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PRODUCTIVITY, EFFICIENCY, SCALE ECONOMIES AND TECHNICAL CHANGE: A NEW DECOMPOSITION ANALYSIS OF TFP APPLIED TO THE JAPANESE PREFECTURES

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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 their relative 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 the efficiency change component drove upturns of productivity in 1984, 1990, and 1996 when supply shocks were not detected.

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1. Introduction

The main purpose of this paper is to examine the productivity of the Japanese economy using data pertaining to the 47 prefectures during the period 1981-2000. During this period in Japan, it is of particular interest to clarify the sources of productivity growth. While the Japanese economy outperformed other developed countries in the 80s, it experienced severe stagnation in the 90s. It should be noted that the average economic growth rate of Japan, which was 4.0 percent during the period 1981-1990, considerably fell to 1.4 percent during the period 1991-2000. Such a sharp contrast provides useful evidence to clarify the relationship between productivity and business cycle.

In the macroeconomic literature, the persistent empirical fact of procyclical productivity has once received much attention[1]. The procyclicality of productivity is alternatively explained by technology shocks, the increasing returns to scale, or procyclical variations in input utilization. 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 favorable for disentangling sources of the productivity growth. While the technical change component represents the effects on productivity of a shift in the production frontier, the efficiency change component measures the effects of deviation from the production frontier. Thus, the efficient change component is expected to capture the variations in input utilization due to such "off production frontier" behavior as labor hoarding or excess capacity. Further, the effects of technology shocks and the increasing returns to scale are identified by the technical change component and the scale change component, respectively. One can say that the decomposition of the HMB index can be used to assess the relative importance of those factors as sources of fluctuations in productivity.

In fact, no other productivity index is more satisfactory for our purpose than the HMB index. Although the Törnqvist index and the Malmquist index are more widely used in the recent literature, their decomposition analyses are incomplete. The Törnqvist productivity index has no efficiency change component because it presumes the optimizing behavior of a producer. On the

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

other hand, the Malmquist productivity index is not indicative of scale change because it is well defined only when the technology exhibits the 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 he productivity change is fully decomposed.

We begin introducing the input- and output-oriented distance functions on which the HMB index is based. In Section 2, the HMB productivity index and its decomposition analysis is presented in terms of the distance functions. Section 3 explains specification of the empirical model to implement the HMB index analysis. The stochastic frontier model is specified by the translog form to estimate the output-oriented distance function using a panel on the Japanese prefectures. In addition, a technique for transforming the output-oriented distance function into the input-oriented distance function is outlined. Section 4 discusses the empirical results on the Japanese prefectures during the period 1981-2000. Section 5 concludes the paper.

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

2.1 Distance function

In general, a productivity index is defined as the ratio of output to input index. The Hicks-Moorsteen-Bjurek (HMB) productivity index employs the Malmquist output and input indexes that aggregate outputs and inputs using the distance functions. This subsection briefly reviews the distance functions and the Malmquist indexes to define the HMB productivity index.

The distance function is defined on the production possibility set at the time t

$$\Omega^t = \{(x,y) \mid x \ can \ produce \ y\}, \tag{1}$$

where $x = (x_1, x_2, \cdots, x_n)'$ is an input vector and $y = (y_1, y_2, \cdots, y_m)'$ is an output vector. The distance function is defined by rescaling the length of an output or an input vector using the production frontier as a reference. The output-oriented distance function is formerly defined by

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

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. Given the production possibility set satisfying the regularity conditions, the output-oriented distance function is monotonic increasing, convex, and linearly homogeneous in outputs, and is monotonic decreasing in inputs.

The input-oriented distance function is defined by

$$D_i^t(x,y) \equiv \max\{\, \delta \mid (x/\delta, y) \in \Omega^t \,\}, \tag{3}$$

where $D_i^t(x,y) < 1$ implies that x cannot produce y. 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 further reduced without decreasing outputs. Given the production possibility set satisfying the regularity conditions, the input-oriented distance function is monotonic increasing, concave, and linearly homogeneous in inputs, and is monotonic decreasing in outputs.

The aggregate output index is constructed by comparing the outputs obtained during the period t+1 to these obtained during the period t. There are two alternatives depending on which of the period t and t+1 is chosen as the reference period. In this paper, we in principle employ the geometric average of the two indexes. Formerly, the Malmquist output index over the period t and t+1 is defined by

$$M_y(x^{t+1}, x^t, y^{t+1}, y^t) = \left\{ \frac{D_o^t(x^t, y^{t+1})\; D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)\; D_o^{t+1}(x^{t+1}, y^t)} \right\}^{\frac{1}{2}}. \tag{4}$$

Similarly,

$$M_x(x^{t+1}, x^t, y^{t+1}, y^t) = \left\{ \frac{D_i^t(x^{t+1}, y^t)\; D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)\; D_i^{t+1}(x^t, y^{t+1})} \right\}^{\frac{1}{2}} \tag{5}$$

defines the Malmquist input index over the period t and t+1.

