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Measuring Energy-Saving Technical Change in Japan

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Abstract

In this paper, we estimate time-varying biases of technical change and their effects on productivity using econometric models of aggregate and industry-level technology in Japan. In our aggregate model, the bias of technical change for energy input was energy-saving in the 1980s but gradually switched to energy-using around 2000. We found little evidence that producers switched to energy-saving technical change by the end of 2008 in response to the recent surge in energy prices. As a result, rising energy prices under the energy-using technical change have contributed to a slowdown in TFP growth. Meanwhile, the labor-saving technical change has made large positive contributions to TFP growth and labor productivity growth. In our models of individual industries, the biases of technical change for energy have been small since the 1980s and those for materials have been substantially materials-saving in many industries.

Keywords: Bias of Technical Change; Productivity; Energy
JEL classification: E23, O30

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1 Introduction

Energy prices have risen enormously in the 2000s. Crude oil prices fell sharply in the second half of 2008, but have surged again since early 2009. These movements remind us of the oil crises that occurred twice in the 1970s, when Japan's economy suffered from significant growth slowdown. In response to the crises, many Japanese producers changed their technology toward energy efficiency, and that helped the substantial economic recovery in the 1980s. It is often argued that a key innovation for the next decade will be in energy-saving technology, which will again help the world economy and Japan's economy recover from the current recession.

In this paper, we estimate biases of technical change and their effects on productivity using econometric models of aggregate and industry-level technology in Japan. Biases of technical change represent the effect of technical change on the share of inputs in the value of output.[1] The bias of technical change for energy, for instance, is energy-using (energy-saving), if the share of energy increases (decreases) with a change in technology at a constant input ratio (or relative input prices). Many theoretical and empirical studies, especially those based on macroeconomic models, consider only unbiased ("neutral") technical change by assuming the Cobb-Douglas production function under which the input shares are unaffected by technical change. In reality, however, many technical changes may benefit some particular factor of production more than others. For instance, there has been no tendency for the returns to the skill to fall in the U.S. since the 1940s, despite a large increase in supply of the skilled labor. The standard explanation for this tendency is that the bias of technical change for skilled labor over the post-war period has been skill-using (skill-biased). By contrast, technical change during the late eighteenth and early nineteenth centuries, when the artisan shop was replaced by the factory, was likely to be skill-saving (unskill-biased).[2]

Our models are based on the standard econometric approach to modeling biases of technical change with the translog functional form, which was intro-

[1] The study on biases of technical change dates back to Hicks (1932).

[2] Acemoglu (2002) investigates theoretical background of these historical tendencies. Acemoglu (2009, chapter 15) deals with this issue more extensively.

duced by Binswanger (1974). Moreover, following Jin and Jorgenson (2008) who estimate biases of technical change using U.S. industry-level data, we assume that the biases of technical change are time-varying, and estimate them by applying the Kalman filter.[3] Many previous empirical studies on biases of technical change, including Kuroda, Yoshioka, and Jorgenson (1984) who estimate the biases using Japanese data, assume constant time trends so that biases are fixed during the sample period. However, the biases of technical change, especially for energy, are likely to change in response to swings in relative input prices.

Together with time-varying biases of technical change, we estimate time-varying rate of technical change and fixed parameters on substitution among inputs in our models.[4] These enable us to consider the effects of the biases of technical change on total factor productivity (TFP) and each factor's average productivity.[5] The rate of technical change corresponds to the growth rate of TFP in our models and can be decomposed into the contribution of the biases of technical change and the neutral technical change. The contribution of the biases of technical change is larger when the bias for an input that is used more than other inputs (or the price of which is lower than that of other inputs) is input-using. Moreover, we can consider the effects of change in inputs (or input prices) on change in TFP growth under biases of technical changes. If the bias for an input is input-using, TFP growth accelerates as the corresponding input increases (or the corresponding input price decreases) relative to other inputs. Many previous empirical studies show that the oil crises in the 1970s under energy-using technical change contributed to a slowdown in TFP growth.[6]

[3] Binswanger (1974) considers time-varying as well as constant biases of technical change. However, his model of time-varying biases does not introduce latent variables as Jin and Jorgenson (2008) and ours do.

[4] León-Ledesma, McAdam, and Willman (2009) provide an alternative approach to jointly estimate the elasticity of substitution and biases of technical change.

[5] Growth in the average productivity of energy is equivalent to reduction in the "basic unit" for energy. Note that the reduction in the basic unit for energy does not necessarily mean the energy-saving technical change.

[6] For instance, Jorgenson (1981) and Kuroda, Yoshioka, and Jorgenson (1984) show that the higher energy price was an important determinant of the productivity slowdown in the 1970s in the U.S. and Japan, respectively.

Our model of the aggregate production technology in which the value of aggregate output is allocated to capital, labor, and imported natural energy resources is estimated using Japanese data from 1970 to 2008. The bias of technical change for energy was energy-using in the 1970s, energy-saving in the 1980s, and gradually switched again to energy-using around 2000. We found little evidence that producers switched to energy-saving technical change by the end of 2008 in response to the recent surge in energy prices. As a result, the rising energy prices under the energy-using technical change have contributed to a slowdown in TFP growth in the 2000s, as they did in the 1970s. Meanwhile, the bias of technical change for labor has been labor-saving throughout the sample period, and its pace accelerated around the late 1990s. The labor-saving technical change has made large positive contributions to TFP growth and labor productivity growth. The bias for capital has been capital-using throughout the sample period.

Our models of Japanese individual industries in which the value of output is allocated to capital, labor, energy, and (non-energy) materials are estimated using Japanese data in the EU-KLEMS database from 1973 to 2005. The biases of technical change for energy and labor have been small in many industries since the 1980s, except that the biases for labor were substantially labor-saving in some non-manufacturing industries in the 2000s. The biases for capital have been capital-using in many industries since the 1980s. Meanwhile, the biases for materials have been material-saving and substantial in magnitude in many industries. The differences in the estimation results between our aggregate model and models of individual industries could be explained by differences in the data, relationships with the biases for materials, and changes in industrial structure.

The remainder of the paper is organized as follows. In Section 2, we describe formally the definition of the biases of technical change and related concepts, our econometric models, and estimation procedures. Section 3 reports the estimation results for our aggregate model, and Section 4 reports those for our models of individual industries. Section 5 concludes.

2 Concepts and Measurement

2.1 Concepts

Before considering biases of technical change, we first clarify the definition of unbiased, i.e., "neutral" technical change. The concept of neutrality in this paper is the "Hicks neutrality" as follows:[7] technical change is said to be neutral if the marginal rate of (technical) substitution stays constant when the input ratio (e.g. capital-labor ratio) is held constant. This means a homothetic inward shift of the unit isoquant, as shown in Figure 1.

We define the biases of technical change as Hicks non-neutrality. If the marginal rate of substitution of an input (e.g. energy) for other inputs (e.g. capital, labor, etc.) increases with a change in technology at a constant input ratio (or relative input prices), the bias of technical change is input-*using* (e.g. energy-using). If, on the other hand, the marginal rate of substitution decreases, the bias of technical change is input-*saving* (e.g. energy-saving). These cases are also shown in Figure 1.

Under cost minimization, the marginal rate of substitution must be equal to the relative input price. Then the biases of technical change represent the effects of technical change on the share of inputs in the value of output. Technical change is neutral, input-using, or input-saving depending on whether the corresponding input share stays constant, increases, or decreases.

Suppose a production function is given by

$$Q = f(X_1, X_2, ..., t), \tag{1}$$

where Q is output, X_i is i-th input, and the level of technology can be represented by time t. The rate of technical change v^t is defined as

$$v^t = \frac{\partial \ln Q}{\partial t}. \tag{2}$$

In the competitive markets for output and all inputs, the elasticity of output

[7] Other concepts for neutral technical change include "Harrod neutrality" and "Solow neutrality."

with respect to each input i is equal to the corresponding input share v^i:

$$v^i = \frac{\partial \ln Q}{\partial \ln X_i}. \tag{3}$$

Now the bias of technical change for input i is expressed as

$$v^{it} = \frac{\partial^2 \ln Q}{\partial \ln X_i \, \partial t} \quad \left(= \frac{\partial v^t}{\partial \ln X_i} = \frac{\partial v^i}{\partial t} \right). \tag{4}$$

If the bias v^{it} is positive, the corresponding input share v^i increases with a change in the level of technology and the technical change is said to be i-using. If, on the other hand, v^{it} is negative, v^i decreases with the i-saving technical change. At the same time, we can also derive the implications of changes in inputs for the rate of technical change. If v^{it} is positive, the rate of technical change *increases* as the corresponding input X_i increases. If, on the other hand, v^{it} is negative, the rate of technical change *decreases* as X_i increases. Note that if the production function is Cobb-Douglas, the biases of technical change are always zero. Then the input shares are unaffected by technical change and the rate of technical change is unaffected by changes in inputs.

If the production function (1) is constant returns to scale, we can utilize an alternative and equivalent description of the technology as the dual price function for the producing unit:

$$P_Q = g(P_1, P_2, ..., t), \tag{5}$$

where P_Q is the unit output price and P_i is the price of i-th input. Under constant returns to scale, the value of output is equal to the value of all inputs, which implies

$$\sum_i v^i \equiv \sum_i \frac{P_i \, X_i}{P_Q \, Q} = 1.$$

We can then rewrite the equations (2) through (4) in terms of the price function as follows:

$$
\begin{aligned}
v^t &= -\frac{\partial \ln P_Q}{\partial t} && (6)\\
v^i &= \frac{\partial \ln P_Q}{\partial \ln P_i} && (7)\\
v^{it} &= \frac{\partial^2 \ln P_Q}{\partial \ln P_i \, \partial t} \quad \left(= -\frac{\partial v^t}{\partial \ln P_i} = \frac{\partial v^i}{\partial t} \right). && (8)
\end{aligned}
$$

From (8), we can derive the implications of changes in input prices for the rate of technical change. If v^{it} is positive, the rate of technical change *decreases* as the corresponding input price P_i increases. If, on the other hand, v^{it} is negative, the rate of technical change *increases* as P_i increases.[8]

2.2 Econometric Models

In our econometric models of individual industries, we assume that the value of output in each industry j is allocated to capital, labor, and (energy and non-energy) materials including intermediate inputs from other industries so that the industry-level production function and price function are expressed as follows:

$$
\begin{aligned}
Q_j &= f_j(K_j, L_j, E_j, M_j, t)\\
P_{Qj} &= g_j(P_{Kj}, P_{Lj}, P_{Ej}, P_{Mj}, t),
\end{aligned}
$$

where K_j is capital input, L_j is labor input, E_j is energy input, M_j is non-energy materials input, and P_{ij} is the input price for factor $i \in \{K, L, E, M\}$ in industry j. Similarly, in our aggregate model, we assume that the value of aggregate output is allocated to capital, labor, and raw materials (natural resources) excluding domestic intermediate inputs so that the aggregate production function and price function are expressed as follows:

$$
\begin{aligned}
Y &= f_Y(K, L, N, t)\\
P_Y &= g_Y(P_K, P_L, P_N, t),
\end{aligned}
$$

[8] Further details are given by Jorgenson (1986).

where Y is aggregate output, K is aggregate capital, L is aggregate labor, N is natural resources, and P_Y, P_K, P_L, and P_N are the corresponding prices.[9]

Following most previous empirical studies on biases of technical change, we estimate the price functions instead of the production functions. It is supposed to be more convenient to work with the price functions in treating data, implementing estimation procedures, and representing substitution and technical change. We assume the following translog form of the aggregate price function:

$$\begin{aligned} \ln P_Y &= \alpha_0 + \sum_i \alpha_i \ln P_i + \alpha_t \cdot t \\ &\quad + \frac{1}{2} \sum_{i,k} \beta_{ik} \ln P_i \ln P_k + \sum_i \beta_{it} \ln P_i \cdot t + \frac{1}{2} \beta_{tt} \cdot t^2. \\ &\quad i, k \in \{K, L, N\} \end{aligned} \tag{9}$$

The same functional form is applied to the industry-level price function. α_0, α_i, β_{ik} are the fixed parameters to be estimated.[10]

Moreover, following Jin and Jorgenson (2008), we assume α_t, β_{it}, and β_{tt} are time-varying and introduce the latent variables $f_{it} \equiv \beta_{it} \cdot t$ and $f_t \equiv \alpha_t \cdot t + (1/2)\beta_{tt} \cdot t^2$. Changes in f_{it} represent biases of technical change and changes in f_t represent neutral technical change, as shown below. Using these latent variables and adding time subscripts t to all variables, we rewrite the price function (9) as

$$\begin{aligned} \ln P_{Yt} &= \alpha_0 + \sum_i \alpha_i \ln P_{it} \\ &\quad + \frac{1}{2} \sum_{i,k} \beta_{ik} \ln P_{it} \ln P_{kt} + \sum_i \ln P_{it} \cdot f_{it} + f_t. \end{aligned} \tag{10}$$

We assume that f_{it} are stationary for all i, f_t is first-difference stationary, and f_{it} and $\Delta f_t (\equiv f_t - f_{t-1})$ follow autoregressive processes as described in the next subsection.

[9] These assumptions imply separability among the aggregates over inputs in the production function and those over input prices in the price function.

[10] In the Cobb-Douglas functional form, β_{ik} and β_{it} are assumed to be zero for all i.

The rate of technical change is now expressed as

$$v_t^t = -\sum_i \ln P_{it} \cdot \Delta f_{it} - \Delta f_t. \tag{11}$$

Differentiating (10) with respect to $\ln P_{it}$ yields the input share equations:

$$v_t^i = \alpha_i + \sum_k \beta_{ik} \ln P_{kt} + f_{it}. \tag{12}$$

If f_{it} is increasing with time, the input share v_t^i increases, holding the input prices constant, which corresponds to the i-using technical change. If, on the other hand, f_{it} is decreasing with time, v_t^i decreases at constant input prices, which corresponds to the i-saving technical change.

Equation (11) implies that the rate of technical change can be decomposed into the contribution of the biases of technical change (the first term of the right-hand side) and the neutral technical change (the second term). The contribution of the biases of technical change is larger when the bias for an input whose price is higher (lower) than other input prices is input-saving (input-using). We can also derive the implication of changes in input prices for the rate of technical change. If the bias for an input is input-using (input-saving) the rate of technical change decreases (increases) as the corresponding input prices increases (decreases) relative to the other input prices.

To incorporate proper implications from the production theory into the model and to keep the estimation feasible, we impose several restrictions on the price function (10). First, the price function is *homogeneous* of degree one so that doubling of all input prices doubles the output price, which requires

$$\begin{aligned} \sum_i \alpha_i &= 1 \\ \sum_i \beta_{ik} &= 0 \quad \text{for each } k. \end{aligned}$$

Then, since the input shares sum to unity, the latent variables representing biases of technology must sum to zero, $\sum_i f_{it} = 0$. Second, the price function must be *monotonic*, which requires

$$v_t^i > 0 \quad \text{for each } i.$$

Third, the parameters representing share elasticities must be *symmetric*, so that

$$\beta_{ik} = \beta_{ki}.$$

Finally, the price function must be *locally concave* when evaluated at the prices observed in the sample period, which requires that

$$\mathbf{B} + \mathbf{v}_t^i \mathbf{v}_t^{i\prime} - \mathbf{V}_t$$

is non-positive definite at each t in the sample period, where $\mathbf{B}$ is the matrix of the parameters representing share elasticities (β_{ik}), $\mathbf{v}_t^i$ is the vector of input shares, and $\mathbf{V}_t$ is a diagonal matrix with the shares along the diagonal.

