Productivity, Efficiency, Scale Economies and Technical Change: a New Decomposition Analysis of TFP Applied to the Japanese Prefectures

Jiro Nemoto
Graduate School of Economics
Nagoya University
Nagoya 464-8601, Japan
e-mail: nemoto@cc.nagoya-u.ac.jp

Mika Goto
Socio-economic Research Center
Central Research Institute of Electric Power Industry
Otemachi 1-6-1, Tokyo 100-8126, Japan

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Abstract:

This paper aims to examine the productivity change of the Japanese economy using the data pertaining to the 47 prefectures during the period 1981—2000. The decomposition analysis of the Hicks-Moorsteen-Bjurek productivity index is conducted to explore the sources of the productivity change. In summary, technical change and efficiency change are two of the most important components driving procyclical productivity. We find that relative their importance varies over periods. Supply shocks captured by technical change component caused upturns in productivity in the mid and late 80s and in 1999 and 2000. Supply shocks also caused downturns in the early and mid 90s. On the other hand, demand shocks captured by efficiency change component drove upturns of productivity in 1984, 1990 and 1996 when supply shocks were not detected.

1. Introduction

The main purpose of this paper is to examine the productivity of the Japanese economy using data pertaining to the 47 prefectures over the period 1981—2000. It is of particular interest to clarify the sources of productivity growth in Japan during this period. While the Japanese economy outperformed other developed economies in the 1980s, it experienced severe stagnation in the 1990s. It should be noted that the average economic growth rate of Japan, which was 4.0 percent during the period 1981—1990, fell considerably to 1.4 percent during the period 1991—2000. Such a sharp decline provides useful evidence for the purpose of clarifying the relationship between productivity and business cycles.

In macroeconomic literature, the persistent empirical fact of procyclical productivity has received much attention[1]. The procyclicality of productivity is alternatively explained by technology shocks, increasing returns to scale, or procyclical variations in input utilization. In order to examine which of these factors is more important, we develop a new decomposition analysis of the productivity change based on the Hicks-Moorsteen-Bjurek (HMB) index. The HMB productivity index is decomposed into four components: technical change, efficiency change, scale change, and the input and output mix effects.

This decomposable property is quite ideal for the purpose of disentangling the sources of productivity growth. The technical change component captures the effects of a shift in the production frontier on productivity. The production frontier changes its position in response to various shocks arising from technical advances, investment in infrastructure, and changes in the economic environment concerning production. In this paper, these shocks are referred to as "supply shocks". On the other hand, the efficiency change component measures the effects of deviations from the production frontier on productivity. There are two major sources of efficiency change: the first is variations in input utilization induced by demand shocks, including changes in exports, autonomous domestic expenditures, and fiscal policy, and the second is changes in managerial efficiency. While the former represent nationwide shocks, the latter are characterized as idiosyncratic shocks confronted by industries. Since this paper analyzes aggregated data spanning all industries, the efficiency change component mainly reflects the nationwide demand shocks and the resulting labor hoarding and excess capacity.

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[1] Recent studies include Baily, Bartelsman and Haltiwanger (2001), Basu (1996), Sbordone (1996,1997), and Chirinko (1995).

In addition to these two components, the effects of the returns to scale are identified by the scale change component. Further, the input and output mix effects are measured separately from the scale effects. In the conventional total factor productivity (TFP) analysis, the scale effects are evaluated on the basis of the difference between two input or output bundles, typically, inputs or outputs observed over adjacent periods. Thus, the effects of changes in input and output mix are compounded with the pure scale change. In this way, the decomposition analysis of the HMB index isolates the scale and mix effects by measuring the scale along a fixed ray. As a result, the input and output mix effects represent the difference in productivity by moving on the given production frontier.

By utilizing the decomposable property, the HMB index is applied in assessing the relative importance of the above mentioned factors as sources of fluctuations in productivity. It is also emphasized that by handling variations in input utilization with the efficiency change, the HMB productivity index mitigates a familiar criticism against the conventional TFP for excluding the behavior of the "off-production frontier," namely, unlike the conventional TFP index, the HMB productivity index is applicable without any ad hoc adjustments in input data even if the varying intensity of input usage conceals true productivity. In fact, no other productivity index is as satisfactory as the HMB index for this study. Although the Törnqvist and the Malmquist indexes are more widely used in recent literature, their decomposition analyses are incomplete. The Törnqvist productivity index does not have an efficiency change component because it presumes the optimizing behavior of a producer. On the other hand, the Malmquist productivity index is not indicative of scale change because it is well defined only when technology exhibits constant returns to scale. As a synthesis of these two conventional indexes, the HMB index serves as a basis for an integrated framework in which the productivity change is fully decomposed.

To realize those desirable properties, the HMB productivity index requires the distance functions. We estimate the output-oriented distance function with inefficiency specified as an asymmetric component of the error term. Compared with the Törnqvist productivity index and the Solow residual, the HMB productivity index identifies the technical change and efficiency change components at cost of estimating such an empirical model of production technology[2].

We begin by introducing the HMB productivity index and its decomposition analysis in Section 2. Section 3 explains specification of the empirical model for implementing the HMB index analysis. The stochastic frontier model is specified in the translog form to estimate the

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[2] Instead, the HMB index is measurable without price data.

output-oriented distance function on the basis of a panel on the Japanese prefectures. Section 4 discusses the empirical results pertaining to the Japanese prefectures for the period 1981—2000. Section 5 presents a conclusion of the paper.

2. Hicks-Moorsteen-Bjurek (HMB) productivity index

Unlike partial productivity indexes such as per capita products, the TFP index is defined as the ratio of aggregate output to aggregate input indexes. Thus, the HMB productivity index also requires a function to aggregate outputs and inputs. For this it employs the Malmquist index based on the distance function. This approach yields the aggregate output change index from the period t to $t+1$ as

$$M_y^{t+1,t} = \left\{ \frac{D_o^t(x^t, y^{t+1})\ D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)\ D_o^{t+1}(x^{t+1}, y^t)} \right\}^{\frac{1}{2}}, \tag{1}$$

where x^τ and y^τ are the input and output vector at the period $\tau = t, t+1$, respectively, and the output-oriented distance function is defined as

$$D_o^t(x,y) \equiv \min\{\ \delta \mid (x, y/\delta\ ) \in \Omega^t\ \} \tag{2}$$

where Ω^t is the production possibility set consisting of any technically feasible pair of inputs and outputs at the period t. By definition, $D_o^t(x,y) > 1$ implies that y is not producible from x. When $D_o^t(x,y) \leq 1$, the output-oriented distance function measures technical efficiency, and $D_o^t(x,y) = 1$ indicates full efficiency in the sense that more outputs cannot be obtained without increasing inputs.

Similarly, input change index from the period t to $t+1$ is given by

$$M_x^{t+1,t} = \left\{ \frac{D_i^t(x^{t+1}, y^t)\ D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)\ D_i^{t+1}(x^t, y^{t+1})} \right\}^{\frac{1}{2}} \tag{3}$$

The input-oriented distance function is defined as

$$D_i^t(x,y) \equiv \max\{ \delta \mid (x/\delta, y) \in \Omega^t \}, \tag{4}$$

where $D_i^t(x,y) < 1$ implies that y is not producible from x. When $D_i^t(x,y) \geq 1$, the input-oriented distance function measures technical efficiency, and $D_i^t(x,y) = 1$ indicates full efficiency in the sense that inputs cannot be reduced further without decreasing the outputs.

The HMB productivity index is defined as the ratio of the output change to input change indexes. A formal definition of the HMB productivity index was given by Bjurek (1996) as

$$HMB^{t+1,t} = M_y^{t+1,t} \,/\, M_x^{t+1,t} . \tag{5}$$

Since $M_y^{t+1,t}$ and $M_x^{t+1,t}$ measure changes in outputs and inputs, taking logarithms yields their proportionate changes. Thus, $\ln HMB^{t+1,t}$ measures the proportionate productivity change for the period t to $t+1$, which is decomposable to four components: technical change, $TC^{t+1,t}$; efficiency change, $EC^{t+1,t}$; scale change, $SC^{t+1,t}$; and input and output mix effects, $ME^{t+1,t}$. In other words, the proportionate change in productivity factorizes in the proportionate changes in the four components as

$$\ln HMB^{t+1,t} = \ln TC^{t+1,t} + \ln EC^{t+1,t} + \ln SC^{t+1,t} + \ln ME^{t+1,t}. \tag{6}$$

The details on these components are presented in Appendix 1.