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

$$HMB(x^{t+1}, x^t, y^{t+1}, y^t) = \frac{M_y(x^{t+1}, x^t, y^{t+1}, y^t)}{M_x(x^{t+1}, x^t, y^{t+1}, y^t)}. \tag{6}$$

2.2 Decomposition of the HMB productivity index

It can be shown that the productivity change from the period t to t+1 measured by the HMB productivity index (6) can be decomposed into four components: technical change, $TC^{t+1,t}$, efficiency change, $EC^{t+1,t}$, scale change, $SC^{t+1,t}$, and the input and output mix effects, $ME^{t+1,t}$. The decomposition equation becomes additive in the logarithmic form, i.e., the proportionate change of productivity factorizes in the proportionate changes of the four components as

$$\ln HMB(x^{t+1},x^{t},y^{t+1},y^{t}) = \ln TC^{t+1,t} + \ln EC^{t+1,t} + \ln SC^{t+1,t} + \ln ME^{t+1,t}. \tag{7}$$

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 the effects on productivity change of technical advance or regress by a shift in the output-oriented distance function while keeping inputs and outputs constant[2]. The efficiency change component measures the effects on productivity change of approaching or going away from the efficient frontier while fixing the output-oriented distance function. These two 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. Eq. (7) thus can be seen as augrmenting the Färe et al's decomposition analysis with the scale change component.

The scale change component is given by

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

[2] Note that the technical change component as well as the other components takes the form of geometric mean of the two indexes referring the period t and t+1 as a base.

where

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

and,

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

As shown in the appendix 1, $\hat{\varepsilon}_o^{\,t}$ 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 used as a scalar measure of the scale change. Since the scale elasticity larger (smaller) than one implies the scale economies (diseconomies), expanding (contracting) the scale always enhances productivity if the scale economies (diseconomies) prevail.

Besides the scale change measured by the Malmquist index, a change in input and output quantities also has the effects of a change in input and output mix. To complete the decomposition of the productivity change, the last component is 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

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

Here, 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 a remarkable property that it becomes almost equivalent to the Törnqvist productivity index if no inefficiency exists[3]. Since the Törnqvist productivity index rules out inefficiency by assumption, this implies that the HMB productivity index naturally extends the Törnqvist productivity index so that the effects of efficiency on productivity can be measured. We eventually have a decomposition of the HMB productivity index as

$$
\begin{aligned}
&\ln HMB(x^{t+1}, x^{t}, y^{t+1}, y^{t}) \\
&\quad = \ln\left\{ \frac{D_o^{t}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^{t}(x^{t}, y^{t})}{D_o^{t+1}(x^{t}, y^{t})} \right\}^{\frac{1}{2}} && (\textit{technical change}) \\
&\quad + \ln\left\{ \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t}(x^{t}, y^{t})} \right\} && (\textit{efficiency change}) \\
&\quad + \left(\frac{\hat{\varepsilon}_o^{t} + \hat{\varepsilon}_o^{t+1}}{2} - 1 \right) \ln s^{t+1,t} && (\textit{scale change}) \\
&\quad + \ln\left\{ \frac{D_o^{t}(s^{t+1,t}x^{t}, r^{t+1,t}y^{t})}{D_o^{t}(x^{t+1}, y^{t+1})} \frac{D_o^{t+1}(x^{t}, y^{t})}{D_o^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, \frac{y^{t+1}}{r^{t+1,t}})} \right\}^{\frac{1}{2}} && (\textit{input and output mix effects}).
\end{aligned}
\tag{8}
$$

3. Empirical model

3.1 Output-oriented distance function

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, real GDP. Let x_{Li}^{t}, x_{Ki}^{t}, and y_i^{t} denote labor, private capital, and real GDP of the prefecture i at the year t, respectively. The share of the manufacturing industry in real GDP, h_i^{t}, is introduced as a control variable to adjust differences in the industrial structure over time and prefectures. Public capital, x_{Gi}^{t}, is also a control variable that is supposed to create "atmosphere" through

[3] Specifically, if no inefficiency exists and the output-oriented distance function is the translog form, the components of technical change and scale change coincide with the corresponding terms of the Törnqvist productivity index. Also, the efficiency change component of the HMB index disappears without inefficiency, which conforms to the Törnqvist productivity index. A proof for those propositions is available on request.

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.

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

$$
\begin{aligned}
\ln D_o^t(x_{Li}^t, x_{Ki}^t, y_i^t \,;\, z_i^t, A^t) &= TL(x_{Li}^t, x_{Ki}^t, y_i^t \,;\, z_i^t, A^t) \\
&\equiv \alpha_0 + \ln y_i^t + \alpha_L \ln x_{Li}^t + \alpha_K \ln x_{Ki}^t \\
&\quad + \frac{1}{2}\alpha_{LL}\left(\ln x_{Li}^t\right)^2 + \frac{1}{2}\alpha_{KK}\left(\ln x_{Ki}^t\right)^2 \\
&\quad + \alpha_{LK}\left(\ln x_{Li}^t\right)\left(\ln x_{Ki}^t\right) \\
&\quad + \gamma_{KG}\left(\ln x_{Ki}^t\right)\left(\ln x_{Gi}^t\right) + \gamma_h h_i^t + \sum_{\tau=2}^{T} \beta_\tau A_\tau^t \\
i &= 1, 2, \cdots, N, \quad t = 1, 2, \cdots, T.
\end{aligned}
\tag{9}
$$

In the above specification, homogeneity in an output is imposed on parameters, which simultaneously ensures monotonicity and convexity in an output in (9).