2.3 Estimation Procedures

Following Jin and Jorgenson (2008), we apply an extension of the Kalman filter to estimate the parameter values and the paths of the latent variables in our models. The state-space form of the models can be expressed as follows.

$$\mathbf{f}_t = \mathbf{F}\,\mathbf{f}_{t-1} + \mathbf{u}_t, \tag{13}$$

$$\mathbf{y}_t = \mathbf{A}\,\mathbf{x}_t + \mathbf{H}\,\mathbf{f}_t + \mathbf{w}_t, \tag{14}$$

The state equation (13) represents autoregressive processes of the stationary latent variables characterizing the nature of technical change.[11] The observation equation (14) represents a system of the price function and the corresponding input share equations. For our model of the aggregate economy, from equations (10) and (12), the vectors and matrices in the above

[11] Jin and Jorgenson (2008) assume that the stationary latent variables follow a vector autoregressive process.

state-space form are defined as follows.

$$
\begin{aligned}
\mathbf{f}_t &= (1, f_{Kt}, f_{Lt}, f_t, f_{t-1})' \\
\mathbf{F} &= \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ \chi_K & \delta_{KK} & 0 & 0 & 0 \\ \chi_L & 0 & \delta_{LL} & 0 & 0 \\ \chi_P & 0 & 0 & 1+\delta_{PP} & -\delta_{PP} \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix} \\
\mathbf{y}_t &= \left(v_t^K,\, v_t^L,\, \ln \frac{P_{Qt}}{P_{Nt}} \right)' \\
\mathbf{x}_t &= \left(1,\, \ln \frac{P_{Kt}}{P_{Nt}},\, \ln \frac{P_{Lt}}{P_{Nt}},\, \frac{1}{2}\left(\ln \frac{P_{Kt}}{P_{Nt}} \right)^2,\, \frac{1}{2}\left(\ln \frac{P_{Lt}}{P_{Nt}} \right)^2,\, \ln \frac{P_{Kt}}{P_{Nt}} \ln \frac{P_{Lt}}{P_{Nt}} \right)' \\
\mathbf{A} &= \begin{pmatrix} \alpha_K & \beta_{KK} & \beta_{KL} & 0 & 0 & 0 \\ \alpha_L & \beta_{KL} & \beta_{LL} & 0 & 0 & 0 \\ \alpha_0 & \alpha_K & \alpha_L & \beta_{KK} & \beta_{LL} & \beta_{KL} \end{pmatrix} \\
\mathbf{H} &= \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & \ln \frac{P_{Kt}}{P_{Nt}} & \ln \frac{P_{Lt}}{P_{Nt}} & 1 & 0 \end{pmatrix}
\end{aligned}
$$

Note that f_{Nt}, v_t^N, and related parameter values can be obtained on the assumption of homogeneity of the price function.[12] The error terms $\mathbf{u}_t$ and $\mathbf{w}_t$ are assumed to be serially uncorrelated and uncorrelated with each other at all lags. The above state-space form can be similarly applied to our models of individual industries.

The Kalman filter algorithm provides estimates of the parameter values and time paths of the latent variables. To estimate the parameter values, we use maximum likelihood estimation. The log-likelihood function based on the normal distribution is computed by the forward recursion (filtering). Given the maximum likelihood estimator, we estimate the latent variables using the backward recursion (smoothing).[13]

[12] We confirmed that replacing f_{Kt} and v_t^K or f_{Lt} and v_t^L in the above model with f_{Nt} and v_t^N makes little differences to the estimation results.

[13] These procedures are described by, for instance, Hamilton (1994).

One important problem in applying the Kalman filter to our models is the potential endogeneity of the explanatory variables, $\mathbf{x}_t$. To deal with this problem, we introduce instrumental variables, $\mathbf{z}_t$, and replace $\mathbf{x}_t$ with its fitted values of the OLS estimates on the instrumental variables, that is, $\hat{\mathbf{x}} = \mathbf{x}\mathbf{z}'(\mathbf{z}\mathbf{z}')^{-1}\mathbf{z}$. Following Jin and Jorgenson (2008), we conduct a test of over-identifying restrictions to check the validity of our instrumental variables.[14]

There are also some minor problems, such as the choice of initial values of the latent variables and parameters to be estimated in the Kalman filter algorism. We randomly generate initial values around empirically plausible values (or simply zero) and check the robustness of the estimation results. At the same time, we have to select a result subject to the local concavity constraint of the price function.

In closing this section, we point out reservations or limitations in our econometric models and estimation procedures stated above. First, our models assume constant returns to scale technology for all industries. This assumption is reasonable for the aggregate economy but may be implausible for some industries. Second, our models assume perfect competition for all industries and do not consider any price distortions. This assumption may also be implausible for some industries in the short run. Third, and most importantly, our models do not consider intertemporal optimization by producers. It is natural to assume that producers pursue a high rate of technical change, given by equation (11), if technical change is not completely exogenous to them. Then we can conjecture that, for instance, producers who face a high energy price or anticipate a future increase in the energy price relative to other input prices may wish to switch to energy-saving technical change, and vice versa. Such an endogenous technical change may be partly captured in our estimated latent variables. Meanwhile, our estimated latent variables may also reflect movements in input shares that are exogenous to producers. Since our models do not consider endogenous technical change explicitly, we

[14]To conduct this test, we have to choose more instrumental variables than endogenous explanatory variables. We check whether the addition of extra instrumental variables to the observation equation will not affect the original Kalman filter by a likelihood ratio test.

cannot identify fundamental sources of movements in the latent variables.[15] We will discuss this point in the next section, which shows our estimation results.

3 Aggregate Technical Change

In this section, we report the estimation results for our model of aggregate production technology. Since most of the natural energy resources for production inputs are imported in Japan, we assume that the value of output is allocated to capital, labor, and imported natural energy resources. Accordingly, output is defined as gross domestic product plus imported natural energy resources.[16] We first describe data used for our estimation procedures, and then summarize the estimation results. We then discuss the effects of the biases of technical change on the aggregate productivity in Japan.

3.1 Data

Our aggregate dataset contains annual data from 1970 to 2008. We use National Accounts, Trade Statistics, Energy Balance Statistics, and statistics on labor and capital (for details, see Appendix Table 1(1).) All price data are calculated by dividing nominal (current price) data by real (constant price) or quantity data. For instance, the price of natural energy resources (primary energy), P_N, is calculated by dividing mineral fuels imports in Trade Statistics by the energy unit of imported primary energy in Energy Balance Statistics. In addition, we introduce instrumental variables such as tax rates, public investment, per-capita private financial wealth, imported oil price, and lagged explanatory variables (see Appendix Table 1(2)).

We also check the results obtained from an extended dataset that starts at 1956. Since the capital input data from "Japan Industrial Productivity

[15] Recent developments in the study on endogenous biases of technical change are summarized in Acemoglu (2009, chapter 15). The earlier literature on "induced technical change" such as Kennedy (1964) considered the endogenous biases.

[16] The aggregate output is calculated using the fixed base-year method with 2000 as the base year.

Database" are unavailable before 1970, we use "Annual Report on Gross Capital Stock of Private Enterprises" up to 1970 in the extended dataset.

3.2 Results

Figure 2 summarizes the estimation results of the latent variables on the biases of technical change and parameter values on the share elasticities. Panel (1) illustrates the historical evolution of the latent variables, f_{Kt}, f_{Lt}, and f_{Nt}, which represent the biases of technical *level*, where the 1970 level is normalized to zero. Panel (2) shows the biases of technical *change* in five-year periods and the full sample period from 1970 through 2008. Since 1970, the biases of technical change have been capital-using, labor-saving, and slightly energy-using. The bias of technical change for energy was energy-using in the 1970s, energy-saving in the 1980s, and gradually switched again to energy-using around 2000. The pace of the capital-using technical change accelerated in the middle of the 1980s and the pace of the labor-saving technical change accelerated around the late 1990s. Lastly, Table (3) shows the estimated and implied parameter values on share elasticities, β_{ik}. It also shows the Allen–Uzawa partial elasticities of substitution between i and k, which is calculated as $\sigma_{ik} \equiv 1 + \{\beta_{ik}/(v^i\, v^k)\}$ where v^i and v^k are the averages of v_t^i and v_t^k in the sample period. According to this measure, capital and labor are complements, capital and energy are complements, and labor and energy are substitutes.[17]

In Figure 3, we plot each latent variable plotted in Figure 2(1) separately, together with the corresponding input share and real input price (deflated by output price). As implied by equation (12), changes in input shares are decomposed into the effects of changes in relative input prices (the second term of the right-hand side) and biases of technical change (the third term). Panel (1) of Figure 3 shows that the estimated latent variable for energy moves almost in parallel with its share and real price. This means that substitution among inputs in response to changes in relative input prices has

[17] Two inputs are substitutes, neutral, and complements depending on whether the partial elasticity of substitution is more than, equal to, and less than unity. In the Cobb-Douglas functional form, the elasticity of substitution is always equal to unity.

only a small effect on the share of energy. At the same time, the estimated latent variable for energy implies that, as mentioned at the end of Section 2, it may reflect the movement in the share of energy that is exogenous to producers. It is conceivable that the energy-saving technical change in the 1980s resulted partially from endogenous technical change in response to the high energy prices following the oil crises in the 1970s rather than simply acted as a reflection of the decrease in energy share in the 1980s. However, by the end of 2008, there was little evidence that producers switched to energy-saving technical change in response to the recent surge in energy prices. Meanwhile, the labor-saving and the capital-using technical change shown in Panels (2) and (3) may be the results of endogenous technical change in response to the increasing trend of real wages and the decreasing trend of real capital costs, respectively.[18]

In Figure 4, we plot the differences between each pair of latent variables, together with the corresponding relative input prices. While the "relative bias" of technical change for energy to labor has been energy-using, that for energy to capital has been energy-saving since the 1980s. The latter may capture energy-saving technical change embodied in capital equipments. Meanwhile, Panel (3) suggests that the relative bias for labor to capital has been labor-saving in response to the increasing trend of the relative price of labor to capital.

In Figure 5, we plot each latent variable estimated from our extended dataset that starts at 1956, together with the corresponding latent variable in the above benchmark results (the same as plotted in Figure 2). Before 1970, the biases of technical change were energy-saving, labor-saving, and capital-using. After 1970, the results from the extended dataset have been similar to the benchmark results. The pace of the recent energy-using technical change has been not so rapid as the benchmark results and as the pace of the recent surge in real energy prices, which could imply that endogenous energy-saving

[18]Real wages and real capital costs, in contrast to real energy prices, have constant trends, which could facilitate endogenous technical change. The shares of labor and capital have been stable as a result of the labor-saving and capital-using technical change as well as input substitution in response to the increasing trend of real wages relative to real capital costs.

technical change has offset to some extent the energy-using technical change.

3.3 Effects on Aggregate Productivity

Based on the above estimation results, we discuss the effects of biases of technical change on aggregate productivity. As implied by equation (11), the rate of technical change, which corresponds to the growth rate of total factor productivity (TFP),[19] can be decomposed into the contribution of the biases of technical change (the first term of the right-hand side) and the neutral technical change (the second term). The decomposition based on our estimation results is shown in Panel (1) of Figure 6.[20] It reveals that the biases of technical change have made a substantial contribution to the TFP growth. Panel (2) shows the breakdown of the contribution of the biases of technical change. As implied by the first term of the right-hand side of equation (11), the contribution of the biases of technical change is larger when the bias for an input whose price is higher (lower) than other input prices is input-saving (input-using). The labor-saving technical change accompanied by the increasing trend of real wages has steadily made a large positive contribution to the TFP growth. By contrast, the energy-using technical change following the surges in real energy prices made a negative contribution to the TFP growth in 1970-75 and 2005-08, which are the only periods when the total contributions of biases of technical change are negative in our sample period.

In Figure 7, we illustrate the decomposition of the average productivity of energy and labor. The growth rate of the average productivity of input i can be decomposed into the TFP growth, v_t^t, and the substitution to the other inputs k, as follows.

$$\Delta \ln Y_t - \Delta \ln X_{it} = v_t^t + \sum_k v_t^i(\Delta \ln X_{kt} - \Delta \ln X_{it}). \tag{15}$$

[19]Since we estimate the price function instead of production function under certain conditions and take imported natural energy resources into account as an input factor, our measure of TFP may be rather different from the standard measures of TFP.

[20]In Fugure 6, the contribution of the neutral technical change includes an estimation error.

Panel (1) shows that the rapid growth in energy productivity (equivalently, the rapid fall in the basic unit for energy) in 1975-1985 was mainly driven by input substitution rather than TFP growth. The input substitution was also important for labor productivity growth. In Panel (2), the contribution of the input substitution to labor productivity growth, which corresponds to the second term of the right-hand side of equation (15), is further decomposed into the contribution of changes in relative input prices and that of labor-saving technical change, as follows.[21]

$$\Delta \ln Y_t - \Delta \ln X_{it} = v_t^t + \sum_k v_t^i \left(1 + \frac{\beta_{ik}}{v_t^i \, v_t^k}\right) (\Delta \ln P_{it} - \Delta \ln P_{kt}) - \frac{\Delta f_{it}}{v_t^i}.$$

The labor-saving technical change has made a large contribution to the labor productivity growth through not only TFP growth but also input substitution. In particular, the labor productivity growth in 1995-2005 was mostly driven by the labor-saving technical change through both channels.

4 Industry-Level Technical Change

In this section, we report the estimation results for our models of individual industries. Following many previous studies, we assume that the value of output is allocated to capital, labor, energy, and (non-energy) materials. We describe data, summarize the estimation results, and discuss the differences from the results for our aggregate model in Section 3 and previous studies on the industry-level technical change.

4.1 Data

All industry-level data we use are in the EU-KLEMS database that covers 1973 to 2005.[22] We estimate the models of 10 industries including 3 material manufacturing industries (metals; chemicals; petroleum and coal products),

[21] $\sigma_{ik} \equiv 1 + \{\beta_{ik}/(v^i \, v^k)\}$ in the second term in the right-hand side is the Allen–Uzawa partial elasticity of substitution.

[22] Japanese data in the EU-KLEMS database are constructed based on "Japan Industrial Productivity (JIP) Database."

3 processing manufacturing industries (machinery; electric machinery; and transport equipment), and 4 non-manufacturing industries (transport and storage; wholesale and retail; construction; and electricity, gas, and water supply). Many industries are integrated into the above 10 industries, except for most of service industries (see Appendix Table 1(1)). The total output share of the integrated 10 industries is around 50 percent.

In the EU-KLEMS database, the intermediate inputs are divided into energy and non-energy materials (including services). The energy inputs in the EU-KLEMS database include intermediate inputs from energy-producing industries for the other industries. For the energy-producing industries such as petroleum and coal products and electricity and gas supply, imported natural energy resources seem to be classified into (non-energy) materials as well as energy. We show a simplified input-output table in Appendix Table 2 and depict the flows of intermediate inputs related to imported natural resources among industries in Appendix Figure.

4.2 Results

Figure 8-1 summarizes the estimation results of the latent variables on the biases of technical change in the full sample period from 1973 to 2005 for each input for each industry. The pattern that occurred most frequently among industries is energy-using, materials-saving, labor-using, and capital-using. The biases for energy are energy-using for all industries except wholesale and retail. The biases for materials are materials-saving for all industries and substantial in magnitude for many industries. The two largest materials-saving biases among industries are, however, in petroleum and coal products and electricity and gas supply, which may include biases for imported natural energy resources as mentioned above. Meanwhile, the biases for labor are almost divided between labor-using and labor-saving. This differs considerably from the result for our aggregate model, in which the labor-saving technical change occurred substantially in magnitude throughout the full sample period. Lastly, the biases for capital are predominantly capital-using, as in our aggregate model.