The technical change component captures the effects of a shift in the production frontier on productivity change. In order to model the production frontier, the output-oriented distance function of the translog form is specified and estimated below. We introduce the time-specific dummies and control variables into the output-oriented distance function in order to measure a shift in the production frontier.

The efficiency change component captures the effects of approaching or receding from the production frontier on productivity change. These effects are measured by changes in the values of the output-oriented distance function. As mentioned earlier, the efficiency change at the macro-level most likely arises from variations in input utilization rates without an accompanying shift in the production frontier. Demand shocks arising from changes in exports, autonomous domestic expenditures, and fiscal policy are considered to be the sources of such variations.

The scale change component captures the effects of the returns to scale on productivity change. If technology exhibits increasing (decreasing) returns to scale, the economy will become more (less) productive by an expansion of the scale. In this case, the scale is measured by a scalar that indicates the level of production activity; more specifically, we use the aggregate index of outputs or inputs as a scale measure.

As a result, the effects of change in the input and output mix are excluded from the scale change component. In order to illustrate this, let two inputs x_1^t and x_2^t be utilized in the period t, and x_1^{t+1} and x_2^{t+1} in the period $t+1$. Suppose an aggregate input index is to be constructed by taking the weighted average of them, with w as the weight. We thus obtain a change index of aggregate inputs as $s = (wx_1^{t+1} + (1-w)x_2^{t+1}) / (wx_1^t + (1-w)x_2^t)$. If s is employed as a scale measure, the scale change component $SC^{t+1,t}$ captures the effects of moving from (x_1^t, x_2^t) to (sx_1^t, sx_2^t) on productivity change. Thus, unless $sx_1^t = x_1^{t+1}$ and $sx_2^t = x_2^{t+1}$, the productivity change is also affected by a difference between (sx_1^t, sx_2^t) and (x_1^{t+1}, x_2^{t+1}). Therefore, the input and output mix effects are necessary to complete the decomposition analysis. With regard to macro-level data, the input and output mix effects will be observed if there is a change in the sectoral composition of the economy over industries that differ in terms of productivity growth.

3. Empirical model

3.1 Estimation of the output-oriented distance function

In order to implement the decomposition analysis of the HMB productivity index, we estimate the output-oriented distance function. Suppose that two inputs, labor and capital, produce a single output, the real GDP[3]. Let x_{Li}^t, x_{Ki}^t, and y_i^t denote labor, private capital, and the real GDP, respectively, of prefecture i for year t. The share of the manufacturing industry in the real GDP, h_i^t, is introduced as a control variable to adjust the differences in the industrial structure over time and across prefectures. Public capital, x_{Gi}^t, is also a control variable that is intended to create "atmosphere" by influencing the marginal productivity of private capital. The two control variables are denoted by $z_i^t = (h_i^t, x_{Gi}^t)$. The state of technology is represented by time-specific dummies $A^t = (A_2^t, A_3^t, \cdots, A_T^t)$, where A_τ^t, $\tau = 2, 3, \cdots, T$ takes unity when $t = \tau$ and zero, otherwise.

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[3] We implicitly assume homotheticity and weak separability of private capital and labor from other intermediate inputs to ensure existence of the value-added function. The translog output-oriented distance function specified just below locally provides a second order approximation to the unknown homothetic value-added function.

The deterministic part of the output-oriented distance function is specified by the translog form as follows:

$$
\begin{aligned}
\ln D_o^t(x_{Li}^t, x_{Ki}^t, y_i^t\, ; z_i^t, A^t) &= TL(x_{Li}^t, x_{Ki}^t, y_i^t\, ; z_i^t, A^t) \\
&\equiv \alpha_0 + \ln y_i^t + \alpha_L \ln x_{Li}^t + \alpha_K \ln x_{Ki}^t \\
&+ \frac{1}{2}\alpha_{LL}\left(\ln x_{Li}^t\right)^2 + \frac{1}{2}\alpha_{KK}\left(\ln x_{Ki}^t\right)^2 \\
&+ \alpha_{LK}\left(\ln x_{Li}^t\right)\left(\ln x_{Ki}^t\right) \\
&+ \gamma_{KG}\left(\ln x_{Ki}^t\right)\left(\ln x_{Gi}^t\right) + \gamma_h h_i^t + \sum_{\tau=2}^{T} \beta_\tau A_\tau^t ,
\end{aligned}
\tag{7}
$$

where $i = 1, 2, \cdots, N,\ \ t = 1, 2, \cdots, T$. By definition, the output-oriented distance function is linearly homogeneous in outputs. Thus, we impose homogeneity in an output in the above specification, which simultaneously ensures that other regularity conditions are satisfied.

In addition, the output-oriented distance function is not greater than unity whenever it is evaluated at an observation. This condition is introduced in the specification of the stochastic part of the output-oriented distance function as

$$
\ln D_o^t(x_{Li}^t, x_{Ki}^t, y_i^t\, ; z_i^t, A^t) = -u_i^t + v_i^t, \qquad t = 1, 2, \cdots, T, \tag{8}
$$

where

$$
\begin{aligned}
u_i^t &= u_i\Big(1 + \sum_{\tau=2}^{T} \varphi_\tau A_\tau^t\Big), \quad (1 + \varphi_t) > 0 \ \ for\ t = 2, 3, \cdots, T, \\
u_i &\sim |N(0, \sigma_u^2)|, \\
v_i^t &\sim N(0, \sigma_v^2),
\end{aligned}
$$

and u_i and v_i^t are assumed to be independent[4]. The technical efficiency of the ith prefecture for the year t is given by $\exp\{-u_i(1 + \varphi_t)\}$.

Combining eqs. (7) and (8), we obtain the estimation equation

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[4] The endogeneity of inputs is not controlled. To cope with the endogeneity bias, it is necessary to specify the input demand equations to be jointly estimated with the output-oriented distance function with the full information maximum likelihood method.

$$TL(x_{Li}^t, x_{Ki}^t, y_i^t\,;\, z_i^t, A^t) = -u_i^t + v_i^t.$$

The log-likelihood function of this model can be obtained by following Battese and Coelli (1992). In particular,

$$\ln L = const. + NT\ln\theta + N\ln\lambda - \frac{1}{2}\theta^2\sum_{i=1}^{N}\left\{\sum_{t=1}^{T}\xi_{it}^2 - \frac{1-\lambda^2}{\sum_{t=1}^{T}(1+\varphi_t)^2}\left(\sum_{t=1}^{T}(1+\varphi_t)\xi_{it}\right)^2\right\}$$
$$+ \sum_{i=1}^{I}\ln\Phi\left(-\theta\sum_{t=1}^{T}(1+\varphi_t)\xi_{it}\sqrt{\frac{1-\lambda^2}{\sum_{t=1}^{T}(1+\varphi_t)^2}}\right), \qquad (9)$$

where $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution,

$$\xi_{it} = -u_i(1+\varphi_t) + v_i^t = TL(x_{Li}^t, x_{Ki}^t, y_i^t\,;\, z_i^t, A^t),$$

$$\theta = 1/\sigma_v,$$

and

$$\lambda = \sigma_v \Big/ \sqrt{\sigma_v^2 + \sigma_u^2\sum_{t=1}^{T}(1+\varphi_t)^2}.$$

Once the output-oriented distance function parameters are estimated, they are used to obtain the input-oriented distance function values required in the HMB productivity index. In Appendix 2, we explain a procedure to transform the output-oriented distance function into an input-oriented one. For further details on measuring the HMB index and its components, refer to Nemoto and Goto (2005).

3.2 Data

The translog output-oriented distance function is estimated using data pertaining to the 47 prefectures in Japan over the period 1980—2000. The data set is compiled from *CRIEPI Regional Economic Database* constructed by the Socio-economic Research Center, Central Research

Institute of Electric Power Industry, Tokyo. In this database, private and public capital stocks are computed by the perpetual inventory method, i.e., accumulating expenditures for net investment using the estimates of capital stocks in the 1970 National Wealth of Japan Survey as a benchmark. Labor is measured by the total number of employed persons. The real GDP is computed by summing up the value-added yielded by 25 industries in terms of 1995 fixed prices. More details are presented in Yamano and Ohkawara (2000).