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

$$
\ln D_o^t(x_{Li}^t, x_{Ki}^t, y_i^t \,;\, z_i^t, A^t) = -u_i^t + v_i^t, \qquad t = 1, 2, \cdots, T, \tag{10}
$$

where

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

and u_i and v_i^t are assumed to be independent. Technical efficiency of the ith prefecture at the year t is given by $\exp\left\{-u_i(1 + \varphi_t)\right\}$.

Combining eqs. (9) and (10), we have an estimation equation

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

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

$$
\begin{aligned}
\ln L = const. + NT\ln\theta + N\ln\lambda - \frac{1}{2}\theta^2\sum_{i=1}^{N}\left\{\sum_{t=1}^{T}\xi_{it}^2 - \frac{1-\lambda^2}{\sum_{t=1}^{T}(1+\varphi_t)^2}\left(\sum_{t=1}^{T}(1+\varphi_t)\xi_{it}\right)^2\right\} \\
+ \sum_{i=1}^{I}\ln\Phi\left(-\theta\sum_{t=1}^{T}(1+\varphi_t)\xi_{it}\sqrt{\frac{1-\lambda^2}{\sum_{t=1}^{T}(1+\varphi_t)^2}}\right),
\end{aligned}
\tag{11}
$$

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

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

3.2 Input-oriented distance function

Once the output-oriented distance function is parametrically specified, it is directly estimable with econometric techniques. However, the HMB approach requires both of input and output-oriented distance functions. This subsection describes a way to obtain the input-oriented distance function values from the estimated output-oriented distance function.[4]

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

$$D_i^t(x,y) = \max\left\{\delta \mid D_o^t(x/\delta, y) \le 1\right\}. \tag{12}$$

---

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

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 (9), we have

$$\frac{1}{2}(\ln\delta^*)^2 \sum_{i=K,L}\sum_{j=K,L}\alpha_{ij} + \varepsilon_o^t \ln\delta^* + \ln D_o^t(x,y) = 0. \tag{13}$$

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

$$\ln D_i^t(x,y) = -\frac{\ln D_o^t(x,y)}{\varepsilon_o^t(x,y)}. \tag{14}$$

If $\sum_i\sum_j\alpha_{ij} \neq 0$, eq. (13) is a quadratic equation. Suppose that there exist real roots $\ln\delta_1^*$ and $\ln\delta_2^*$. Then, non-smaller one of them is relevant by definition of the input distance function. Therefore,

$$\ln D_i^t(x,y) = \max\left\{\ln\delta_1^*, \ln\delta_2^*\right\}. \tag{15}$$

Eq. (13) has real roots as long as the output distance function (9) 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 with this technique given the output-oriented distance function parameters. We show details on measurement of the four components in the appendix 2.

3.3 Data

The translog output-oriented distance function is estimated with data pertaining to the 47 prefectures in Japan during 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. From this database, real GDP, labor, private capital, public capital, and share of the manufacturing industry are obtained.

4. Results

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. Without the restrictions, the output-distance function is estimated with technical regress for several years. Although technical regress is empirically implausible, the concerned coefficients mostly suggest that it is insignificant. We then assume that neither technical progress nor regress occurred in the years when the significant shifts in the production frontier were not detected[5].

The resulting parameter estimates ensure that the output-oriented distance function is monotonic decreasing in labor and private capital within sample. The coefficient of manufacturing industry share is significantly negative, indicating that the manufacturing industry is more productive than other sectors and, thereby, an increase in its weight extends the production frontier. The interaction term of public and private capital is positively related to the output-oriented distance. 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. Turning to the stochastic part, we find that the variance of efficiency overwhelms the variance of statistical noise. If efficiency terms are neglected in the empirical production model, it easily leads to misspecification.

Tables 2 and 3 report the HMB productivity index and its factorized components based on eq. (8). All figures in the tables are measured in percentage change over adjacent years, i.e., measurements of each term of eq. (8) multiplied by a hundred. In Table 2, the decomposition analysis is conducted at the sample mean. An overview of Table 2 suggests that the effects of technical and efficiency changes on productivity dominate over those of the other two components. The residual factor does not systematically affect the productivity change even though it is not negligible for several years. In Table 3, the upper and lower quartiles of the results of the 47 prefectures are shown for each year. The sum of the components does not equal productivity change because these quartiles represent different prefectures. Subsequently, we illustrate the results in Table 3 by each component.

Figure 1 depicts the development of upper and lower quartiles of the HMB productivity index. The growth rate of nationwide GDP are also designated by the dotted line. Procyclicality of the productivity change is clearly evident. Synchronizing with fluctuations in nationwide GDP, the productivity growth declined around 1986, 1992 and 1998, and it rose during the years 1994, 1987-1990, 1996, and 1999-2000. Of particular interest here is whether the procyclical movement is due more to technology shocks or demand shocks.

