electricity, Petroleum products, Coal products, and Gas and heat supply).

Input share of total cost (s_i) Input share of total cost is obtained by simply dividing the nominal cost of each input with total cost.

The summary statistics of the data are shown in the following table.

Table 10: Summary Statistics (1974–2008)

	(1) Manufacturing				(2) Services			
	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Total cost (c)	0.937	0.332	0.051	2.397	0.836	0.257	0.193	1.392
Capital share (s_k)	0.085	0.040	0.009	0.263	0.159	0.121	0.024	0.546
Labor share (s_l)	0.227	0.088	0.021	0.493	0.399	0.142	0.101	0.667
Electricity share (s_e)	0.023	0.024	0.000	0.160	0.011	0.013	0.000	0.055
Energy share (s_{e2})	0.027	0.081	0.000	0.708	0.029	0.032	0.001	0.147
Materials share (s_m)	0.637	0.111	0.205	0.966	0.401	0.111	0.174	0.677
Capital price (w_k)	1.094	0.257	0.616	2.070	1.125	0.394	0.443	4.537
Wage (w_l)	0.838	0.219	0.273	3.040	0.833	0.196	0.318	1.204
Electricity price (w_e)	1.073	0.286	0.470	6.105	1.082	0.232	0.409	1.718
Energy price (w_{e2})	1.071	0.502	0.085	5.046	0.982	0.472	0.241	3.574
Materials price (w_m)	1.043	0.213	0.316	3.183	0.926	0.153	0.377	1.268
Real output (y)	0.911	0.339	0.004	2.276	0.875	0.240	0.216	1.593
Ob.	1,610				385			

Source: JIP 2011.
Note: All variables other than input shares are normalized by year 2000.

B Industry Classification

Table 11: Industry Classification

Industry	JIP Code	JIP Sector
Food and Beverage	8	Livestock products
	9	Seafood products
	10	Flour and grain mill products
	11	Miscellaneous foods and related products
	12	Prepared animal foods and organic fertilizers
	13	Beverages
Textiles and Leather	15	Textile products
	21	Leather and leather products
Wood	16	Lumber and wood products
	17	Furniture and fixtures
Paper	18	Pulp, paper, and coated and glazed paper
	19	Paper products
	20	Printing, plate making for printing and bookbinding
Rubber and Plastic	22	Rubber products
	58	Plastic products
Chemicals	23	Chemical fertilizers
	24	Basic inorganic chemicals
	25	Basic organic chemicals
	26	Organic chemicals
	27	Chemical fibers
	28	Miscellaneous chemical products
	29	Pharmaceutical products
Nonmetallic Mineral Products	32	Glass and its products
	33	Cement and its products
	34	Pottery
	35	Miscellaneous ceramic, stone and clay products
Primary Metals	36	Pig iron and crude steel
	37	Miscellaneous iron and steel
	38	Smelting and refining of non-ferrous metals
Metal Products	39	Non-ferrous metal products
	40	Fabricated constructional and architectural metal products
	41	Miscellaneous fabricated metal products
Machinery	42	General industry machinery
	43	Special industry machinery
	44	Miscellaneous machinery
	45	Office and service industry machines
Electrical Products	46	Electrical generating, transmission, distribution and industrial apparatus
	47	Household electric appliances
	48	Electronic data processing machines, digital and analog computer equipment and accessories
	49	Communication equipment
	50	Electronic equipment and electric measuring instruments
	51	Semiconductor devices and integrated circuits
	52	Electronic parts
	53	Miscellaneous electrical machinery equipment
	57	Precision machinery & equipment
Transportation Equipment	54	Motor vehicles
	55	Motor vehicle parts and accessories
Construction	60	Construction
	61	Civil engineering
Wholesale and Retail	67	Wholesale
	68	Retail
Finance	69	Finance
	70	Insurance
Transportation	73	Railway
	74	Road transportation
	75	Water transportation
	76	Air transportation
	77	Other transportation and packing