4. Results

4.1 Output-oriented distance function

The estimated parameters of the output-oriented distance function are displayed in Table 1. The coefficients of some adjacent time-specific dummies are restricted to be equal, implying that the production frontier does not shift in these years. In the absence of these restrictions, the estimated output distance function exhibits technical regress for several years. Although technical regress is empirically implausible, the concerned coefficients largely suggest that it is insignificant. We therefore assume that neither technical progress nor regress occurred in the years when no significant shifts in the production frontier were detected[5].

The resulting parameter estimates ensure that the output-oriented distance function satisfies the regularity conditions within the sample. The coefficient of the manufacturing industry share is significantly negative, indicating that the manufacturing industry is more productive than other sectors and, thereby, an increase in its weight advances the production frontier. The interaction term of public and private capital is positively correlated to the value of output-oriented distance function. This suggests that the marginal productivity of private capital decreases with an increase in public capital. In this sense, public and private capital are substitutes. With regard to the stochastic part, we observe that the variance of efficiency far exceeds the variance of statistical noise. Neglecting efficiency terms in the empirical production model easily leads to misspecification.

4.2 HMB productivity index

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[5] As a result, the production frontier is supposed to halt in the years 1981—1984, 1986, 1991—1995, and 1997—1998. This does not significantly impact the empirical results. The shape of the fluctuations in the technical change component does not depend on the restrictions although the fluctuations in the mid 1980s become slightly more moderate in their absence.

Tables 2 and 3 and Figure 1 report the HMB productivity index and its factorized components based on eq. (6). All the figures in the tables are measured in terms of percentage change over adjacent years, i.e., measurements of each term of eq. (6) are multiplied by 100. Table 2 and Figure 1 present the results of the decomposition analysis conducted at the sample mean. An overview of Table 2 and Figure 1 indicates that the effects of technical and efficiency changes on productivity outweigh those of the other two components. The residual factor does not systematically affect the productivity change although it is not negligible for several years. Table 3 lists the upper and lower quartiles of the results pertaining to the 47 prefectures for each year. The sum of the components does not equal productivity change because these quartiles represent different prefectures.

Figure 2 depicts the development of the upper and lower quartiles of the HMB productivity index. The growth rate of nationwide GDP is indicated by the dotted line. From this figure, the procyclicality of the productivity change is evident. In synchrony with the fluctuations in nationwide GDP, the productivity growth declined in 1986, 1992, and 1998, and increased in 1994, 1987—1990, 1996, and 1999—2000. It is of particular interest in this context to examine whether it is supply shocks or demand shocks that have a greater contribution in causing the procyclical movement. We illustrate the results of this examination in Table 3 by each component.

4.3 Technical change component

Figure 3 shows the development of the technical change component. While the coefficients of the time dummies are the primary sources of the technical change component, they are invariant over the prefectures. This is a possible explanation for the inter-quartile range of the technical change component being considerably narrow.

Technical change contributed to the increase in productivity and GDP growth in the mid and late 1980s, except 1986, and the last two years of the analysis period. In contrast, technical change was responsible for downturns in productivity and GDP in the early and mid 1990s. It should be noted that the technical change component did not increase during the period 1994—1996, when a surge of productivity and GDP growth was observed. As elucidated below, the efficiency change component played a more important role as compared to the technical change component during this period.

Measurements of the technical change component shown in Figure 3 are estimated by $\ln TC^{t+1,t}$, which incorporates the effects of the control variables. In the present model, the pure technical factor, resulting solely due to the coefficients of the time dummies, is isolated from $\ln TC^{t+1,t}$. To present an overview, Figure 4 shows the accumulated index of pure technical change normalized at one in 1980. Technical advances are observed in the late 80s, 1999, and 2000. In general, the technical level remained unaltered for the remaining periods, mainly due to the parameter restrictions imposed on the output-oriented distance function. The accumulated index reached 1.16 in 2000, implying that the technology was enhanced to produce an excess of 16 percent output from the same amount of input employed in 1980.

Reverting to Figure 3, we observe a prominent surge in the technical change component in 1985. One possible explanation for this is the advent of the microelectronic technology. According to Japanese production statistics, integrated circuits and semiconductor devices were first introduced in 1983 and their shipment indexes exhibited a remarkably rapid growth in 1984[6]. As long as these indexes represent emerging new technology, the dominance of the technical change component in the latter half of the 1980s is sufficiently explained. Furthermore, fluctuations in the technical change component during 1985—1987 appear to follow the shipment of integrated circuits with a one-year lag. In fact, the shipment of integrated circuits dropped sharply by 41 percent in 1985 after a remarkable increase in 1984. This suggests that it took some time to adapt the production processes to the newly installed microelectronic devices before significant enhancements in productivity were realized.

4.4 Efficiency change component

Figure 5 shows the development of the efficiency change component. Although the estimate of σ_u^2 implies substantially large variations in prefecture-specific efficiency, the efficiency change component shows a rather narrow inter-quartile range. However, this is not surprising since with the exception of a few years, the time-variant factors of efficiency, $\varphi^{t+1} - \varphi^{t}$, are so small that the variations in efficiency change across prefectures are limited.

We observe that improvement in efficiency furthered growth in productivity and GDP over the period 1994—1996, particularly in 1996. Demand shocks are captured by the efficiency factor while, as mentioned earlier, technology shocks were not prominent; therefore, the economic recovery during this period was possibly driven by fiscal expansion. Further, the efficiency change component has peaks in 1984 and 1990. In these two years, we observe a pattern similar to 1996,

[6] In 1984, the shipment of integrated circuits grew at the rate of 59 percent, the highest during the period of analysis. This is remarkable as evident from the fact that the second and the third highest rates are 37 percent in 1988 and 35 percent in 2000, respectively. A similar pattern is observed in the shipment of semiconductor devices.

that is, an improvement in efficiency furthered productivity and GDP growth in the absence of technical advances. In contrast, as compared to the technical change factor, efficiency was not a major contributor to the recovery in productivity and GDP in 1999 and 2000.

In general, the efficiency change and the technical change components tend to move in opposite directions. A possible explanation for this is that real GDP does not promptly follow advances in the production frontier. Consequently, positive supply shocks create a greater distance between the frontier and the actual point of production, implying lower efficiency, at least in the short-run.

4.5 Scale change component

Figure 6 shows the development of the scale change component. The effects of scale change are much smaller than those of technical change and efficiency change. Thus it is difficult to explain procyclical productivity in terms of the short run increasing returns to scale. As illustrated in Figure 6, the development of the upper and lower quartiles of the scale change component exhibits a mirror image. This is because increasing and decreasing returns technologies coexist in the 47 prefectures and movement of the scale is rather common among them. The scale change component is defined as the product of the scale change and the average scale elasticity minus one, that is, $(\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1})/2 - 1$[7]. If the scale change is common, the increasing returns [$(\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1})/2 > 1$] and decreasing returns [$(\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1})/2 < 1$] technologies yield a symmetric pattern of movement in the scale change components. Table 4 presents the measurements of the scale elasticity of the five largest and smallest prefectures as well as the quartiles. Reflecting the agglomeration economies, prefectures including the metropolitan areas tend to exhibit the scale economies.

4.6 Input and output mix effects

Figure 7 shows the input and output mix effects. Since there is a single output in the present specification, the mix effects represent changes in the ratio of the two inputs, namely, capital and labor. Thus, Figure 7 suggests that a continuous increase in the capital to labor ratio over the two decades of the study period enhanced productivity. However, these effects are considerably small and do not appear to be important factors in productivity change. As noted earlier, the input and output mix effects should be larger if the change in the industrial structure is taken into

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[7] See Appendix 1 for the formal expression of the scale change component. Also refer to Nemoto and Goto (2005) for measurement of the scale elasticity.

consideration. However, in time series data, the effects of the industrial structure might be smaller than expected. Further, these effects are possibly absorbed in the technical change component because the share of the manufacturing industry is incorporated in the output-oriented distance function.

5. Conclusion

This paper applies the HMB productivity index to examining the productivity of the Japanese economy using the data pertaining to the 47 prefectures over the period 1981—2000. In summary, technical change and efficiency change are two of the most important components driving procyclical productivity. We observe that their relative importance varies over different periods. Supply shocks, captured by the technical change component, caused upturns in productivity in the mid and late 1980s and in 1999, and 2000. Further, supply shocks caused downturns in the early and mid 90s. On the other hand, demand shocks, captured by the efficiency change component, caused upturns of productivity in 1984, 1990, and 1996, when supply shocks were not detected.