Figure 2 shows the development of the technical change component. While the coefficients of the time dummies are the main source of the technical change component, they are invariant over

[5] As a result, the production frontier is supposed to halt during the years 1981-1984, 1986, 1991-1995, 1997-1998.

the prefectures. This probably explains why the inter-quartile range of the technical change component is considerably narrow. Technical change contributed to raising the productivity and the GDP growth in the mid and late 80s, except 1986, and the last two years in the period of analysis. Conversely, technical change was responsible for downturns in the productivity and GDP in the early and mid 90s. 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 is observed. As can be seen below, the efficiency change component played a more important role than the technical change during this period.

In Figure 2, measurements of technical change shown are $\ln TC^{t+1,t}$ that contains the effects of the control variables. In the present model, the pure technical factor solely due to the coefficients of the time dummies is isolated from $\ln TC^{t+1,t}$.[6] To give an overview, Figure 3 shows its accumulated index normalized at one in 1980. Technical advances are found in the late 80s and in 1999 and 2000. During the rest of the period, the technical level is generally unaltered, which is 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 sixteen percent more outputs from the same amount of inputs in 1980.

Figure 4 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 over prefectures are limited.

We see that improvement in efficiency supported upturns of productivity and GDP during the period 1994-1996, especially in 1996. Since demand shocks are captured by the efficiency factor while, as noted above, technology shocks were not prominent, the economic recovery during this period was likely to be driven by fiscal expansion. The efficiency change component also has peaks in 1984 and 1990. In these years, we find a pattern similar to 1996: improvement in efficiency supported productivity and GDP growth without technical advances. Conversely, compared with the technical change factor, efficiency was not a main contributor to recovery in productivity and GDP in 1999 and 2000.

In general, the efficiency change component tends to move in the opposite direction to the

[6] Measurement of the pure technical factor, $\ln\widetilde{TC}_i^{t+1,t}$, is explained in the appendix 2.

technical change component. A possible explanation for this is that real GDP does not promptly follow advances in the production frontier. As a result, positive supply shocks make the frontier more distant from the actual point of production, implying lower efficiency at least in the short-run.

Figure 5 shows the scale change component. The effects of scale change are much smaller than those of technical change and efficiency change. It is thus difficult to explain procyclical productivity by the short run increasing returns to scale. As seen in Figure 5, development of upper and lower quartiles of the scale change component exhibits a mirror image. This is because increasing and decreasing returns technologies coexist in 47 prefectures while movement of the scale is rather common among them. By construction, the scale change component is the product of scale change and the average scale elasticity minus one, $(\hat{\varepsilon}_o^t + \hat{\varepsilon}_o^{t+1})/2 - 1$. 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 shows measurements of the scale elasticity of the five largest and the five smallest as well as the quartiles. Reflecting the aggromelation economies, prefectures including the metropolitan areas tend to exhibit the scale economies.

Figure 6 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 two inputs, capital and labor. Thus, Figure 6 suggests that increasing the capital to labor ratio over the two decades continuously enhanced productivity. However, these effects are considerably small and do not seem to be a very important factor in productivity change.

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 during the period 1981-2000. 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 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 drove 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 of the productivity and efficiency analyses yet. While the efficiency component in the decomposition analysis represents technical efficiency, it is not indicative of the allocative efficiency. This is 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 a change in relative prices of inputs and outputs and is thus not indicative of the allocative efficiency. Further studies should focus on an extended HMB approach including allocative efficiency as a component of the decomposition analysis of productivity.

Appendix 1 Scale elasticity in terms of the output-oriented distance function

This appendix reviews the output-oriented scale elasticity and shows that $\hat{\varepsilon}_o^t$ is obtained by a discrete approximation. For any $\lambda > 0$ and $(x,y) \in \Omega^\tau$, μ is supposed to satisfy

$$D_o^t(\lambda x, \mu y) = 1. \tag{A.1}$$

Since the output distance function is linearly homogenous in y,

$$\mu = 1/D_o^t(\lambda x, y). \tag{A.2}$$

The output-oriented scale elasticity at (x,y) relative to Ω^τ is defined as

$$\varepsilon_o^t(x,y) = \left.\frac{d\ln\mu}{d\ln\lambda}\right|_{\lambda=1}. \tag{A.3}$$

Logarithmically differentiating both sides of (A.2), we have

$$\varepsilon_o^t(x,y) = -\nabla_{\ln x}\ln D_o^t(x,y)'i, \tag{A.4}$$

where $i = (1, 1, \cdots, 1)'$.