In Figure 8-2, we show the biases of technical change in each decade. Together with Figure 9, which plots the latent variables for each input for each industry, we can follow the historical evolution of the biases of technical change.[23] The energy-using technical change occurred in all industries in the 1970s, but the biases for energy have been small since the 1980s. The materials-saving technical change continued almost steadily in many industries until the 1990s, but switched to material-using in some industries in the 2000s. The labor-using technical change occurred substantially in magnitude in some industries in the 1970s, but the biases for labor have been small in most industries since the 1980s. In the 2000s, the biases for labor are labor-saving for most industries, and their magnitudes are particularly large in some non-manufacturing industries such as transport and storage and wholesale and retail. The capital-using technical change has continued in many industries since the 1980s, though the capital-saving technical change occurred substantially in magnitude in some industries in the 1970s.

4.3 Comparison with Aggregate Technical Change

We compare the above estimation results for our models of individual industries with the results for our aggregate model in Section 3. The main differences are that the energy-saving technical change in the 1980s did not occur substantially, and that the labor-saving technical change throughout the sample period did not occur predominantly in the industry level.

As for the energy-saving technical change, differences in the definitions of energy inputs in the data are important for the macro-micro differences. As mentioned above, materials-saving technical change in petroleum and coal products and electricity and gas supply in the 1980s could be regarded as energy-saving technical change in the aggregate economy. Meanwhile, secondary energy sources such as electric power are not regarded as energy inputs in the aggregate economy. In addition, changes in industrial structure may also be important: shifts from energy-using industries to energy-saving

[23] The AR(1) parameters for the latent variables for some industries are close to but less than unity.

industries could make a significant contribution to the energy-saving technical change in the aggregate economy.

As for the labor-saving technical change, the relationship with the materials-saving technical change may be important for the macro-micro differences. The industries that experienced labor-using technical change in the full sample period, except electrical machinery, experienced materials-saving technical change substantially in magnitudes. The materials-saving technical change for those industries may appear as labor-saving technical change in the aggregate economy. In addition, the coverage of our models of individual industries may also be important. In some service industries that are excluded from our coverage, labor-saving technical change might occur substantially, especially in the 2000s, as in transport and storage and wholesale and retail.

4.4 Comparison with Previous Studies

Lastly, we compare our results with previous studies. Many previous empirical studies focus on biases of technical change in individual industries rather than those in the aggregate economy.

Jin and Jorgenson (2008) estimate time-varying biases of technical change in 35 U.S. industries from 1960 to 2005 by similar estimation procedures to ours. Their results for the U.S. industries are basically similar to our results for Japanese industries. The pattern that occurred most frequently among U.S. industries is energy-using, materials-saving, labor-saving, and capital-using, which is the same pattern as our results, except for labor. An important difference is, however, in the historical evolution of the biases for energy. In their estimation results for divided sub-samples, the biases for energy are energy-using in the 1960–1980 sub-period but energy-saving in the 1980–2005 sub-period. It is not clear how the data problem mentioned above could explain the difference between their results and ours.

Kuroda, Yoshioka, and Jorgenson (1984) estimate fixed parameters on biases of technical change in 30 Japanese industries from 1960 to 1979, based on the constant time trend models, given by equation (9). The pattern that occurred most frequently among Japanese industries in their results is energy-using, materials-saving, labor-using, and capital-saving, which is consistent with our results for the 1970s.

5 Concluding Remarks

In this paper, we estimate time-varying biases of technical change and their effects on productivity using econometric models of aggregate and industry-level technology in Japan. We found little evidence that producers switched to the energy-saving technical change by the end of 2008 in response to the recent surge in energy prices. As a result, rising energy prices under the energy-using technical change have contributed to a slowdown in TFP growth. Meanwhile, the labor-saving technical change has made large positive contributions to TFP growth and labor productivity growth.

Our estimation results imply that considering biases of technical change is important for productivity analysis. At the same time, however, we realized that measuring and understanding biases of technical change are not easy tasks. In particular, since our models do not consider endogenous technical change explicitly, we cannot identify fundamental sources of the biases of technical change. A fruitful direction for future research would be theoretical investigation into endogenous technical change. Another promising direction would be refining the dataset and developing econometric models for improved measurement of technical change.

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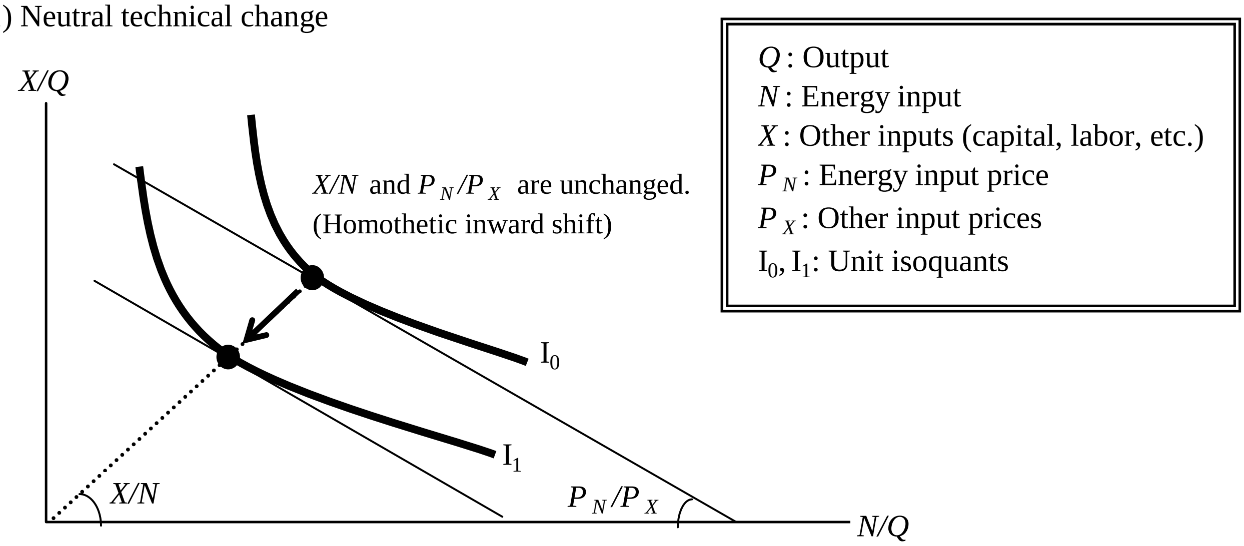
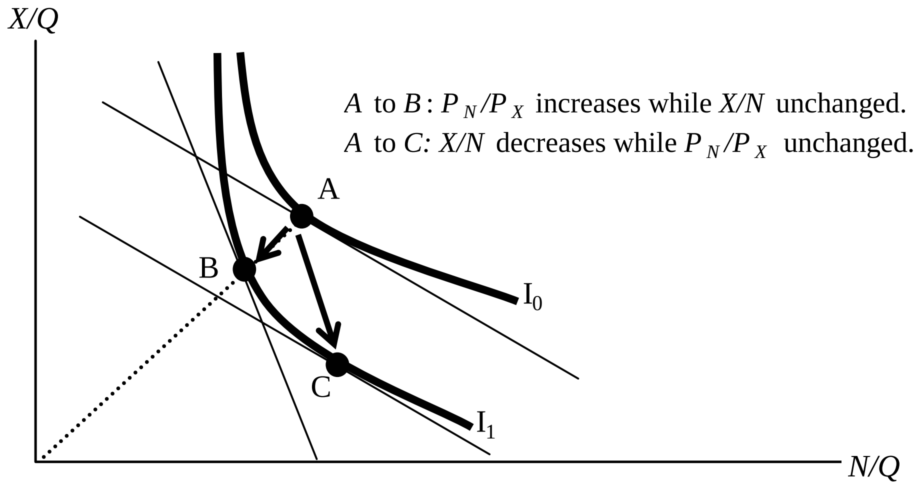
[11] León-Ledesma, M. A., McAdam, P., and Willman, A. (2009), "Identifying the Elasticity of Substitution with Biased Technical Change," European Central Bank Working Paper 1001.

Figure 1. Biases of Technical Change (Concepts)

(1) Neutral technical change



(2) Energy-using technical change



(3) Energy-saving technical change

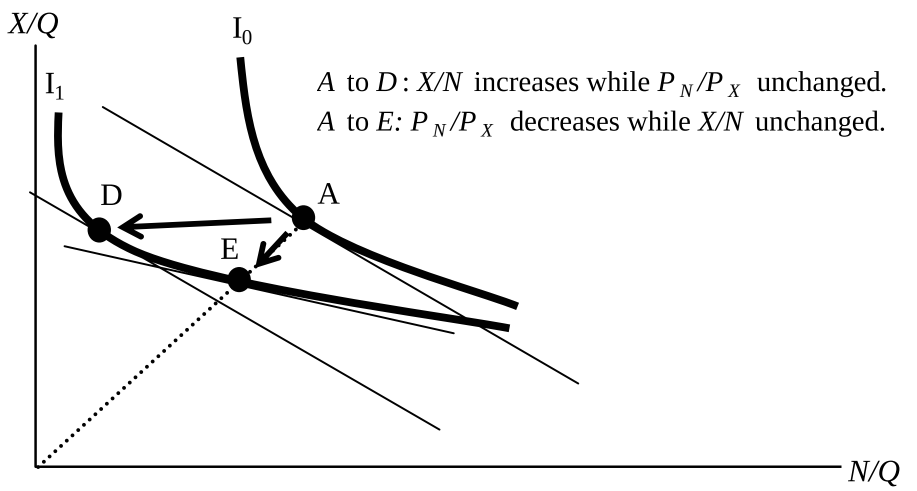
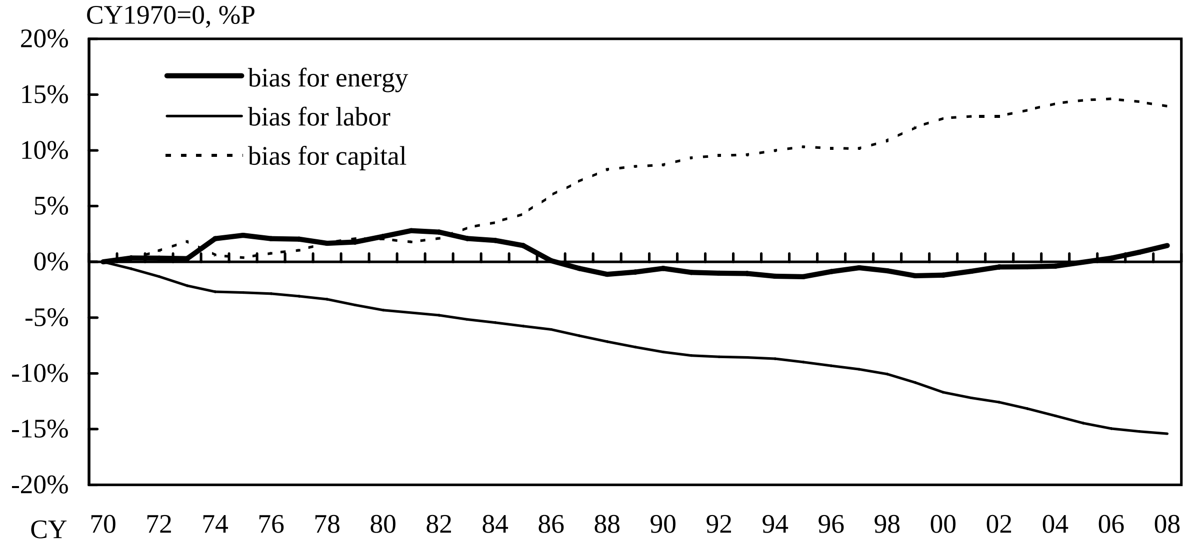
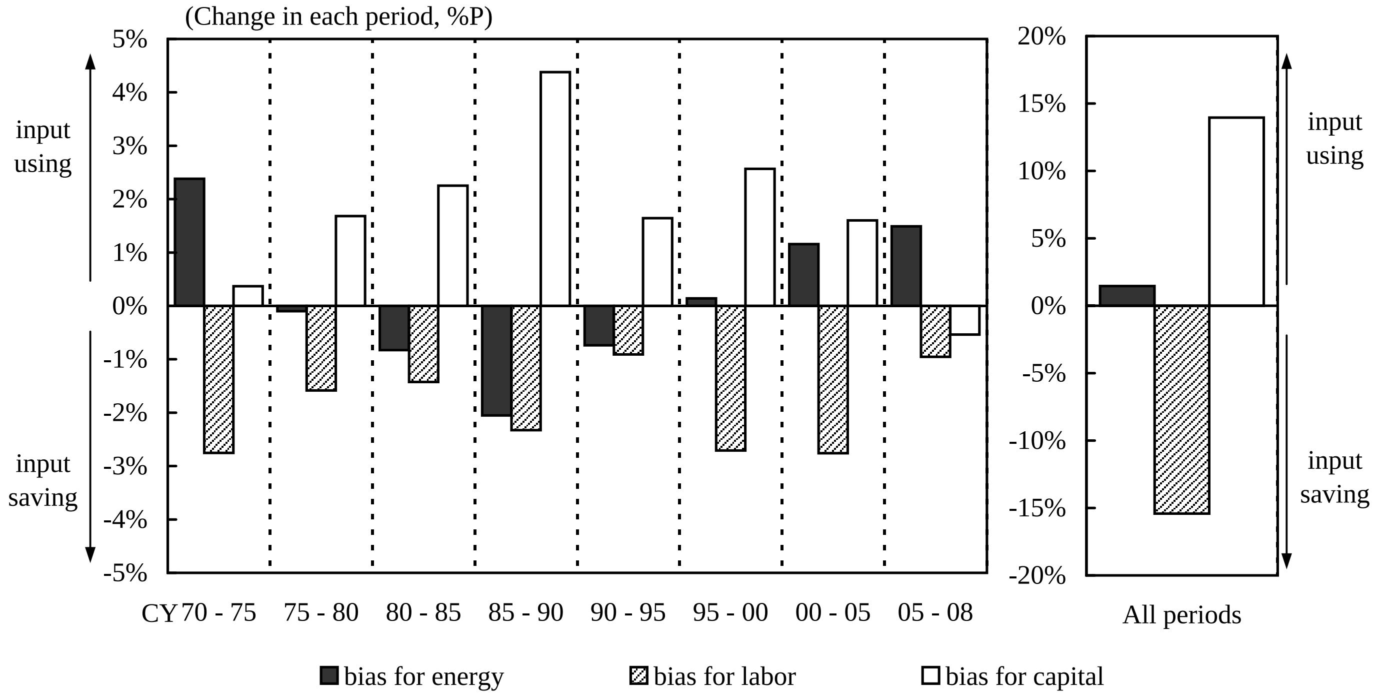


Figure 2. Biases of Technical Change (Aggregate Dataset)