However, it should be noted that the HMB index approach still does not provide a fully integrated framework for the productivity and efficiency analyses. While the efficiency component in the decomposition analysis represents technical efficiency, it is not indicative of the allocative efficiency because efficiency is measured along the fixed ray passing through an observed combination of inputs and outputs. As long as the ray is fixed, the productivity index is insensitive to changes in the relative prices of inputs and outputs and is thus not indicative of the allocative efficiency. Future studies should focus on an extended HMB approach that includes allocative efficiency as a component in the decomposition analysis of productivity. Modeling allocative efficiency also helps us control the endogeneity bias in estimation of the distance function.

Appendix 1 Components of the HMB productivity index

The HMB productivity index is decomposed as shown in eq. (6). This appendix presents formal expressions of each component of eq. (6).

The technical change and efficiency change components are given by

$$\ln TC^{t+1,t} = \ln\left\{\frac{D_o^{t+1}(x^t,y^t)\,D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)\,D_o^t(x^{t+1},y^{t+1})}\right\}^{\frac{1}{2}}$$

and

$$\ln EC^{t+1,t} = \ln\left\{\frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)}\right\},$$

respectively. The technical change component measures a shift in the output-oriented distance function while keeping inputs and outputs constant[8]. The technical change and efficiency change components are equivalent to the corresponding factors of the decomposition analysis proposed by Färe, Grosskopf, Norris and Zhang (1994) in the context of the Malmquist productivity index. Thus, eq. (6) can be considered as augmenting Färe et al's decomposition analysis with the scale change component.

The scale change component is given by

$$\ln SC^{t+1,t} = \left(\frac{\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1}}{2} - 1\right)\ln s^{t+1,t},$$

where

[8] It should be noted that the technical change component as well as the other components takes the form of the geometric mean of the two indexes using the period t and t+1 as a base.

$$\hat{\varepsilon}_o^t = -\frac{\ln\left\{\dfrac{D_o^t(s^{t+1,t}x^t, y^t)}{D_o^t(x^t, y^t)}\right\}}{\ln\left\{\dfrac{D_i^t(s^{t+1,t}x^t, y^t)}{D_i^t(x^t, y^t)}\right\}}, \quad \hat{\varepsilon}_o^{t+1} = -\frac{\ln\left\{\dfrac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, y^{t+1})}\right\}}{\ln\left\{\dfrac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, y^{t+1})}\right\}},$$

and,

$$s^{t+1,t} = M_x(x^{t+1}, x^t, y^{t+1}, y^t).$$

As shown in Nemoto and Goto (2005), $\hat{\varepsilon}_o^t$ and $\hat{\varepsilon}_o^{t+1}$ are estimates of the scale elasticity. The scale change component takes the form of the scale elasticity factor $(\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1})/2 - 1$ multiplied by the Malmquist input index that is used as a scalar measure of the scale change. Since a scale elasticity larger (smaller) than one implies scale economies (diseconomies), expanding (contracting) the scale always enhances productivity, provided the scale economies (diseconomies) prevail.

Besides the scale change measured by the Malmquist index, a change in input and output quantities also affects productivity change. The decomposition of the productivity change is completed by the input and output mix effects. This is given by

$$\ln ME^{t+1,t} = \frac{1}{2}\ln\left\{\frac{D_o^t(s^{t+1,t}x^t, r^{t+1,t}y^t)}{D_o^t(x^{t+1}, y^{t+1})}\right\} + \frac{1}{2}\ln\left\{\frac{D_o^{t+1}(x^t, y^t)}{D_o^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, \frac{y^{t+1}}{r^{t+1,t}})}\right\},$$

where

$$r^{t+1,t} = M_y(x^{t+1}, x^t, y^{t+1}, y^t).$$

In this case, the Malmquist output index is used to capture the scale change along the output quantities.

Although the methodological aspect of the analysis is not of primary concern, the HMB productivity index has the remarkable property of becoming almost equivalent to the Törnqvist productivity index provided that no inefficiency exists[9]. The Törnqvist productivity index rules out inefficiency by assumption, which implies that the HMB productivity index naturally extends the Törnqvist productivity index such that the effects of efficiency on productivity can be measured. We finally obtain a decomposition of the HMB productivity index as

$$
\begin{aligned}
&\ln HMB(x^{t+1},x^{t},y^{t+1},y^{t}) \\
&\quad = \ln\left\{\frac{D_o^{t}(x^{t+1},y^{t+1})}{D_o^{t+1}(x^{t+1},y^{t+1})}\frac{D_o^{t}(x^{t},y^{t})}{D_o^{t+1}(x^{t},y^{t})}\right\}^{\frac{1}{2}} && (\textit{technical change}) \\
&\quad + \ln\left\{\frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^{t}(x^{t},y^{t})}\right\} && (\textit{efficiency change}) \\
&\quad + \left(\frac{\hat{\varepsilon}_o^{t}+\hat{\varepsilon}_o^{t+1}}{2}-1\right)\ln s^{t+1,t} && (\textit{scale change}) \\
&\quad + \ln\left\{\frac{D_o^{t}(s^{t+1,t}x^{t},r^{t+1,t}y^{t})}{D_o^{t}(x^{t+1},y^{t+1})}\frac{D_o^{t+1}(x^{t},y^{t})}{D_o^{t+1}(\frac{x^{t+1}}{s^{t+1,t}},\frac{y^{t+1}}{r^{t+1,t}})}\right\}^{\frac{1}{2}} && (\textit{input and output mix effects}).
\end{aligned}
$$

[9] In particular, if no inefficiency exists and the output-oriented distance function is in the translog form, the components of technical change and scale change coincide with the corresponding terms of the Törnqvist productivity index. Further, the efficiency change component of the HMB index disappears in the absence of inefficiency, which conforms to the Törnqvist productivity index.

Appendix 2 Input-oriented distance function

Once the output-oriented distance function is parametrically specified, it is directly estimable by using econometric techniques. However, the HMB approach requires both the input and output-oriented distance functions. This appendix describes a method to obtain the input-oriented distance function values from the estimated output-oriented distance function[10].

Since $D_o^t(x,y) \le 1$ implies $(x,y) \in \Omega^t$, the input-oriented distance function is alternatively defined as

$$D_i^t(x,y) = \max\left\{\delta \mid D_o^t(x/\delta, y) \le 1\right\}.$$

Letting $D_i^t(x,y) = \delta^*$, $D_o^t(x/\delta^*, y) = 1$ follows under the regular production possibility set. Thus, δ^* is obtained by solving $\ln D_o^t(x/\delta^*, y) = 0$. Given the translog output-oriented distance function (7), we have

$$\frac{1}{2}(\ln\delta^*)^2 \sum_{i=K,L} \sum_{j=K,L} \alpha_{ij} + \varepsilon_o^t \ln\delta^* + \ln D_o^t(x,y) = 0.$$

If $\sum_i\sum_j \alpha_{ij} = 0$, then

$$\ln D_i^t(x,y) = -\frac{\ln D_o^t(x,y)}{\varepsilon_o^t(x,y)}.$$

If $\sum_i\sum_j \alpha_{ij} \neq 0$, we obtain a quadratic equation. Suppose that there exist real roots $\ln\delta_1^*$ and $\ln\delta_2^*$. In this case, non-smaller one of them is relevant by the definition of the input-oriented distance function. Therefore,

$$\ln D_i^t(x,y) = \max\left\{\ln\delta_1^*, \ln\delta_2^*\right\}.$$

Real roots exist as long as the output distance function (7) is decreasing in inputs over a sufficiently large domain around (x,y).

The distance function values required to measure the HMB productivity index and its components are evaluated using this technique, given the output-oriented distance function parameters.

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[10] The same procedure is applicable for obtaining the output-oriented distance function values from the input-oriented distance function.