Suppose that the output-oriented distance function takes the translog form with a time-varying constant and time-varying first order parameters

$$\begin{aligned}\ln D_o^t(x,y) = \alpha_0^t + \sum_i \alpha_i^t \ln x_i + \sum_i \beta_i^t \ln y_i + \frac{1}{2}\sum_i\sum_j \alpha_{ij}\ln x_i \ln x_j \\ + \frac{1}{2}\sum_i\sum_j \beta_{ij}\ln y_i \ln y_j + \sum_i\sum_j \gamma_{ij}\ln x_i \ln y_j,\end{aligned} \tag{A.5}$$

$$\alpha_{ij} = \alpha_{ji},\ i,j = 1,2,\cdots,m, \quad \beta_{ij} = \beta_{ji},\ i,j = 1,2,\cdots,n.$$

Since the constant and first order parameters are time-varying, they are allowed to depend on the control variables and the time trend. Thus, eq. (9) specified in the main text is a special case of eq. (A.5). From (A.4), the scale elasticity implied by (A.5) can be written as

$$\varepsilon_o^t = -\Big(\sum_i \alpha_i^t + \sum_i \sum_j \alpha_{ij}^t \ln x_j + \sum_i \sum_j \gamma_{ij}^t \ln y_j \Big) . \tag{A.6}$$

To measure the scale elasticity with eq. (A.4), the output-oriented distance function parameters are required to evaluate the first order derivatives. Instead of differentiation, a discrete approximation enables us to measure the scale elasticity with nonparametric techniques. Taking a discrete approximation to eq. (A.3) at (x, y), we have

$$\hat{\varepsilon}_o^t(x, y) = \frac{\Delta\mu}{\Delta\lambda}\frac{\lambda}{\mu}\bigg|_{\lambda=1} = \frac{1}{\Delta\lambda}\left\{ \frac{D_o^t(\lambda x, y)}{D_o^t((1+\Delta\lambda)x, y)} - 1 \right\}. \tag{A.7}$$

Set $x = x^t$, $y = y^t$, and $\Delta\lambda = s^{t+1,t} - 1$. We then have

$$\hat{\varepsilon}_o^t(x^t, y^t) = -\frac{\ln\left\{\dfrac{D_o^t(s^{t+1,t}x^t, y^t)}{D_o^t(x^t, y^t)}\right\}}{\ln\left\{\dfrac{D_i^t(s^{t+1,t}x^t, y^t)}{D_i^t(x^t, y^t)}\right\}}. \tag{A.8}$$

An approximation formula $\ln(1+x) \doteq x$ is utilized here. Similarly, setting $x = x^{t+1}$, $y = y^{t+1}$, and $\Delta\lambda = 1/s^{t+1,t} - 1$ yields

$$\hat{\varepsilon}_o^{t+1}(x^{t+1}, y^{t+1}) = -\frac{\ln\left\{\dfrac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, y^{t+1})}\right\}}{\ln\left\{\dfrac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(\frac{x^{t+1}}{s^{t+1,t}}, y^{t+1})}\right\}}. \tag{A.9}$$

In the main text, $\hat{\varepsilon}_o^t(x^t, y^t)$ and $\hat{\varepsilon}_o^{t+1}(x^{t+1}, y^{t+1})$ are abbreviated as $\hat{\varepsilon}_o^t$ and $\hat{\varepsilon}_o^{t+1}$, respectively.

Estimation of the scale elasticity by taking a discrete approximation was initially proposed by Löthgren and Tambour (1996) in the context of the data envelopment analysis. Our estimates $\hat{\varepsilon}_o^t$ and $\hat{\varepsilon}_o^{t+1}$ always lie between their upper and lower bound estimates.

Appendix 2 Measurement of the four components of the HMB productivity index

This appendix explains measurement of the four components of the decomposition analysis based on eq. (8). In the following, a "^" indicates an estimate. Firstly, according to Battese and Coelli (1992), technical efficiency $\hat{u}_i^t$ is estimated as the conditional expectation of $u_i^t = u_i(1 + \varphi_t)$ on ξ_{it}. Then, efficiency change is measured as

$$\ln \hat{EC}_i^{t+1,t} = -\hat{u}_i^{t+1} + \hat{u}_i^t.$$

Notice that $-\hat{u}_i^t$ and $-\hat{u}_i^{t+1}$ differ from $TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^t, A^t)$ and $TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^{t+1}, A^{t+1})$ by estimation residuals, i.e., letting $\hat{v}_i^t$ be the residuals, $-\hat{u}_i^t = TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^t, A^t) - \hat{v}_i^t$ and $-\hat{u}_i^{t+1} = TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^{t+1}, A^{t+1}) - \hat{v}_i^{t+1}$. As a result, a residual factor due to this difference emerges in the decomposition analysis.

Technical change is computed as

$$\begin{aligned}\ln \hat{TC}_i^{t+1,t} = &\ \frac{1}{2}\left\{ TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^t, A^t) - TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^{t+1}, A^{t+1}) \right\} \\ &+ \frac{1}{2}\left\{ TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^t, A^t) - TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^{t+1}, A^{t+1}) \right\}.\end{aligned}$$

Although $\ln \hat{TC}_i^{t+1,t}$ represents a shift in the production frontier, some amount of the shift is due to changes in the control variables z_i^t. Recalling that the effects of technology shocks are supposed to be captured by the time-specific dummies, we define pure technical change which is solely due to A^t as

$$\begin{aligned}\ln \hat{\tilde{TC}}_i^{t+1,t} = &\ \frac{1}{2}\left\{ TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^{t+1}, A^t) - TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ;\ z_i^{t+1}, A^{t+1}) \right\} \\ &+ \frac{1}{2}\left\{ TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^t, A^t) - TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ;\ z_i^t, A^{t+1}) \right\}.\end{aligned}$$