(1) Latent variables on biases of technical level



(2) Biases of technical change



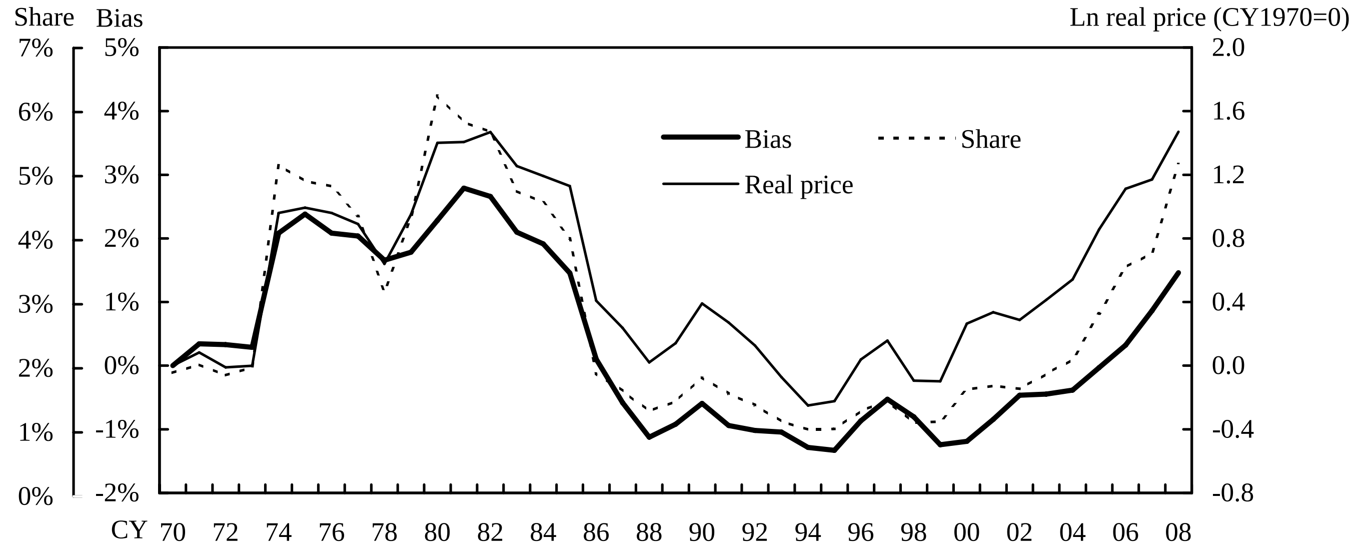
(3) Parameters on elasticities

Parameters on share elasticities				Elasticities of substitution	
β_{KK}	0.1221 [0.0165]**	β_{KL}	-0.1148 [0.0158]**	σ_{KL}	0.5110
β_{LL}	0.1128 [0.0192]**	β_{KN}	-0.0073	σ_{KN}	0.2207
β_{NN}	0.0053	β_{LN}	0.0019	σ_{LN}	1.1855

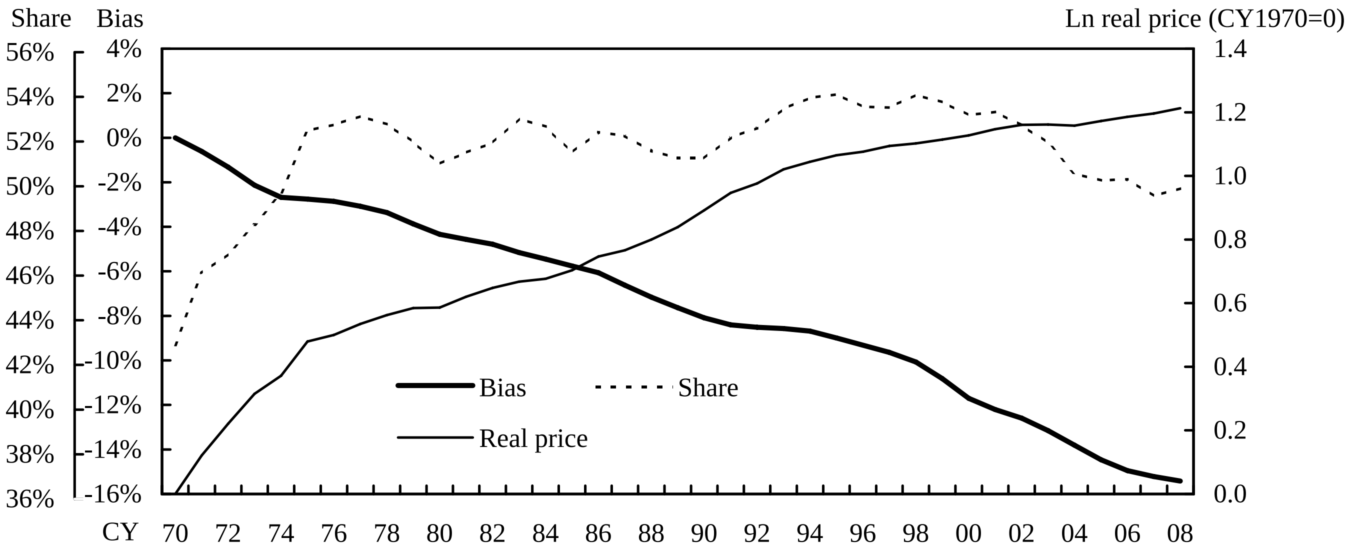
Note: The symbols ** indicate statistical significance at the 1% level.

Figure 3. Input Shares, Real Input Prices, and Biases of Technical Change

(1) Energy



(2) Labor



(3) Capital

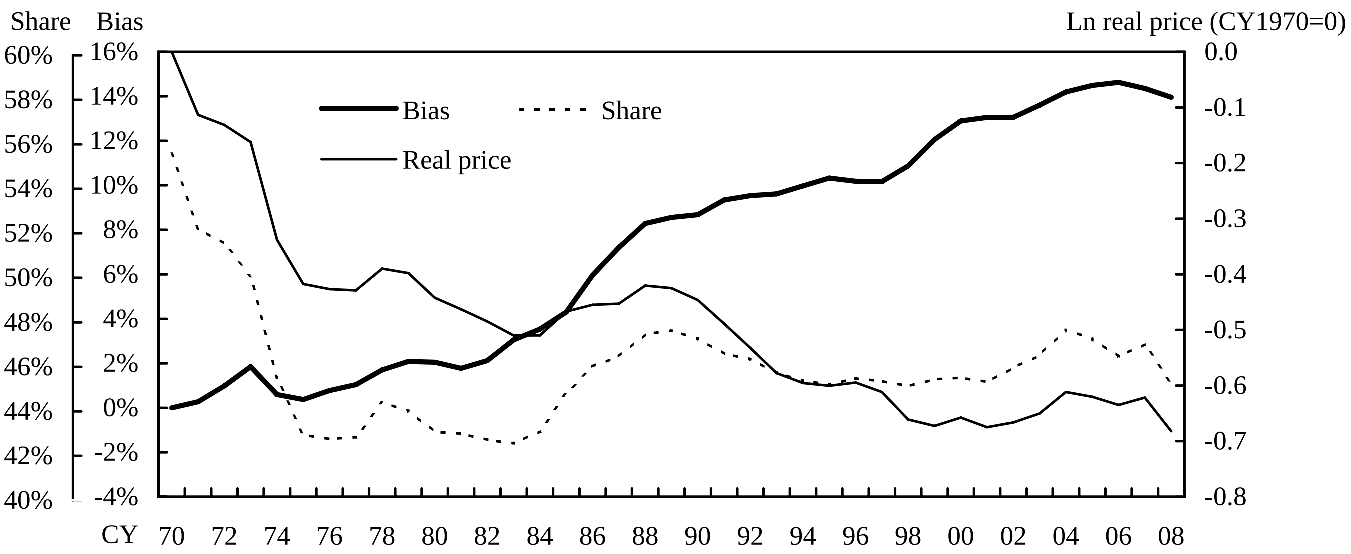
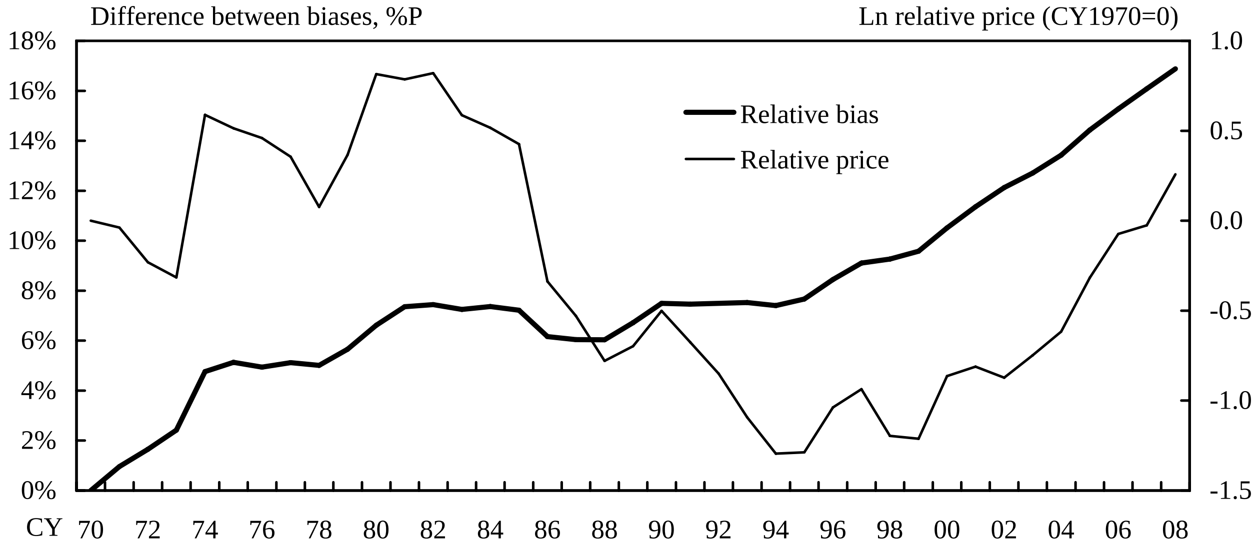
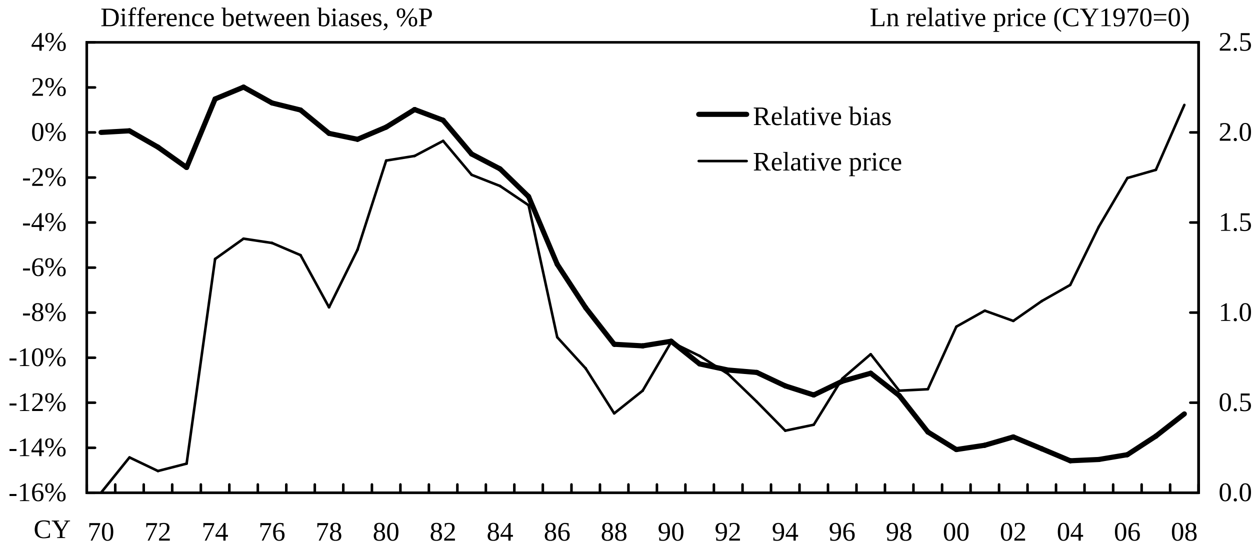


Figure 4. Relative Input Prices and Differences between Biases

(1) Energy to labor



(2) Energy to capital



(3) Labor to capital

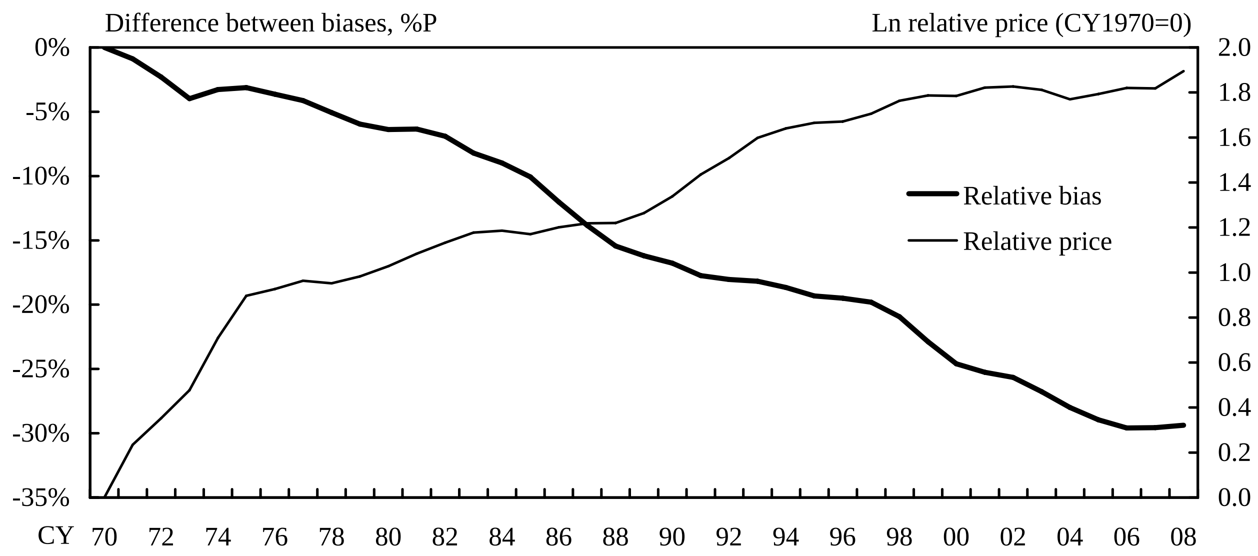
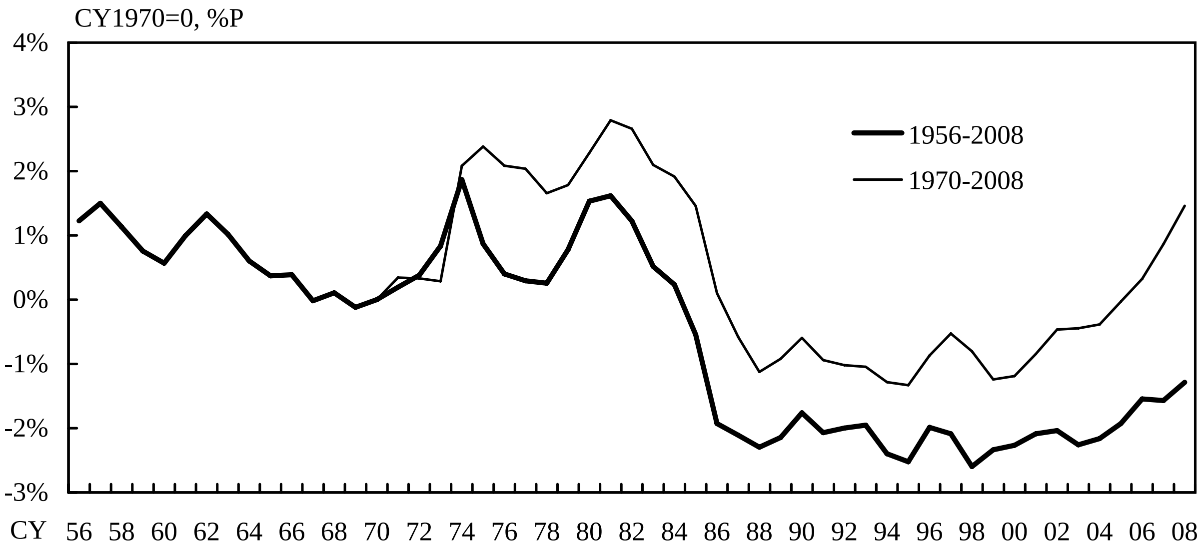
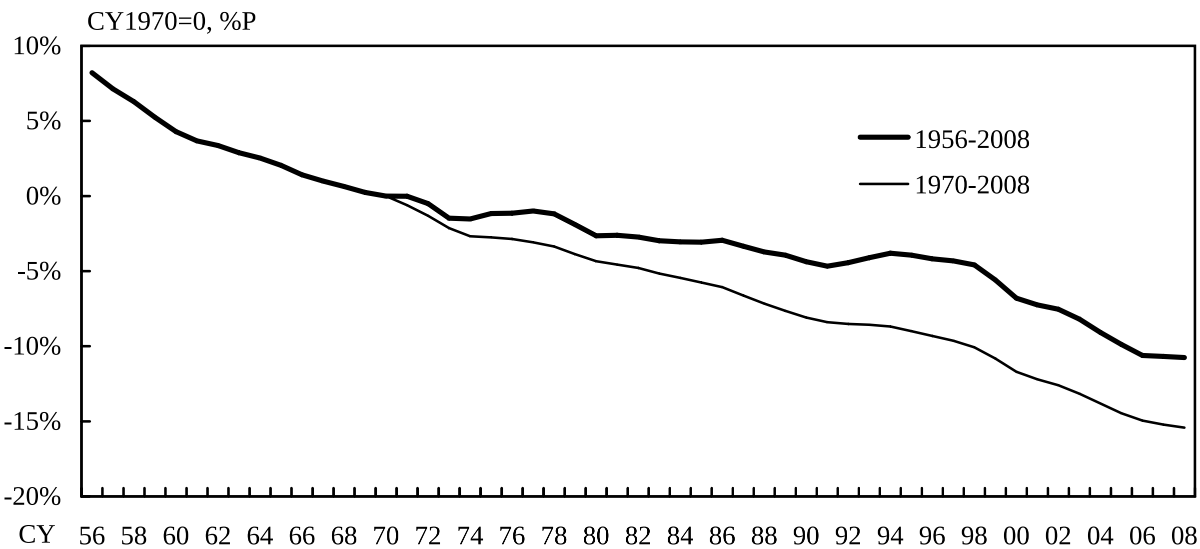