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Table 1. Parameter estimates of the output-oriented distance function

	Parameter Estimate	Standard Error		Parameter Estimate	Standard Error
α_0	0.1862	(0.0144)**	φ_5	0.0776	(0.0533)
α_L	-0.8353	(0.0194)**	φ_6	0.0196	(0.0539)
α_K	-0.2021	(0.0184)**	φ_7	0.1034	(0.0701)
α_{LL}	-0.0032	(0.0270)	φ_8	0.1665	(0.0698) *
α_{KK}	-0.0738	(0.0174)**	φ_9	0.1568	(0.0707) *
α_{LK}	-0.0389	(0.0227)	φ_{10}	-0.0307	(0.0493)
γ_{KG}	0.0577	(0.0107)**	φ_{11}	0.0142	(0.0502)
γ_h	-0.6080	(0.0385)**	φ_{12}	0.0675	(0.0515)
β_5	-0.0447	(0.0068)**	φ_{13}	0.0952	(0.0542)
β_7	-0.0844	(0.0096)**	φ_{14}	0.0440	(0.0539)
β_8	-0.1202	(0.0102)**	φ_{15}	0.0014	(0.0539)
β_9	-0.1423	(0.0112)**	φ_{16}	-0.2200	(0.0504) **
β_{10}	-0.1325	(0.0109)**	φ_{17}	-0.1557	(0.0513) **
β_{16}	-0.1183	(0.0141)**	φ_{18}	-0.1705	(0.0524) **
β_{19}	-0.1288	(0.0169)**	φ_{19}	-0.2385	(0.0640) **
β_{20}	-0.1507	(0.0176)**	φ_{20}	-0.2525	(0.0621) **
φ_1	0.0376	(0.0340)	σ_u	0.1519	(0.0183) **
φ_2	0.0042	(0.0341)	σ_v	0.0242	(0.0006) **
φ_3	-0.0160	(0.0358)			
φ_4	-0.1556	(0.0356)**			

Note: "*" indicates significance at the 5% level.
"**" indicates significance at the 1% level.

Table 2. Decomposition of the HMB productivity index evaluated at the sample mean

unit: percentage

year	Productivity change	Technical change	Efficiency change	Scale change	Input and Output mix effects	Residuals
1981	0.3549	0.3848	-0.4862	-0.0340	-0.0016	0.4920
1982	0.9171	0.2261	0.4321	-0.0131	0.0061	0.2660
1983	1.2488	0.5915	0.2614	-0.0106	0.0028	0.4038
1984	2.1133	0.3276	1.8102	-0.0037	0.0072	-0.0281
1985	1.9335	5.0333	-3.0191	0.0110	0.0306	-0.1223
1986	1.3967	-0.5182	0.7489	0.0168	0.0120	1.1372
1987	3.7524	4.1824	-1.0811	0.0360	0.0172	0.5979
1988	4.1822	4.1320	-0.8114	0.0555	0.0071	0.7989
1989	2.8745	2.4664	0.1245	0.0640	0.0112	0.2084
1990	2.9973	-0.7268	2.4173	0.0902	0.0067	1.2100
1991	-1.0300	0.2062	-0.5807	0.1310	0.0058	-0.7923
1992	-2.2280	-0.4790	-0.6877	0.0750	0.0043	-1.1405
1993	-1.5671	-0.2908	-0.3562	0.0643	0.0022	-0.9866
1994	0.2593	0.1075	0.6595	0.0437	0.0036	-0.5549
1995	0.7145	0.3713	0.5505	0.0768	0.0005	-0.2846
1996	2.3327	-1.3915	2.8744	0.0642	0.0015	0.7842
1997	-0.9433	0.1713	-0.8379	0.0235	0.0043	-0.3044
1998	-0.7341	-0.6619	0.1930	0.0283	0.0040	-0.2975
1999	2.3085	1.1473	0.8864	-0.0248	0.0041	0.2956
2000	2.5128	2.6889	0.1824	0.0121	0.0036	-0.3742
Average	1.1698	0.8984	0.1640	0.0353	0.0067	0.0654

Table 3. Decomposition of the HMB productivity index

unit: percentage

year	Productivity change		Technical change		Efficiency change		Scale change		Input and output mix effects	
	lower quartile	upper quartile	lower quartile	upper quartile	lower quartile	upper quartile	lower quartile	upper quartile	lower quartile	upper quartile
1981	-1.06	1.14	0.12	0.98	-0.70	-0.29	-0.20	0.00	-0.01	0.02
1982	0.18	2.12	0.00	0.82	0.26	0.62	-0.06	0.02	0.00	0.04
1983	0.17	2.25	0.36	1.09	0.16	0.38	-0.06	0.02	0.00	0.04
1984	1.51	3.23	-0.04	0.83	1.07	2.60	-0.06	0.05	0.01	0.06
1985	0.61	2.87	4.65	5.57	-4.35	-1.79	-0.10	0.04	0.03	0.16
1986	-0.28	1.37	-0.88	0.13	0.45	1.08	-0.03	0.04	0.01	0.07
1987	2.05	4.49	4.02	4.57	-1.56	-0.64	-0.07	0.04	0.02	0.11
1988	2.01	4.67	3.95	4.57	-1.18	-0.48	-0.09	0.06	0.01	0.05
1989	1.81	3.45	2.18	2.91	0.07	0.18	-0.08	0.06	0.02	0.06
1990	2.08	3.44	-0.94	-0.27	1.44	3.50	-0.09	0.07	0.01	0.06
1991	-1.40	0.54	-0.02	0.55	-0.84	-0.35	-0.13	0.13	0.02	0.08
1992	-2.89	-0.81	-0.76	-0.04	-0.99	-0.41	-0.06	0.08	0.01	0.03
1993	-1.85	0.16	-0.52	0.30	-0.52	-0.21	-0.05	0.07	0.00	0.02
1994	-0.21	1.87	-0.03	0.43	0.39	0.95	-0.04	0.04	0.00	0.01
1995	0.35	1.83	0.16	0.70	0.33	0.80	-0.04	0.07	0.00	0.01
1996	1.64	3.08	-1.61	-1.01	1.70	4.13	-0.03	0.07	0.00	0.01
1997	-1.34	-0.14	-0.15	0.50	-1.20	-0.49	0.00	0.03	0.01	0.03
1998	-1.57	0.50	-0.83	-0.24	0.11	0.28	0.00	0.02	0.01	0.02
1999	1.78	3.11	0.83	1.48	0.52	1.27	-0.02	0.02	0.01	0.03
2000	1.80	4.10	2.34	3.08	0.11	0.26	-0.01	0.02	0.01	0.03

Table 4. Scale elasticity

rank	prefecure	scale elasticity	
1	Tokyo	1.22	
2	Osaka	1.17	
3	Aichi	1.17	
4	Kanagawa	1.15	
5	Hyogo	1.10	
12	Hiroshima	1.04	upper quartile
24	Toyama	0.97	median
36	Fukui	0.93	lower quartile
43	Shimane	0.88	
44	Tokushima	0.88	
45	Okinawa	0.87	
46	Kochi	0.86	
47	Tottori	0.84	

Note: Elasticities are averaged over the period 1981-2000.