The scale change component is computed as

$$\ln \hat{SC}_i^{t+1,t} = \frac{1}{2}\left\{ TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ; z_i^t, A^t) - TL(\hat{s}_i^{t+1,t} x_{Li}^t, \hat{s}_i^{t+1,t} x_{Ki}^t, y_i^t\ ; z_i^t, A^t) \right\}$$
$$+ \frac{1}{2}\left\{ TL(\frac{x_{Li}^{t+1}}{\hat{s}_i^{t+1,t}}, \frac{x_{Ki}^{t+1}}{\hat{s}_i^{t+1,t}}, y_i^{t+1}\ ; z_i^{t+1}, A^{t+1}) - TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ; z_i^{t+1}, A^{t+1}) \right\}.$$

An estimate of $s_i^{t+1,t}$ is obtained by the technique explained in the last subsection[7].

Finally, the input and output mix effects are computed by

$$\ln \hat{ME}^{t+1,t} = \frac{1}{2}\left\{ TL(\hat{s}_i^{t+1,t} x_{Li}^t, \hat{s}_i^{t+1,t} x_{Ki}^t, \hat{r}_i^{t+1,t} y_i^t\ ; z_i^t, A^t) - TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ; z_i^t, A^t) \right\}$$
$$+ \frac{1}{2}\left\{ TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ; z_i^{t+1}, A^{t+1}) - TL(\frac{x_{Li}^{t+1}}{\hat{s}_i^{t+1,t}}, \frac{x_{Ki}^{t+1}}{\hat{s}_i^{t+1,t}}, \frac{y_i^{t+1}}{\hat{r}_i^{t+1,t}}\ ; z_i^{t+1}, A^{t+1}) \right\}.$$

where

$$\hat{r}_i^{t+1,t} = \left[\exp\left\{ TL(x_{Li}^t, x_{Ki}^t, y_i^t\ ; z_i^t, A^t) - TL(x_{Li}^t, x_{Ki}^t, y_i^{t+1}\ ; z_i^t, A^t) \right\} \right.$$
$$\left. + \left\{ TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1}\ ; z_i^{t+1}) - TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^t\ ; z_i^{t+1}, A^{t+1}) \right\} \right]^{\frac{1}{2}}.$$

[7] Among the four input-oriented distance functions constituting $s_i^{t+1,t}$, $D_i^t(x_{Li}^t, x_{Ki}^t, y_i^t)$ and $D_i^{t+1}(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^{t+1})$ are estimated by substituting $-\hat{u}_i^t$ and $-\hat{u}_i^{t+1}$ into the term of output-oriented distance function in eq. (13), respectively. For the other part of $s_i^{t+1,t}$, $TL(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^t\ ; z_i^t, A^t) - \hat{v}_i^t$ and $TL(x_{Li}^t, x_{Ki}^t, y_i^{t+1}\ ; z_i^{t+1}, A^{t+1}) - \hat{v}_i^{t+1}$ are used with eq. (13) in estimation of $D_i^t(x_{Li}^{t+1}, x_{Ki}^{t+1}, y_i^t)$ and $D_i^{t+1}(x_{Li}^t, x_{Ki}^t, y_i^{t+1})$. By adjusting residuals in this way, the residuals are canceled out and do not disturb the estimates of $\hat{s}_i^{t+1,t}$.

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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: percent

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: percent

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	mean
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.