Figure 5. Results from Extended Dataset

(1) Biases for energy



(2) Biases for labor



(3) Biases for capital

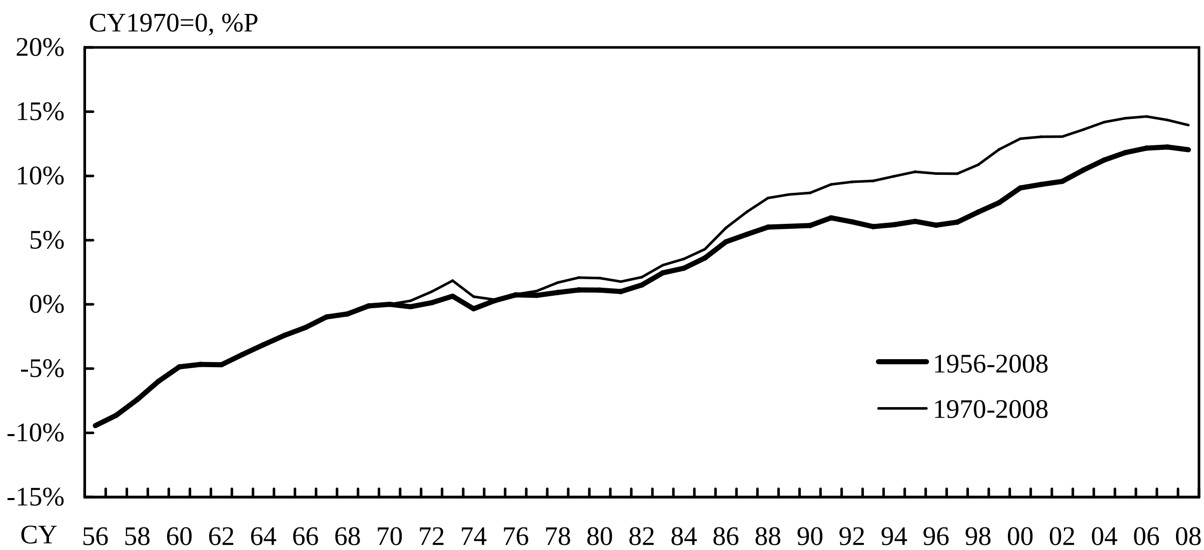
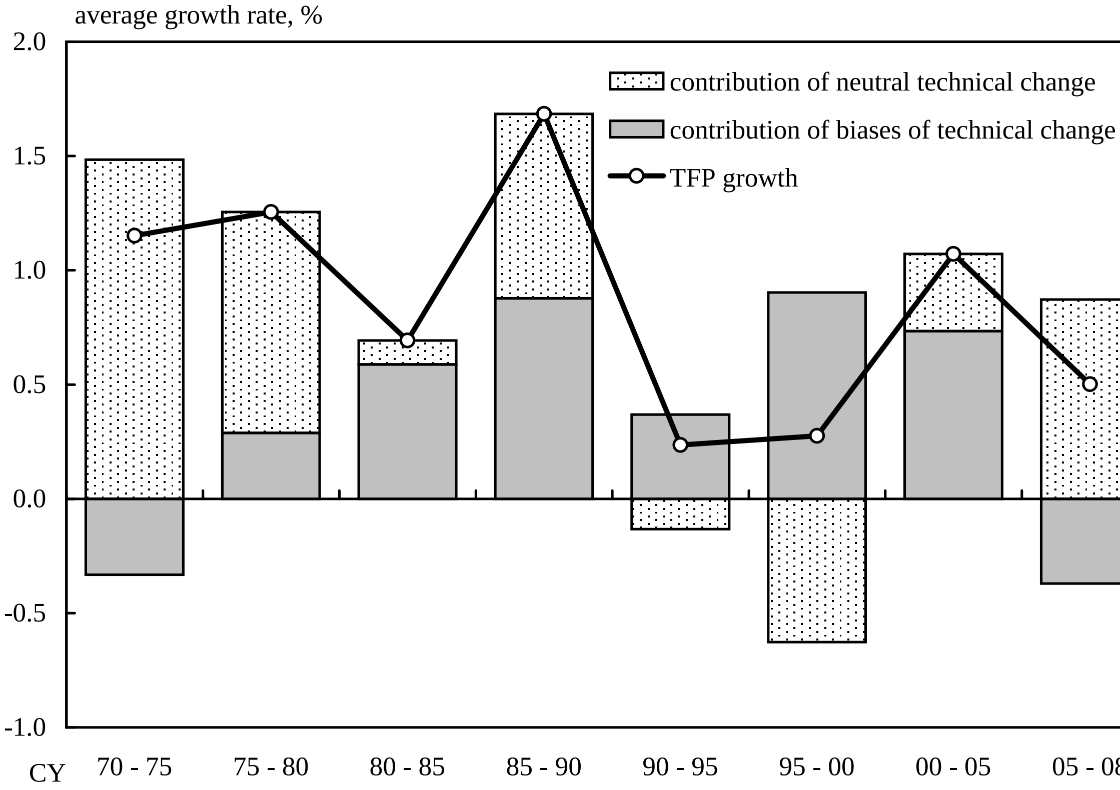


Figure 6. TFP Growth and Technical Change

(1) TFP growth and contributions of neutral technical change and biases of technical change



(2) Contribution of biases of technical change

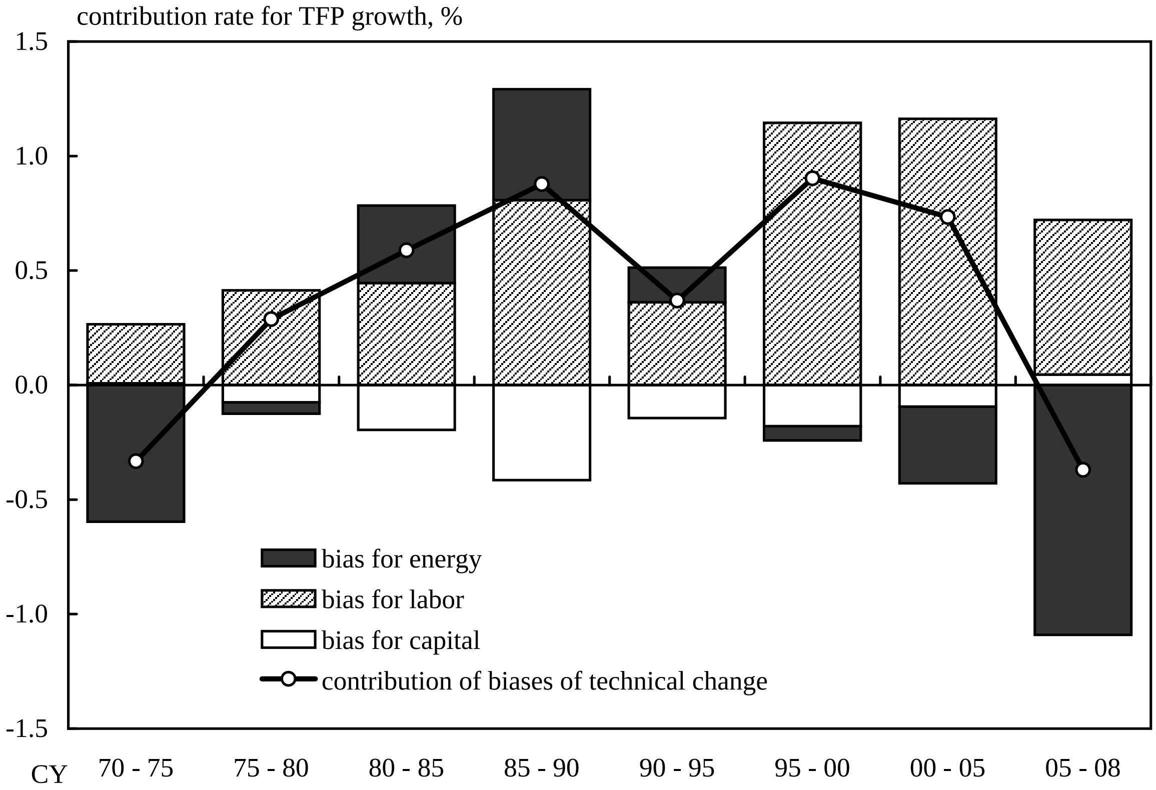
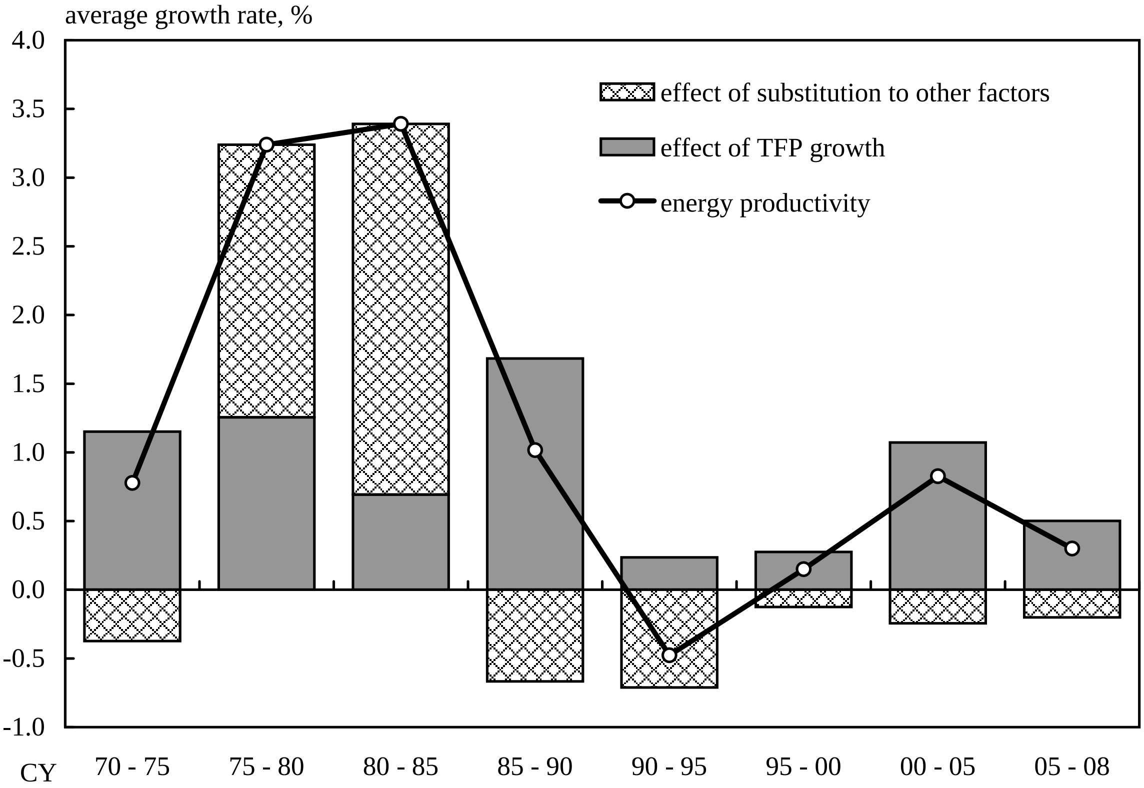