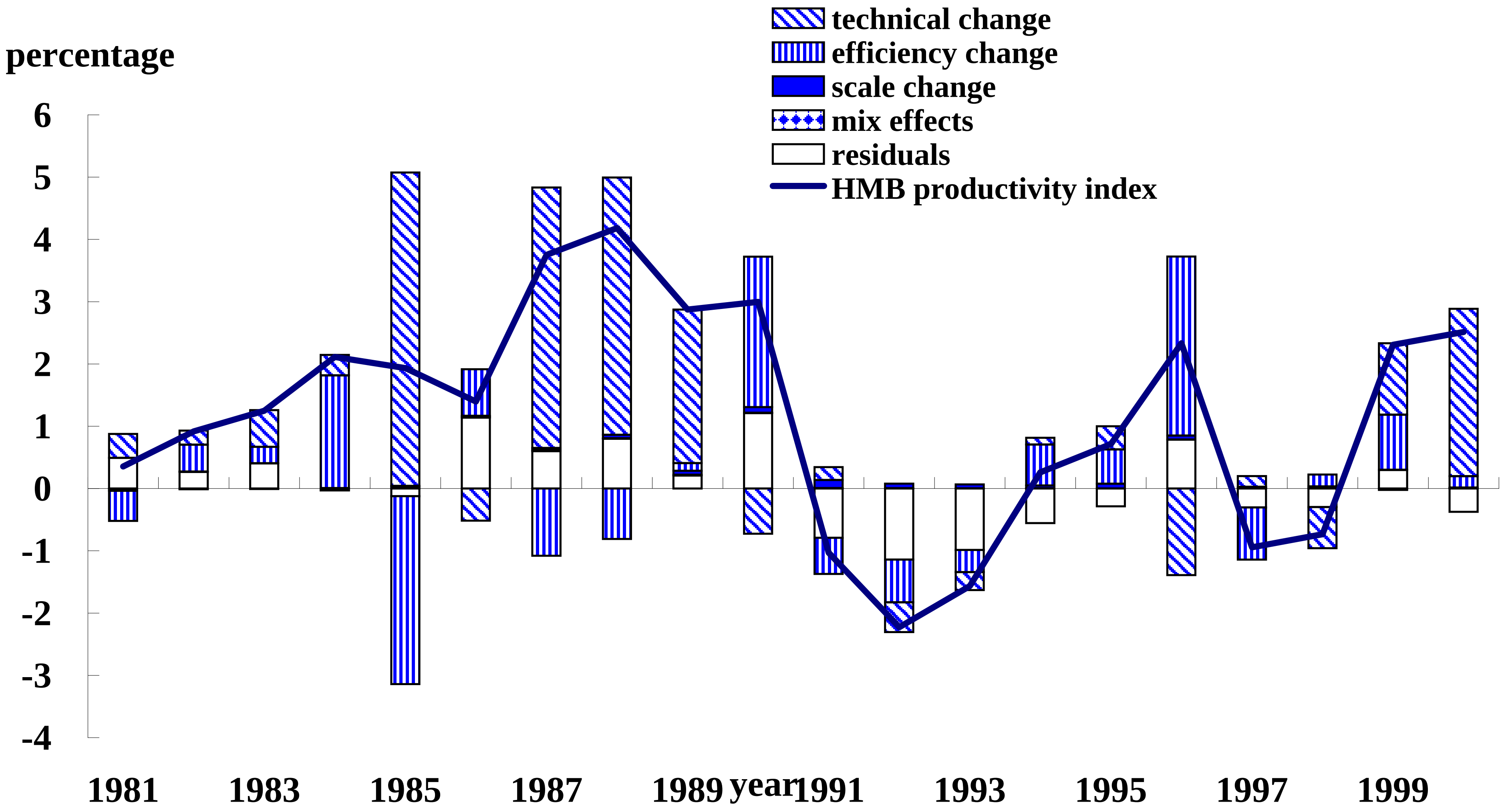

Fig. 1 Decomposition of the HMB productivity index evaluated at the sample mean

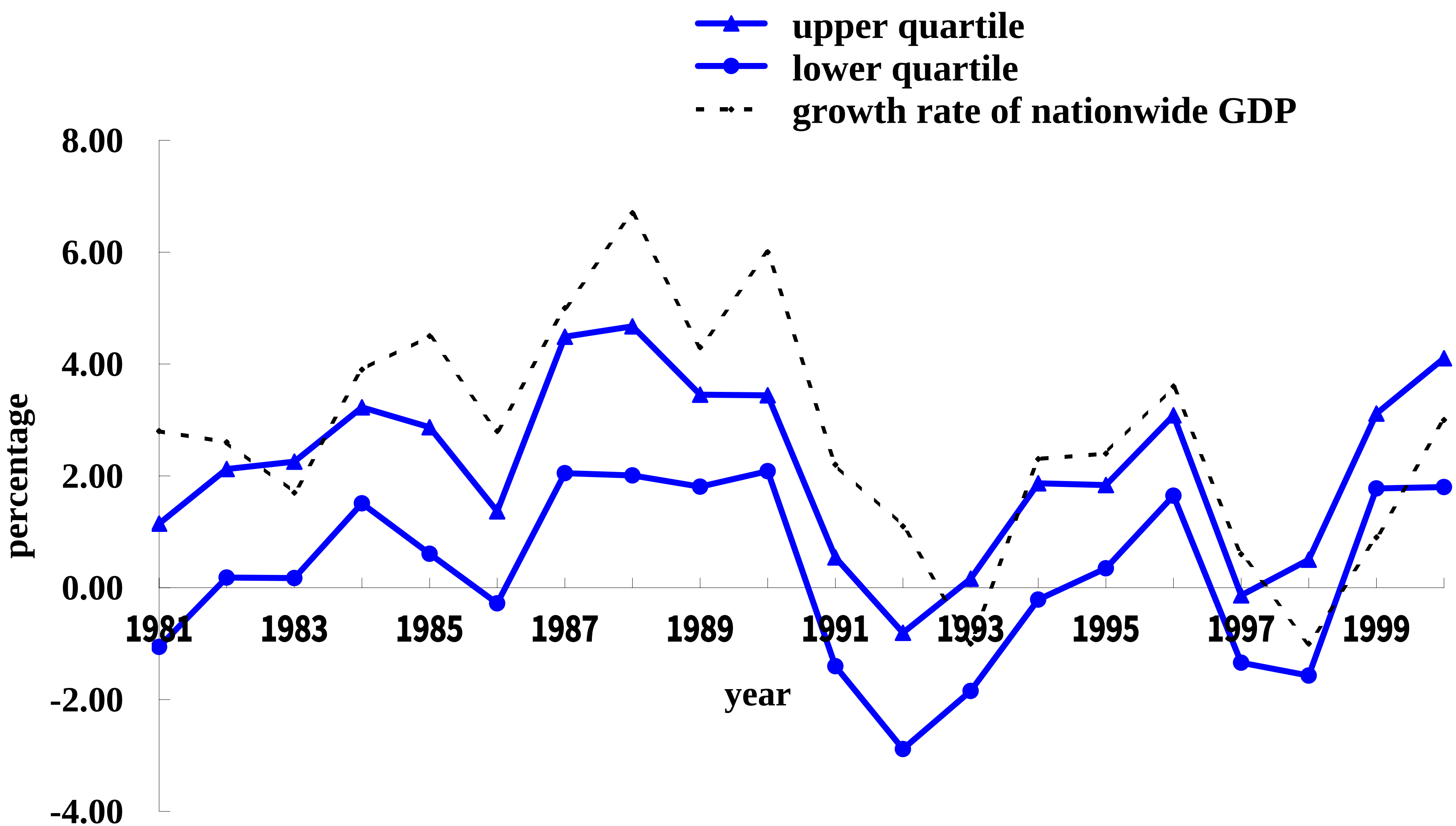

Fig. 2 HMB productivity index

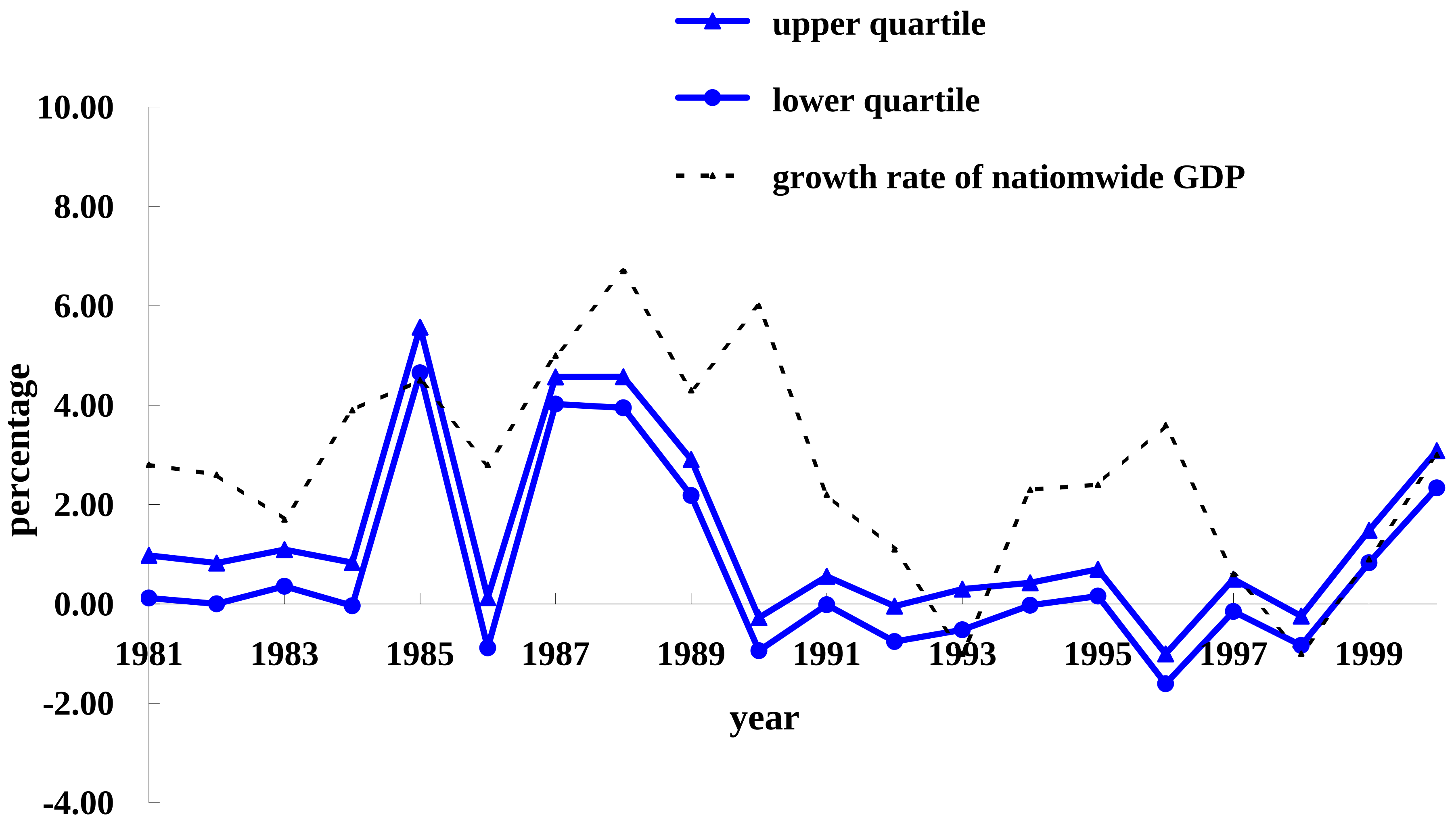