C Estimated Equations for Factor Augmentation

The translog cost function with factor augmenting technical change is given by

$$\ln c = \alpha_0 + \sum_i \alpha_i \ln R_i + \alpha_y \ln y + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln R_i \ln R_j + \frac{1}{2}\gamma_{yy}(\ln y)^2 + \sum_i \gamma_{iy} \ln R_i \ln y, \quad (15)$$

where $R_i = e^{\phi_i t} w_i$. Substituting $\ln R_i = \phi_i t + \ln w_i$ into the cost function, we obtain

$$\begin{aligned}\ln c = & \alpha_0 + \sum_i \alpha_i \ln w_i + \alpha_y \ln y + \sum_i \alpha_i \phi_i t + \frac{1}{2}\sum_i\sum_j \gamma_{ij}\phi_i\phi_j t^2 \\ & + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln w_i \ln w_j + \frac{1}{2}\gamma_{yy}(\ln y)^2 + \sum_i \gamma_{iy} \ln w_i \ln y \\ & + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln w_i \phi_j t + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln w_j \phi_i t + \sum_i \phi_i t \ln y,\end{aligned}$$

and the corresponding share equations

$$s_i = \alpha_i + \sum_j \gamma_{ij} \ln w_j + \gamma_{iy} \ln y + \sum_j \gamma_{ij}\phi_j t.$$

With the parameter restrictions (and dropping the cost share equation for materials), the system of equations bcomes as follows:

$$\begin{aligned}\ln(c/w_m) = & \alpha_0 + \sum_{i\neq m} \alpha_i \ln(w_i/w_m) + \alpha_y \ln y + (\sum_{i\neq m} \alpha_i(\phi_i - \phi_m) + \phi_m)t \\ & + \frac{1}{2}\sum_{i\neq m}\sum_{j\neq m} \gamma_{ij}[\phi_i - \phi_m][\phi_j - \phi_m]t^2 + \frac{1}{2}\sum_{i\neq m}\sum_{j\neq j} \gamma_{ij} \ln(w_i/w_m)\ln(w_j/w_m) \\ & + \frac{1}{2}\gamma_{yy}(\ln y)^2 + \sum_{i\neq m} \gamma_{iy} \ln(w_i/w_m) \ln y \\ & + \sum_{i\neq m}\sum_{j\neq m} \gamma_{ij} \ln(w_i/w_m)(\phi_j - \phi_m)t + \sum_i \phi_i t \ln y,\end{aligned}$$

and

$$s_i = \alpha_i + \sum_{j\neq m} \gamma_{ij} \ln(w_j/w_m) + \gamma_{iy} \ln y + \sum_{j\neq m} \gamma_{ij}(\phi_j - \phi_m)t,$$

Taking first–differentiation leads to the equations used for estimation:

$$\begin{aligned}\Delta \ln(c/w_m) &= \sum_{i\neq m}\alpha_i(\phi_i-\phi_m)+\phi_m-\frac{1}{2}\sum_{i\neq m}\sum_{j\neq m}\gamma_{ij}[\phi_i-\phi_m][\phi_j-\phi_m] \\ &+\sum_{i\neq m}\alpha_i\Delta\ln(w_i/w_m)+\alpha_y\Delta\ln y+\frac{1}{2}\sum_{i\neq m}\sum_{j\neq m}\gamma_{ij}[\phi_i-\phi_m][\phi_j-\phi_m]t \\ &+\frac{1}{2}\sum_{i\neq m}\sum_{j\neq j}\gamma_{ij}\Delta\ln(w_i/w_m)\ln(w_j/w_m)+\frac{1}{2}\gamma_{yy}\Delta(\ln y)^2+\sum_{i\neq m}\gamma_{iy}\Delta\ln(w_i/w_m)\ln y \\ &+\sum_{i\neq m}\sum_{j\neq m}\gamma_{ij}\Delta\ln(w_i/w_m)(\phi_j-\phi_m)t+\sum_i\phi_i\Delta(t\ln y),\end{aligned}$$

and

$$\Delta s_i=\sum_{j\neq m}\gamma_{ij}\Delta(\ln w_j-\ln w_m)+\gamma_{iy}\Delta\ln y+\sum_{j\neq m}\gamma_{ij}(\phi_j-\phi_m).$$