Figure 7. Average Productivity and Technical Change

(1) Energy productivity



(2) Labor productivity

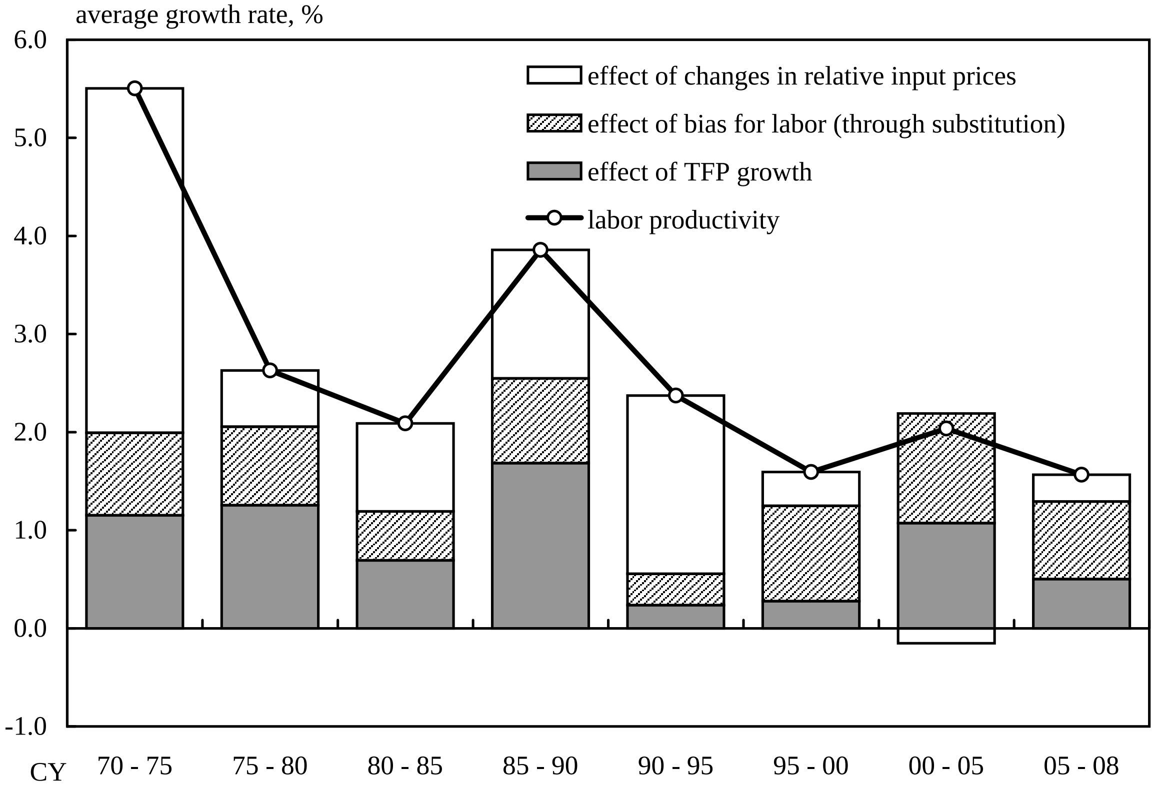
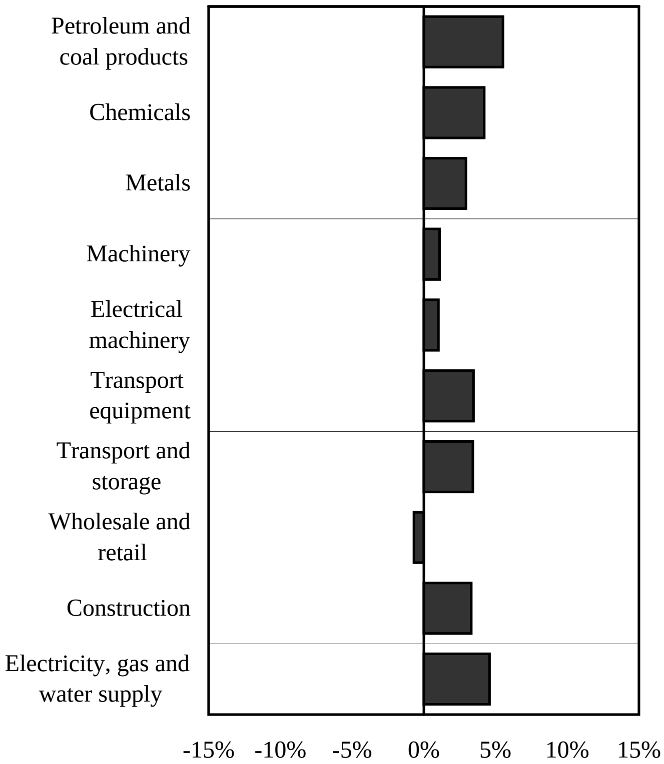


Figure 8-1. Biases of Technical Change (Industry-Level Dataset)

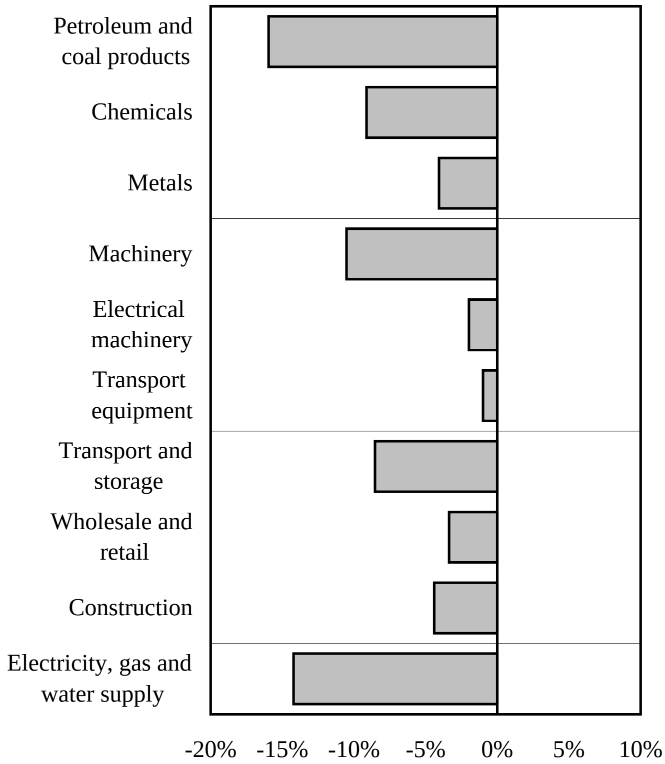
(1) Biases for energy

< 73 - 05 >



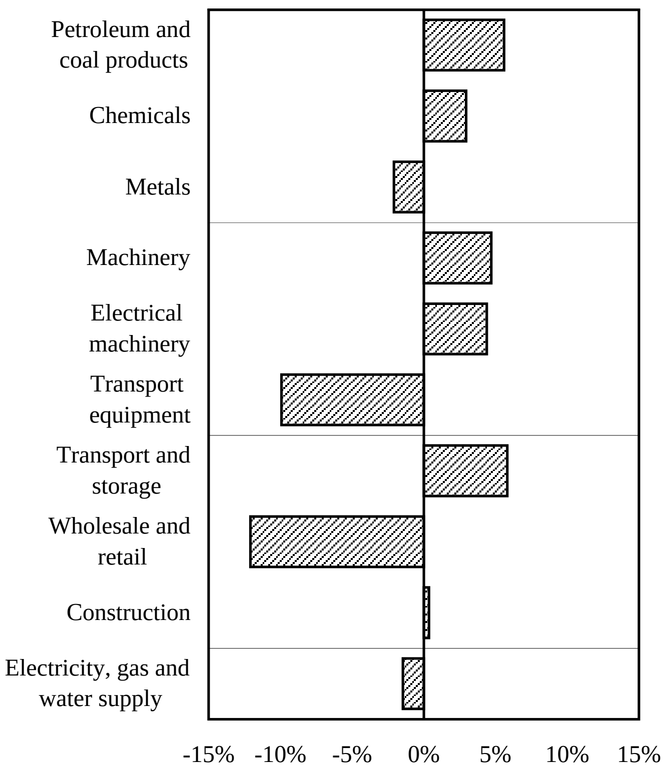
(2) Biases for materials

< 73 - 05 >



(3) Biases for labor

< 73 - 05 >



(4) Biases for capital

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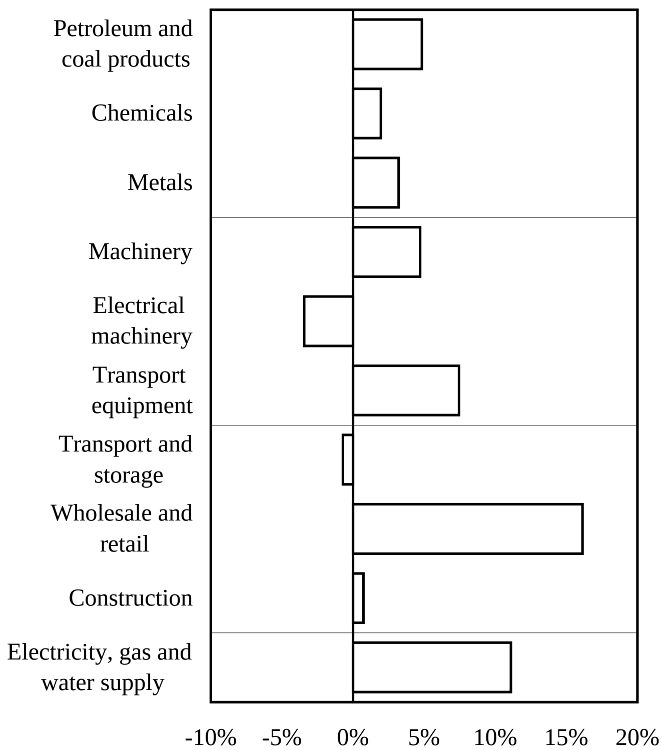
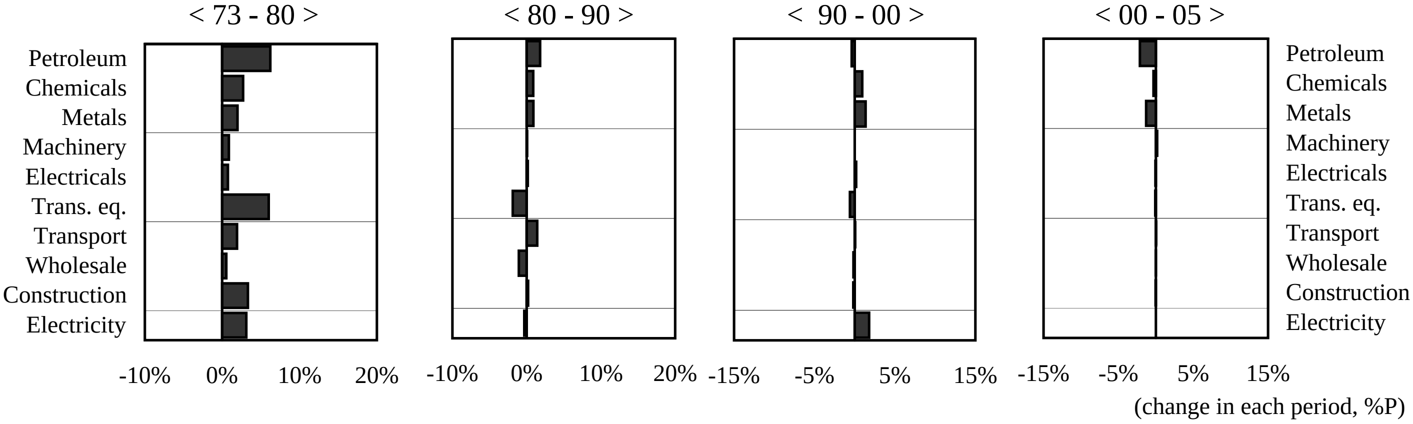
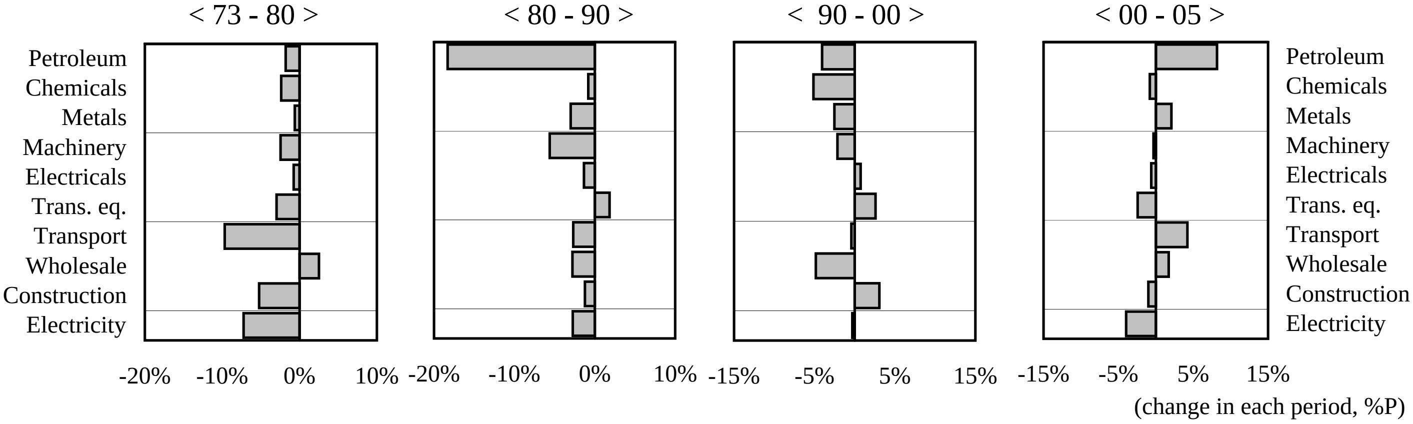


Figure 8-2. Biases of Technical Change (Industry-Level Dataset)