Fig. 3 Effects of technical change on productivity

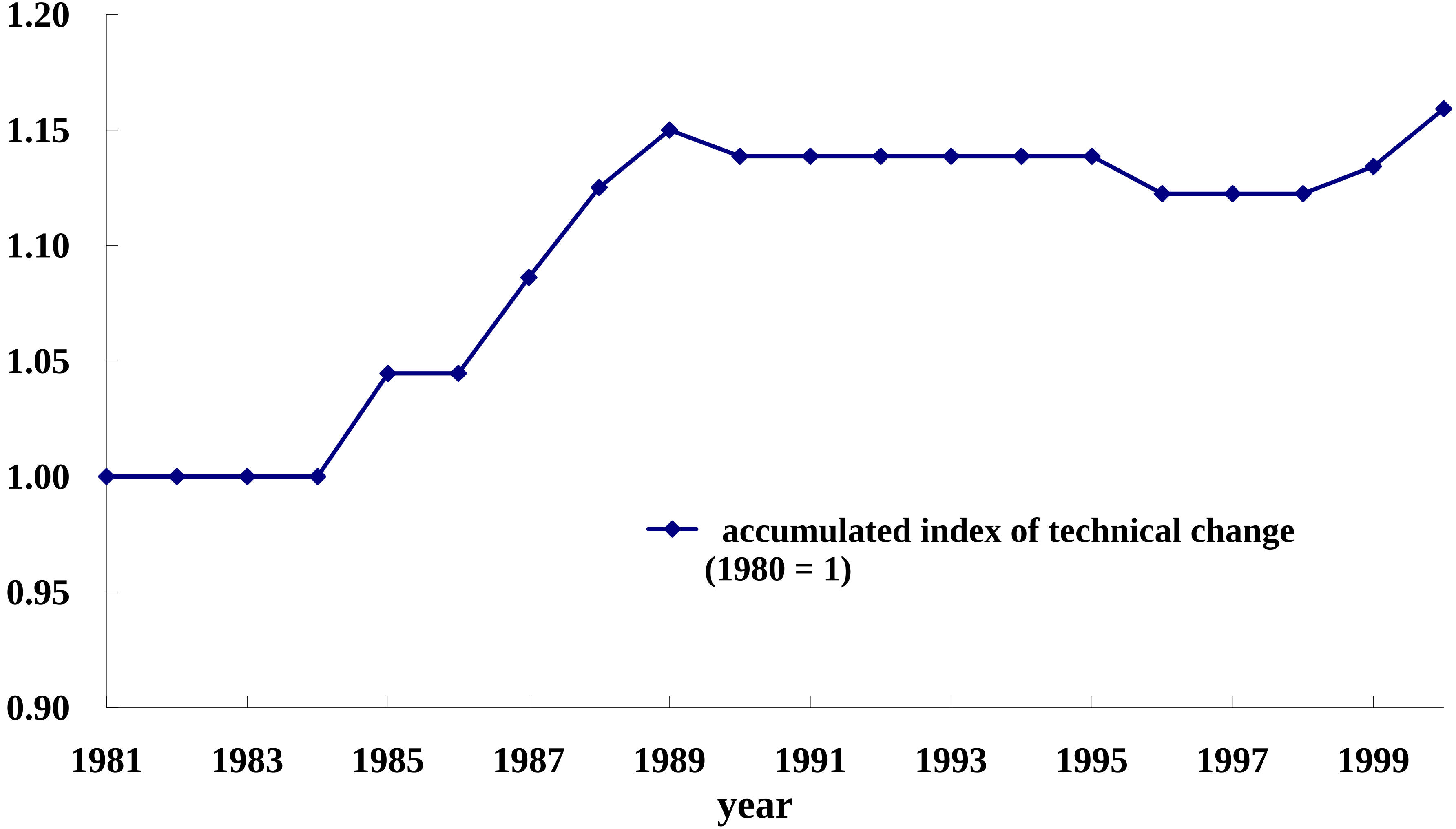

Fig. 4 Accumulated pure technical change

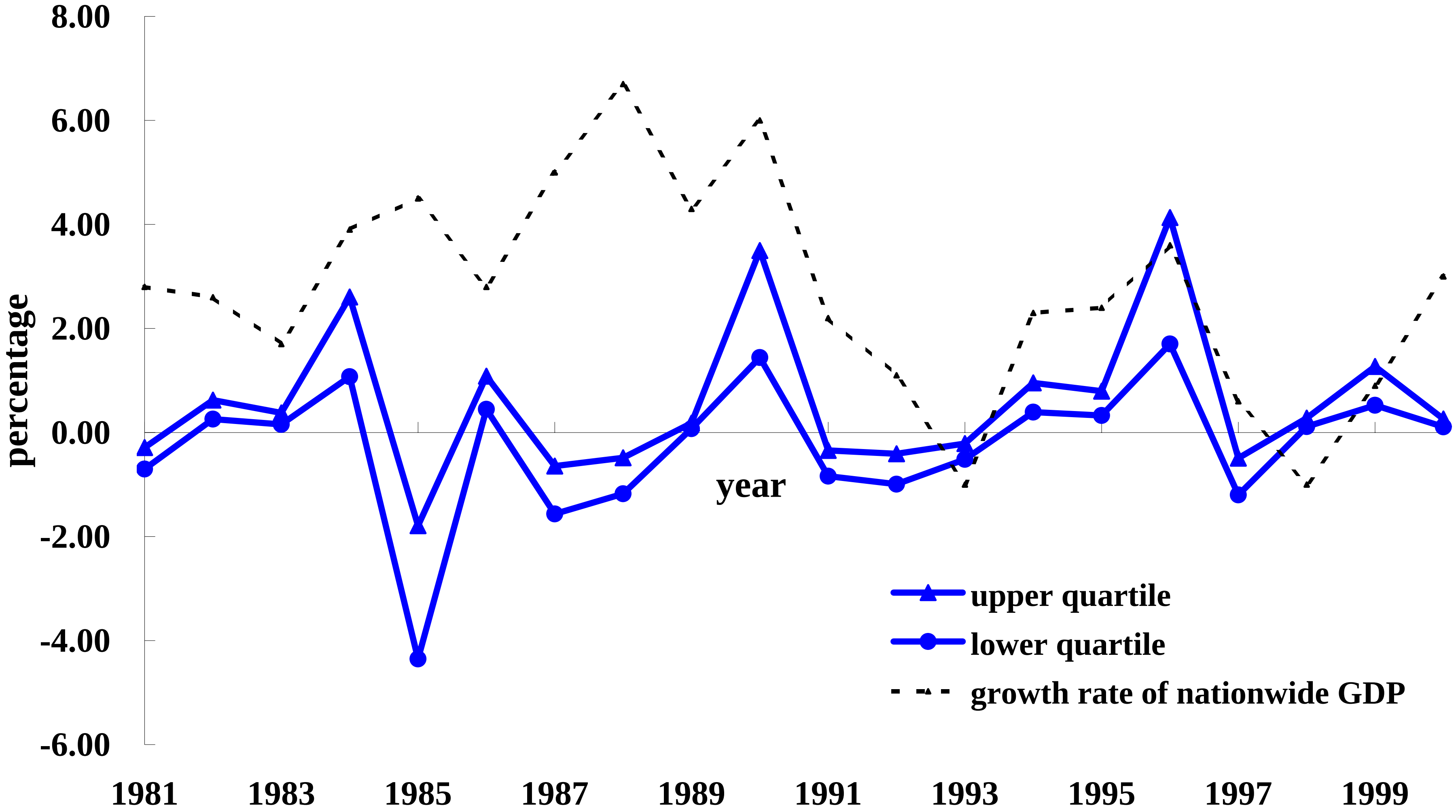