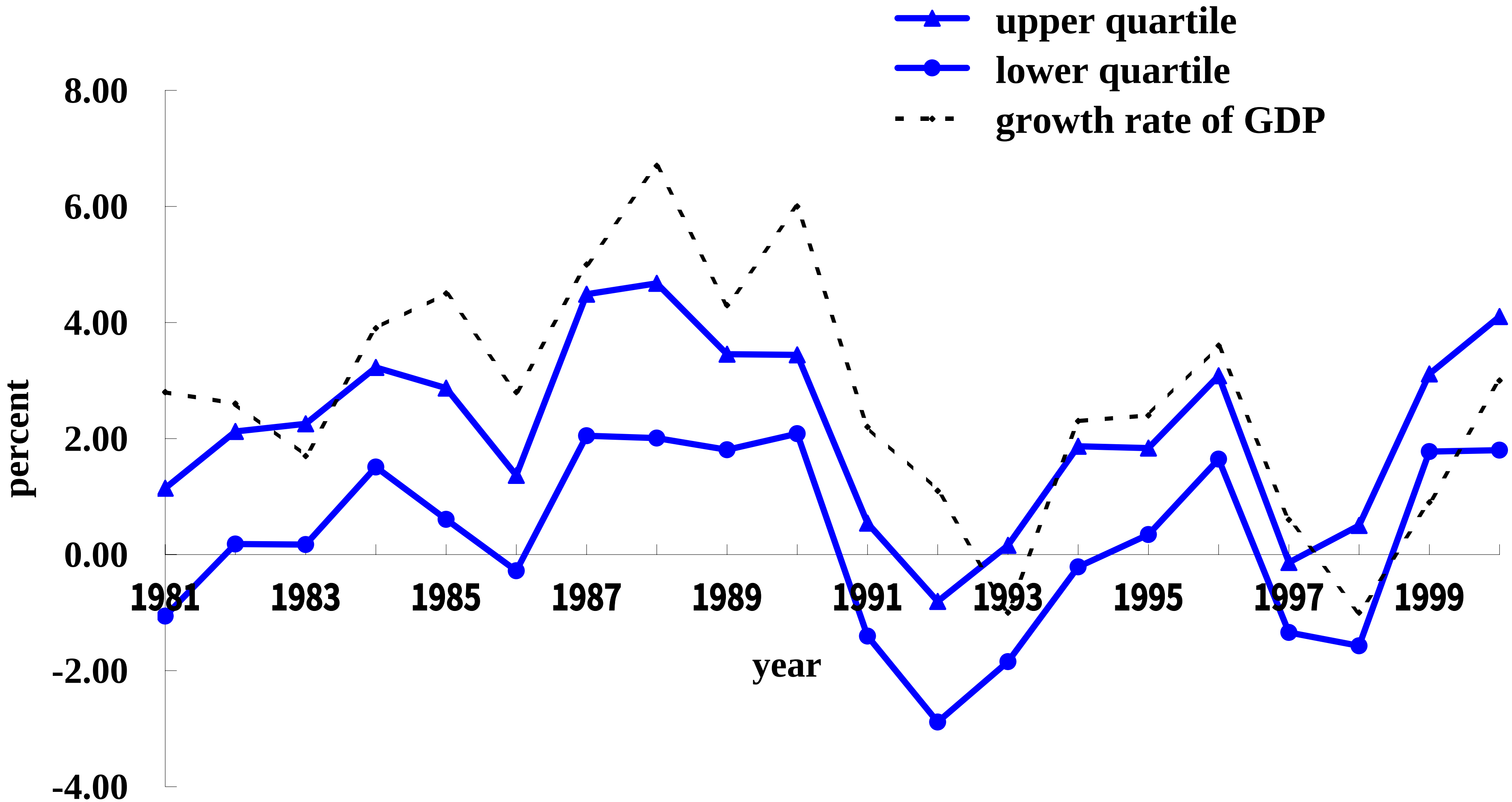

Fig. 1 HMB productivity index

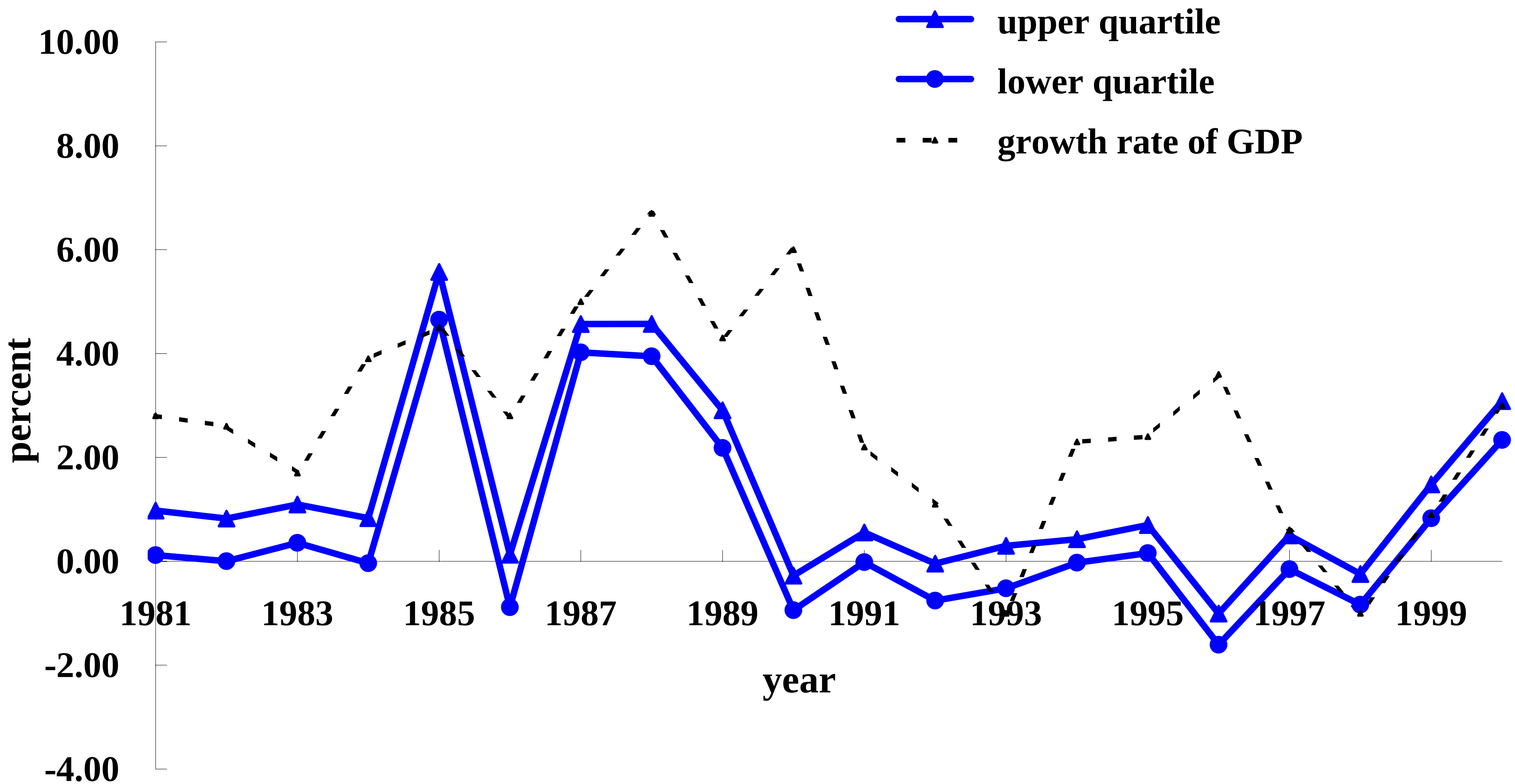