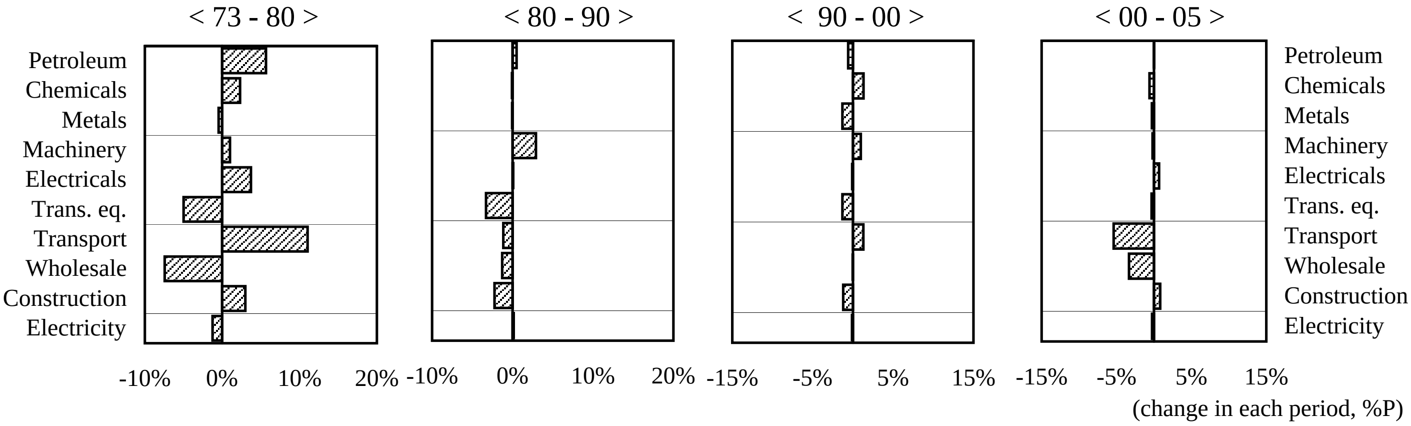
(1) Biases for energy



(2) Biases for materials



(3) Biases for labor



(4) Biases for capital

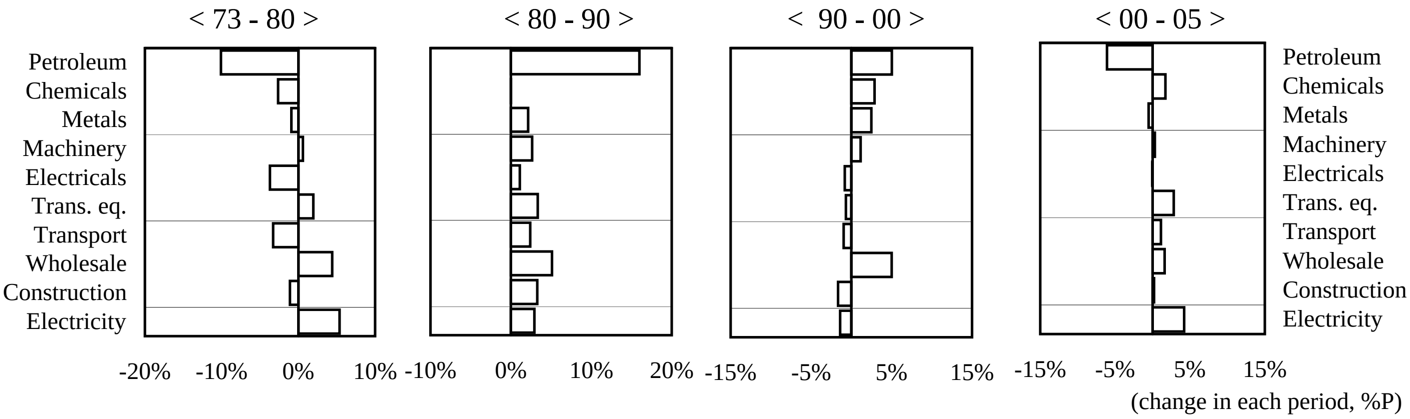


Figure 9-1. Biases for Energy

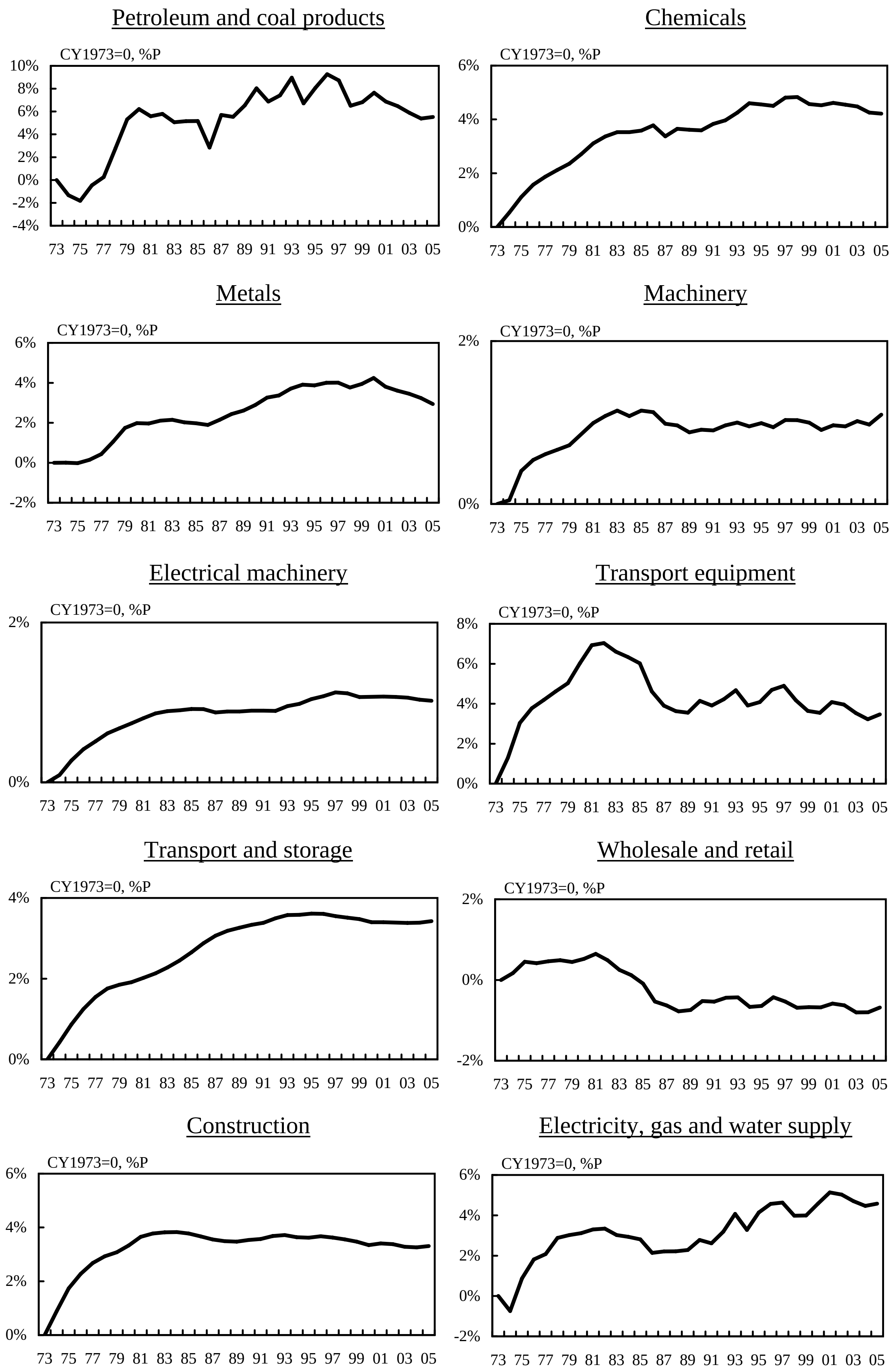


Figure 9-2. Biases for Materials

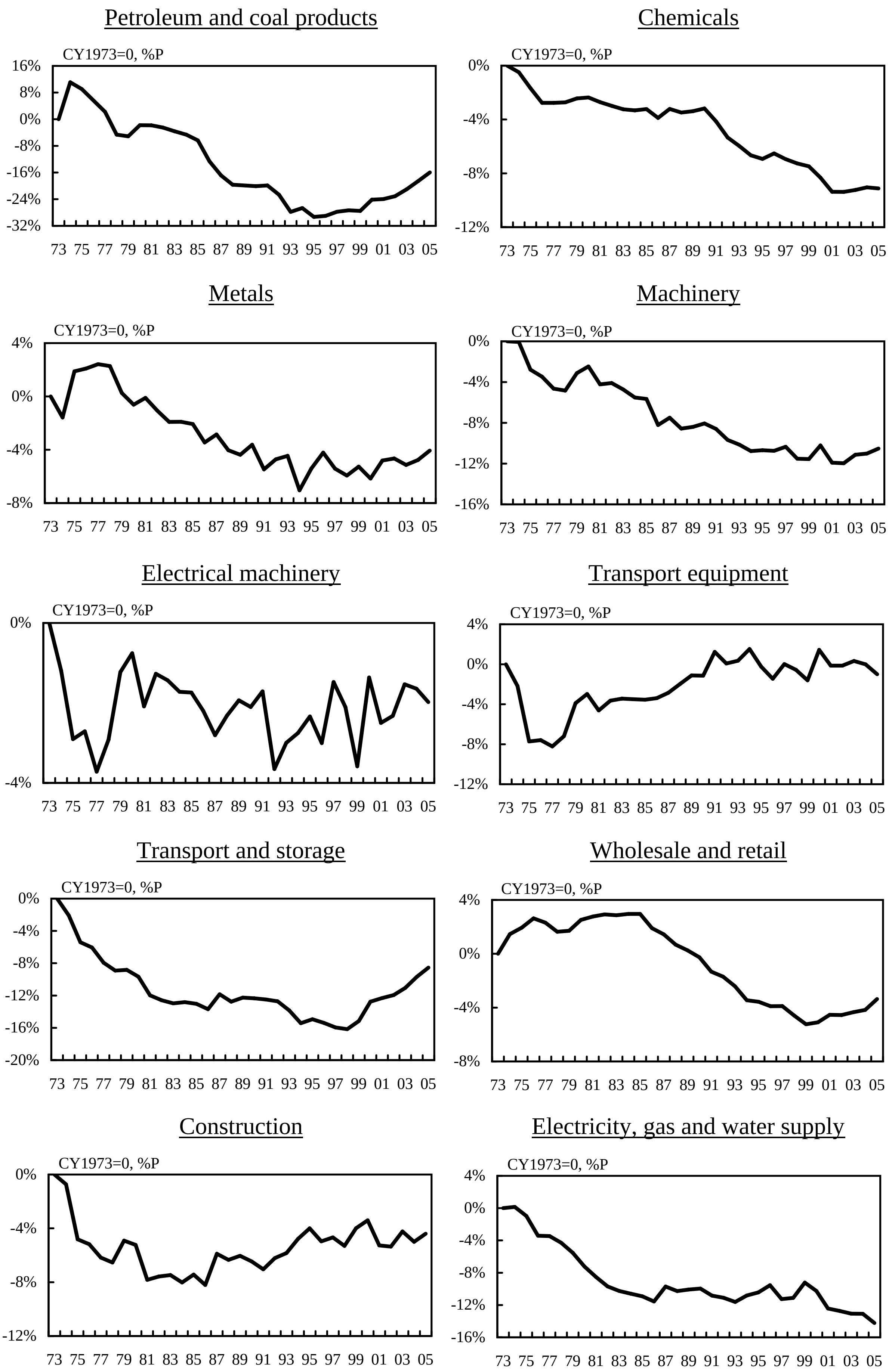


Figure 9-3. Biases for Labor

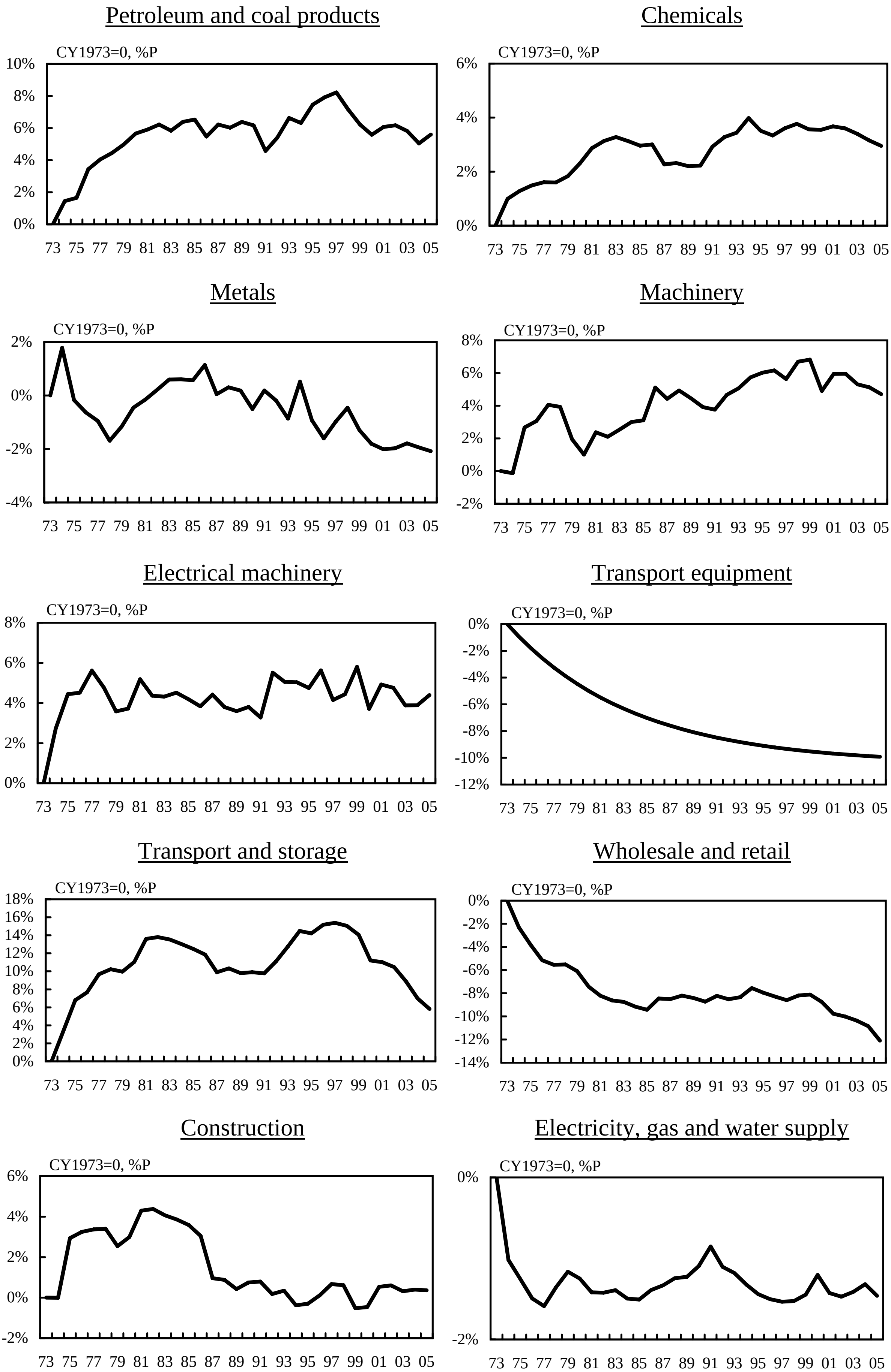
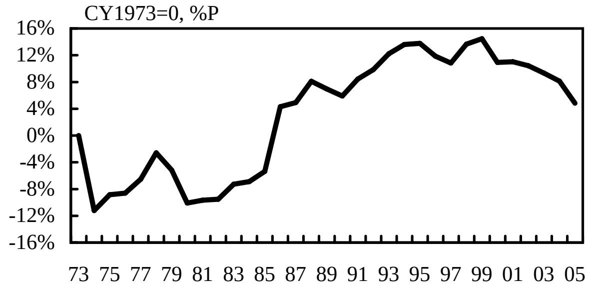
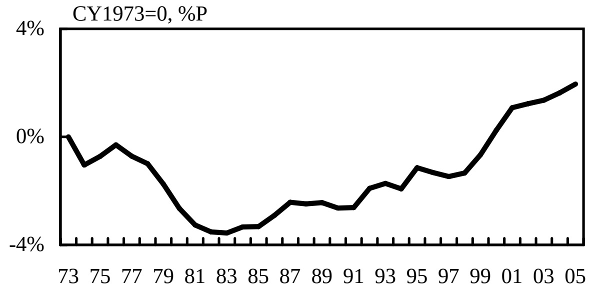