Fig. 5 Effects of efficiency change on productivity

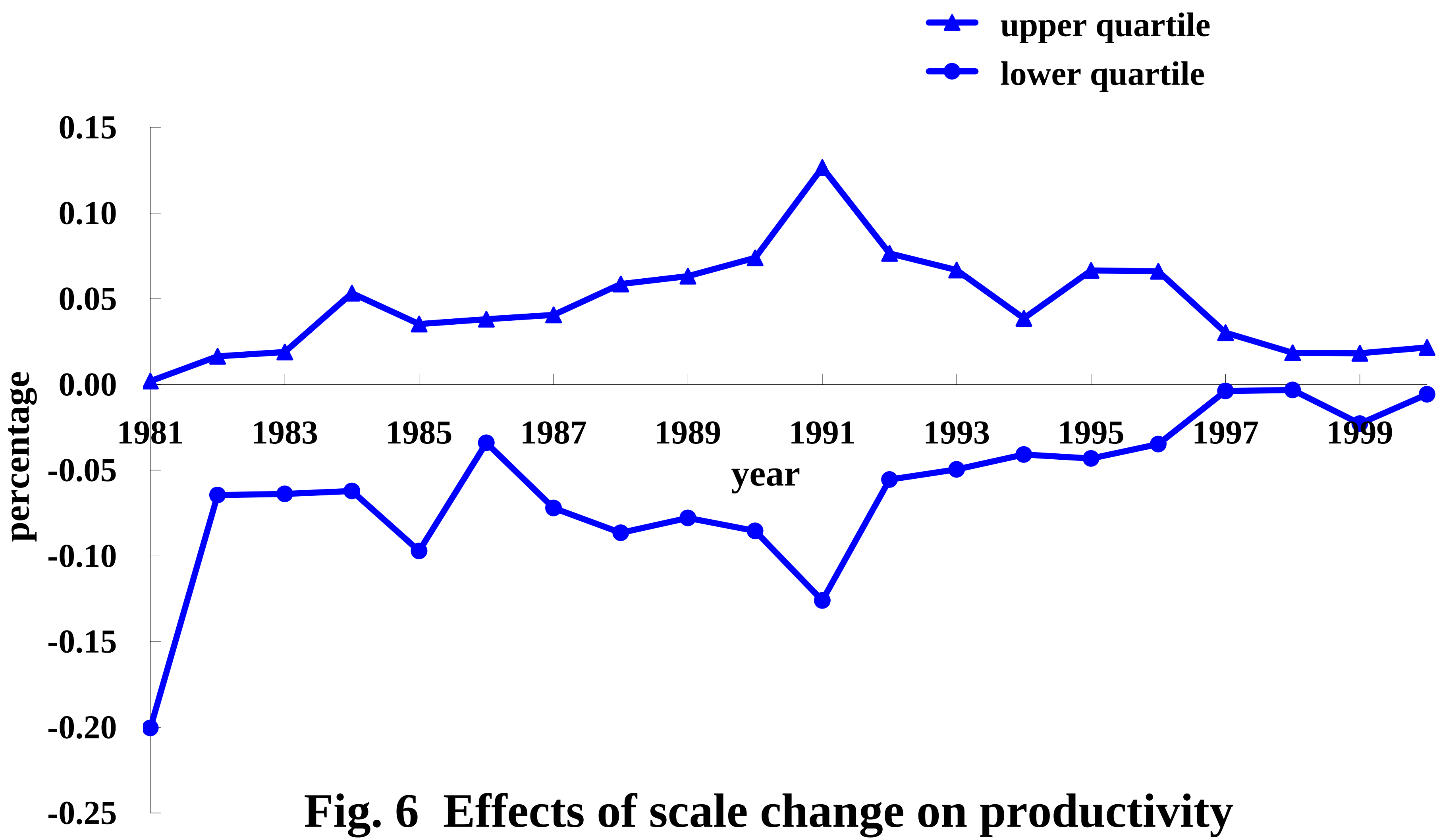

Fig. 6 Effects of scale change on productivity

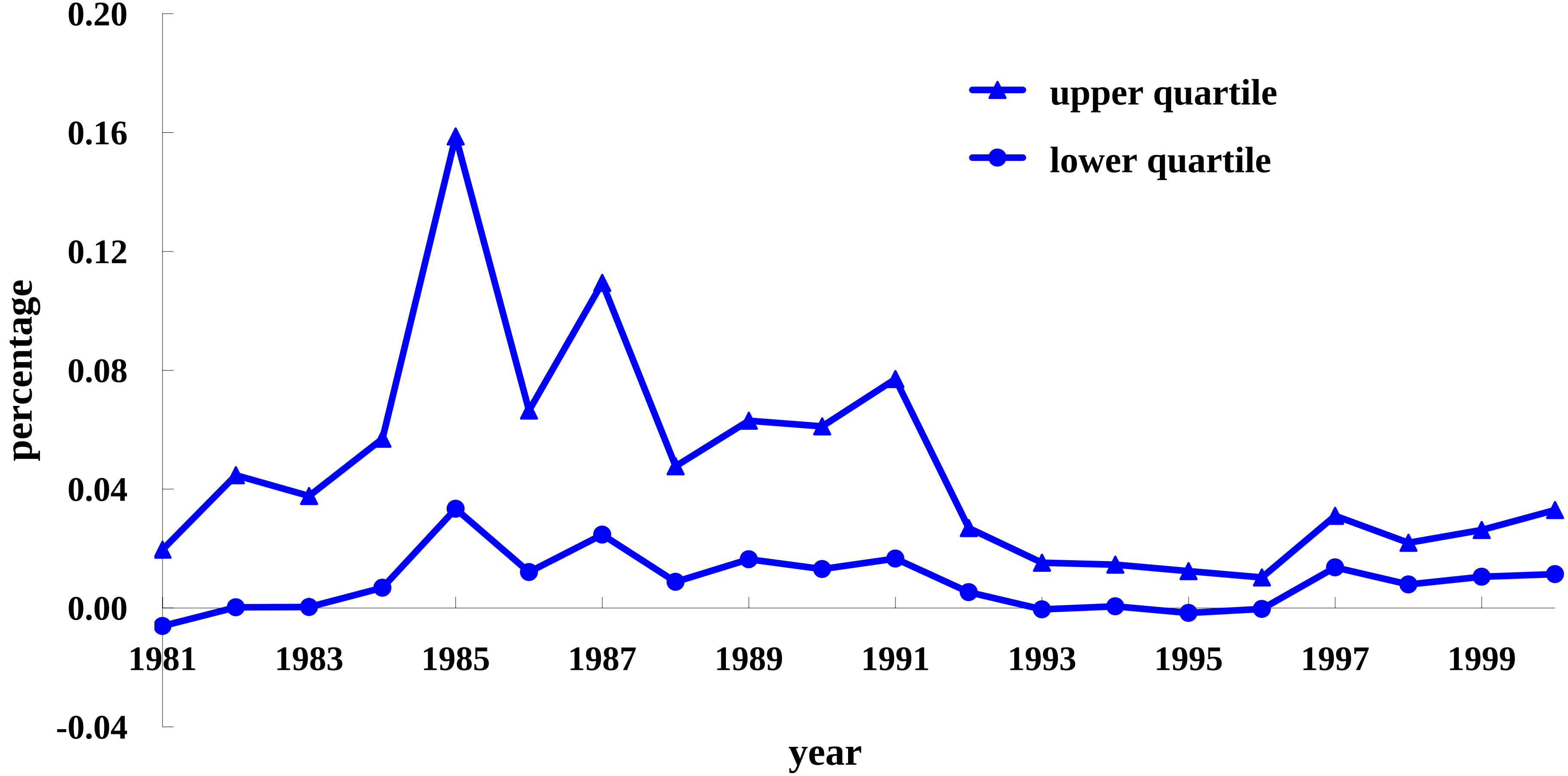

Fig. 7 Input and output mix effects on productivity