Figure 9-4. Biases for Capital

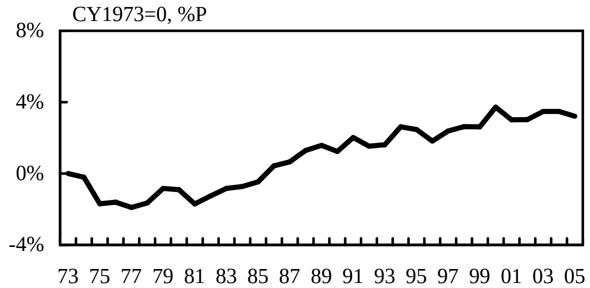
Petroleum and coal products



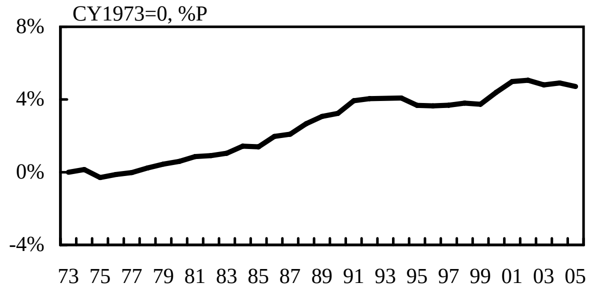
Chemicals



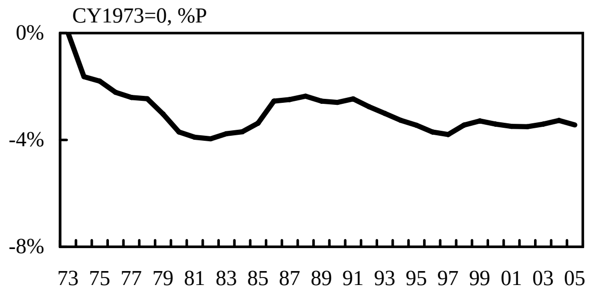
Metals



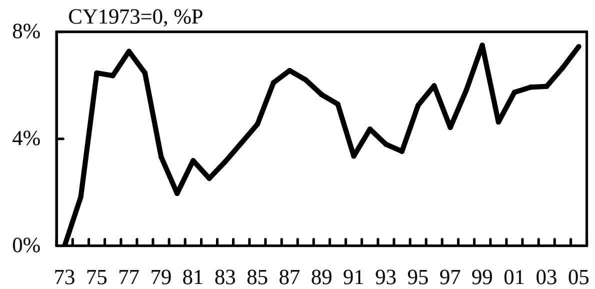
Machinery



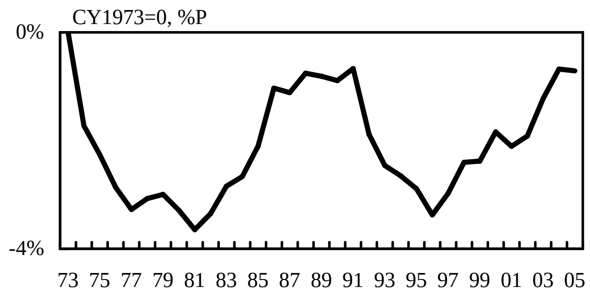
Electrical machinery



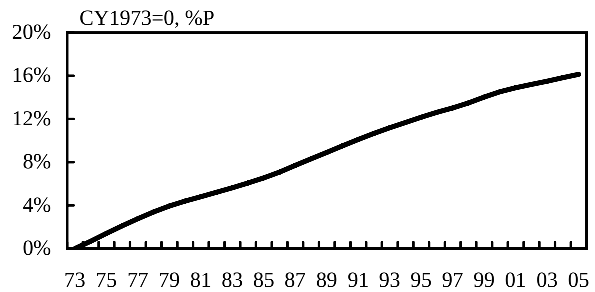
Transport equipment



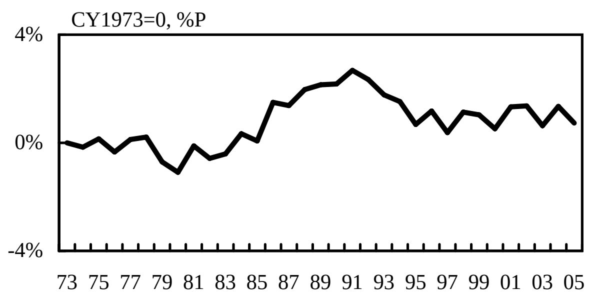
Transport and storage



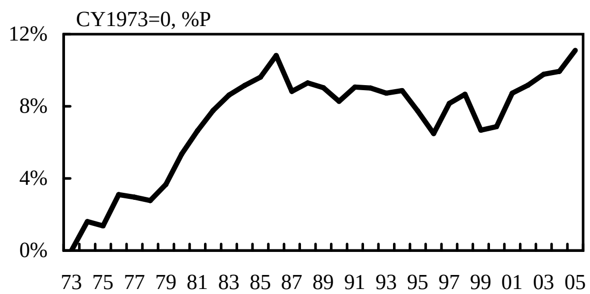
Wholesale and retail



Construction



Electricity, gas and water supply



Appendix Table 1. Data

(1) Details of our datasets

<table>
<tr><th colspan="3"></th><th>Aggregate Dataset</th><th colspan="2">Industry-Level Dataset</th></tr>
<tr><td colspan="3">Sample Period</td><td>1970 - 2008
(Extended Dataset: 1956 - 2008)</td><td colspan="2">1973 - 2005</td></tr>
<tr><td colspan="3">Data Sources</td><td>Cabinet Office, "National Accounts of Japan"
Ministry of Finance, "Trade Statistics of Japan"
Institute of Energy Economics, Japan, "Energy Balance Statistics"
Ministry of Internal Affairs and Communications, "Labour Force Survey"
Ministry of Health, Labour and Welfare, "Monthly Labour Survey"
Research Institute of Economy, Trade and Industry, "Japan Industrial Productivity Database"
Cabinet office, "Annual Report on Gross Capital Stock of Private Enterprises"</td><td colspan="2">All data are from EU-KLEMS
(http://www.euklems.net/)</td></tr>
<tr><td colspan="3" rowspan="11">Industrial Classification</td><td rowspan="11">All industries</td><td colspan="2">Classified into following 10 industries</td></tr>
<tr><td>Metals:</td><td>Basic metals and fabricated metal</td></tr>
<tr><td>Chemicals:</td><td>Chemicals and chemical products</td></tr>
<tr><td>Petroleum and coal products:</td><td>Coke, refined petroleum and nuclear fuel</td></tr>
<tr><td>Machinery:</td><td>Machinery, not elsewhere classified</td></tr>
<tr><td>Electrical machinery:</td><td>Office, accounting and computing machinery
Electrical engineering
Medical, precision and optical instruments</td></tr>
<tr><td>Transport equipment:</td><td>Transport equipment</td></tr>
<tr><td>Transport and storage:</td><td>Transport and storage</td></tr>
<tr><td>Wholesale and retail:</td><td>Wholesale and retail trade</td></tr>
<tr><td>Construction:</td><td>Construction</td></tr>
<tr><td>Electricity, gas and water supply:</td><td>Electricity, gas and water supply</td></tr>
<tr><td rowspan="9">Data Definitions</td><td rowspan="2">Output</td><td>Nominal</td><td>Nominal GDP plus mineral fuels imports</td><td colspan="2" rowspan="2">Gross output</td></tr>
<tr><td>Real</td><td>Real GDP plus imported primary energy</td></tr>
<tr><td rowspan="2">Energy</td><td>Nominal</td><td>Mineral fuels imports</td><td colspan="2" rowspan="2">Intermediate energy inputs</td></tr>
<tr><td>Real</td><td>Imported primary energy (energy unit)</td></tr>
<tr><td colspan="2">Materials</td><td>-</td><td colspan="2">Intermediate inputs excluding energy inputs
(Intermediate material inputs and intermediate service inputs)</td></tr>
<tr><td rowspan="2">Labor</td><td>Nominal</td><td>Compensation of employees</td><td colspan="2">Labour compensation</td></tr>
<tr><td>Real</td><td>Man-hours input calculated by employed person and total hours worked</td><td colspan="2">Labour services</td></tr>
<tr><td rowspan="2">Capital</td><td>Nominal</td><td>Nominal GDP minus compensation of employees</td><td colspan="2">Capital compensation</td></tr>
<tr><td>Real</td><td>Capital input from "Japan Industrial Productivity Database"
("Annual Report on Gross Capital Stock of Private Enterprises")</td><td colspan="2">Capital services</td></tr>
</table>

(2) Instrumental variables list

1	Constant
2	Average tax rate on personal labor income
3	Average tax rate on corporate income
4	Nominal public investment
5	Private financial wealth per population over 15 years old
6	Imported oil price
7	Lagged price of output
8	Lagged price of labor service

Appendix Table 2. Details of Intermediate Inputs

(1) Breakdown of intermediate inputs (ratio to nominal output)

(%)

		All Intermediate inputs	Intermediate Energy: *Imported*	Intermediate Energy: *Domestic*	Intermediate Materials: *Imported*	Intermediate Materials: *Domestic*	From the same industry
Basic Materials							
Iron and steel	<1.9>	71.7	0.1	5.3	4.1	2.1	44.3
Non-ferrous metal	<0.7>	66.2	0.0	4.1	21.6	2.8	14.4
Fabricated metal	<1.5>	52.3	0.0	2.1	1.7	23.8	5.8
Chemicals	<2.9>	69.4	0.0	5.2	7.5	4.0	25.1
Petroleum and coal products	<1.4>	58.8	44.3	0.9	0.2	0.5	4.9
Other	<3.1>	57.3	0.1	3.7	2.2	3.2	21.5
Processing							
Machinery	<2.7>	59.1	0.0	1.2	0.3	13.9	17.5
Electrical machinery	<6.4>	67.2	0.0	1.2	1.0	8.2	23.7
Transport equipment	<4.7>	76.4	0.0	1.1	0.6	8.2	41.9
Precision instruments	<0.4>	58.0	0.0	1.3	0.7	7.8	6.1
Other	<7.9>	61.1	0.0	1.6	0.7	10.1	15.2
Non-Manufacturing							
Transport and storage	<5.3>	52.0	0.0	10.3	0.9	0.9	7.8
Wholesale and retail	<10.7>	28.3	0.0	1.1	0.0	1.7	0.8
Construction	<8.4>	53.7	0.0	1.4	0.6	18.4	0.3
Service activities	<38.0>	34.9	0.0	1.8	0.2	4.2	17.0
Electricity and gas supply	<2.1>	45.5	10.2	2.8	0.5	0.7	3.5
Mining	<0.2>	50.8	0.0	3.7	0.3	3.0	0.2
Agriculture	<1.6>	43.2	0.0	1.7	0.7	5.6	10.0

Notes: 1. Output shares are shown in angle brackets.
2. Shaded cells indicate the number is more than 5 %.
3. Intermediate Energy is composed of imported energy resources and input from the petroleum and electricity sectors.
4. Intermediate Materials are composed of imported mineral resources and basic materials, and input from basic materials sectors.

(2) Simplified input-output table

tril. Yen

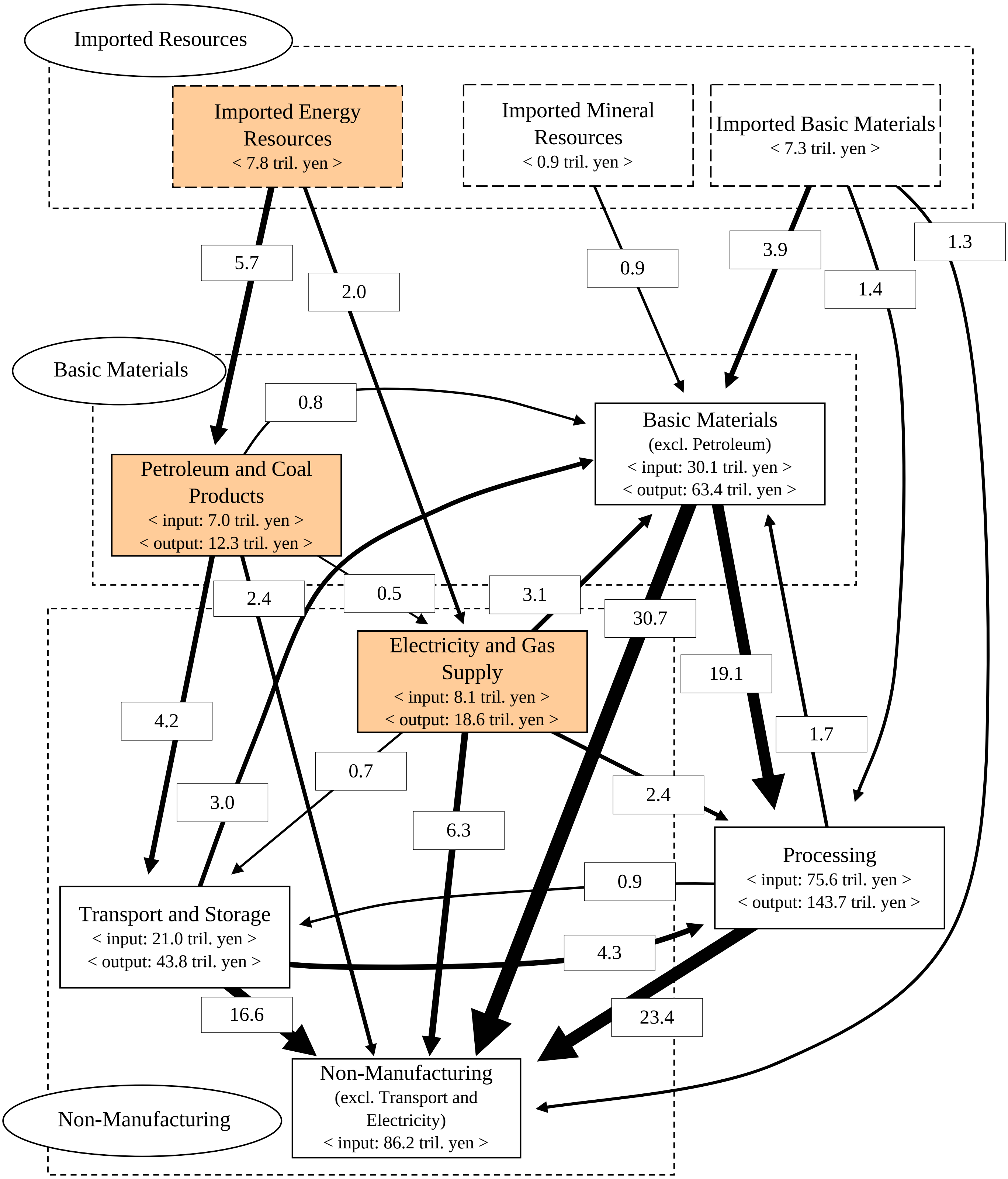
	Petroleum	Electricity	Basic Metals	Processing	Transport	Non-Manufacturing	Intermediate outputs	Final Demand	Domestic Product
Petroleum and coal products		0.5	0.8	0.3	4.2	2.4	8.2	4.1	12.3
Electricity and gas supply	0.1		3.1	2.4	0.7	6.3	12.6	6.0	18.6
Basic Materials (excl. petroleum)	0.1	0.1		19.1	0.4	30.7	50.4	13.0	63.4
Processing	0.0	0.0	1.7		0.9	23.4	26.1	117.6	143.7
Transport and storage	0.4	0.4	3.0	4.3		16.6	24.8	19.0	43.8
Non-Manufacturing (excl. transport and electricity)	0.6	4.8	15.9	38.4	13.0		72.8	349.2	422.0
Imported energy resources	5.7	2.0	0.1	0.0	0.0	0.0	7.8		
Imported mineral resources	0.0	0.0	0.9	0.0	0.0	0.0	0.9		
Imported basic materials	0.0	0.1	3.9	1.4	0.4	1.3	7.3		
Inputs from the same industry		0.0		7.4	1.3	1.8	10.5		
Other imports	0.0	0.0	0.7	2.3	0.1	3.6	6.7		
Intermediate inputs	7.0	8.1	30.1	75.6	21.0	86.2	227.9		

Notes: 1. Intermediate inputs from the same sectors are excluded.
2. Shaded numbers indicate more than 0.5 trillion yen.

Source: Ministry of Internal Affairs and Communications, "2000 Input-Output Tables for Japan."

Appendix Figure. Intermediate Input Flows Related to Imported Resources

(1) Intermediate input flows (CY2000, nominal value, trillion yen)



Notes: 1. Arrows are shown when the amount of the flow is more than 0.5 trillion yen, except inflows from the non-manufacturing sectors and imports excluding resources.

2. Thickness of arrows indicates the amount of flow.

3. Intermediate inputs from the same sectors are excluded.

4. Shaded sectors indicate energy-producing sector. Other sectors indicate energy-using sector.

Source: Ministry of Internal Affairs and Communications, "2000 Input-Output Tables for Japan."