Fig. 2 The effects of technical change on productivity

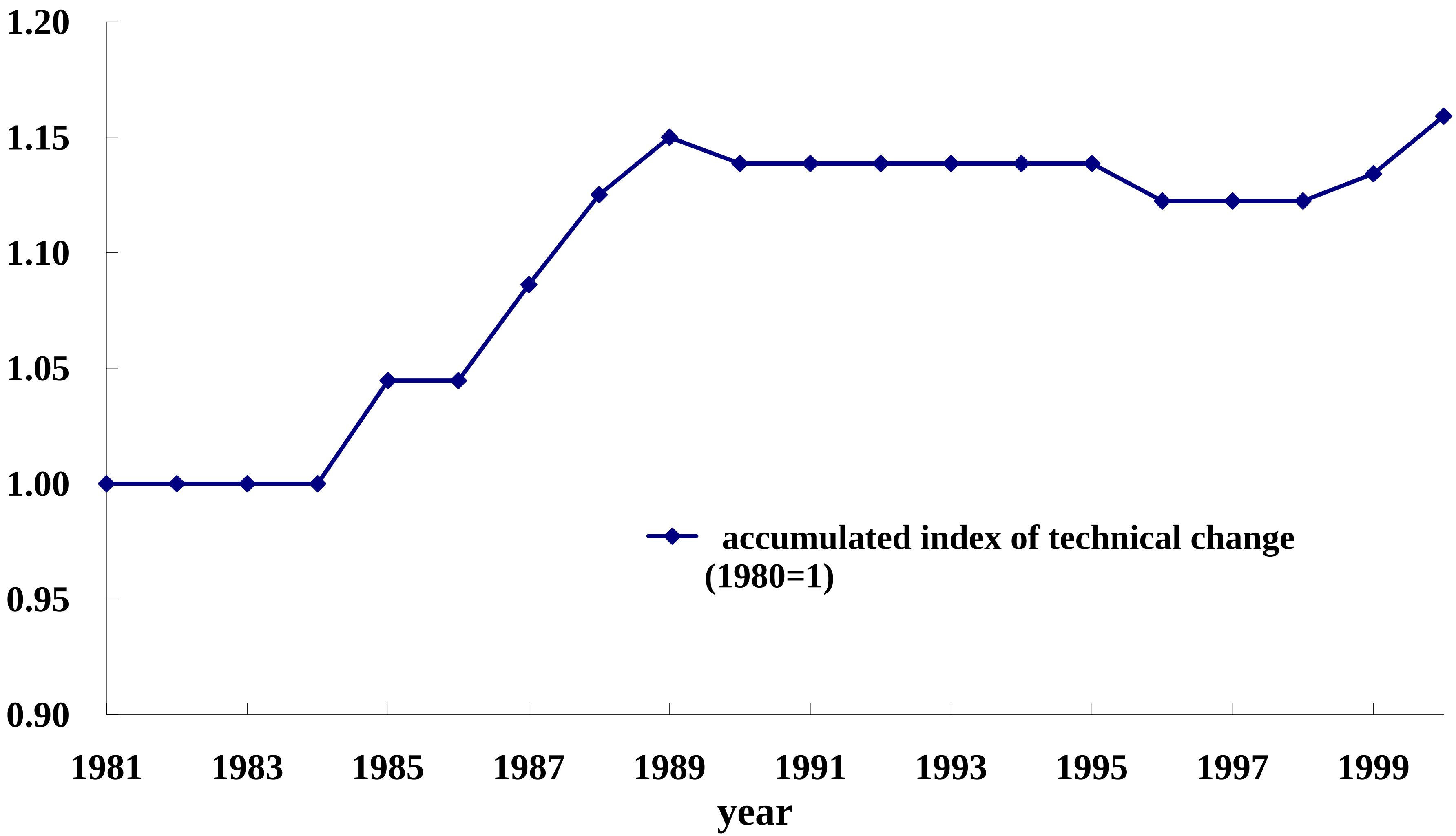

Fig. 3 Accumulated technical change

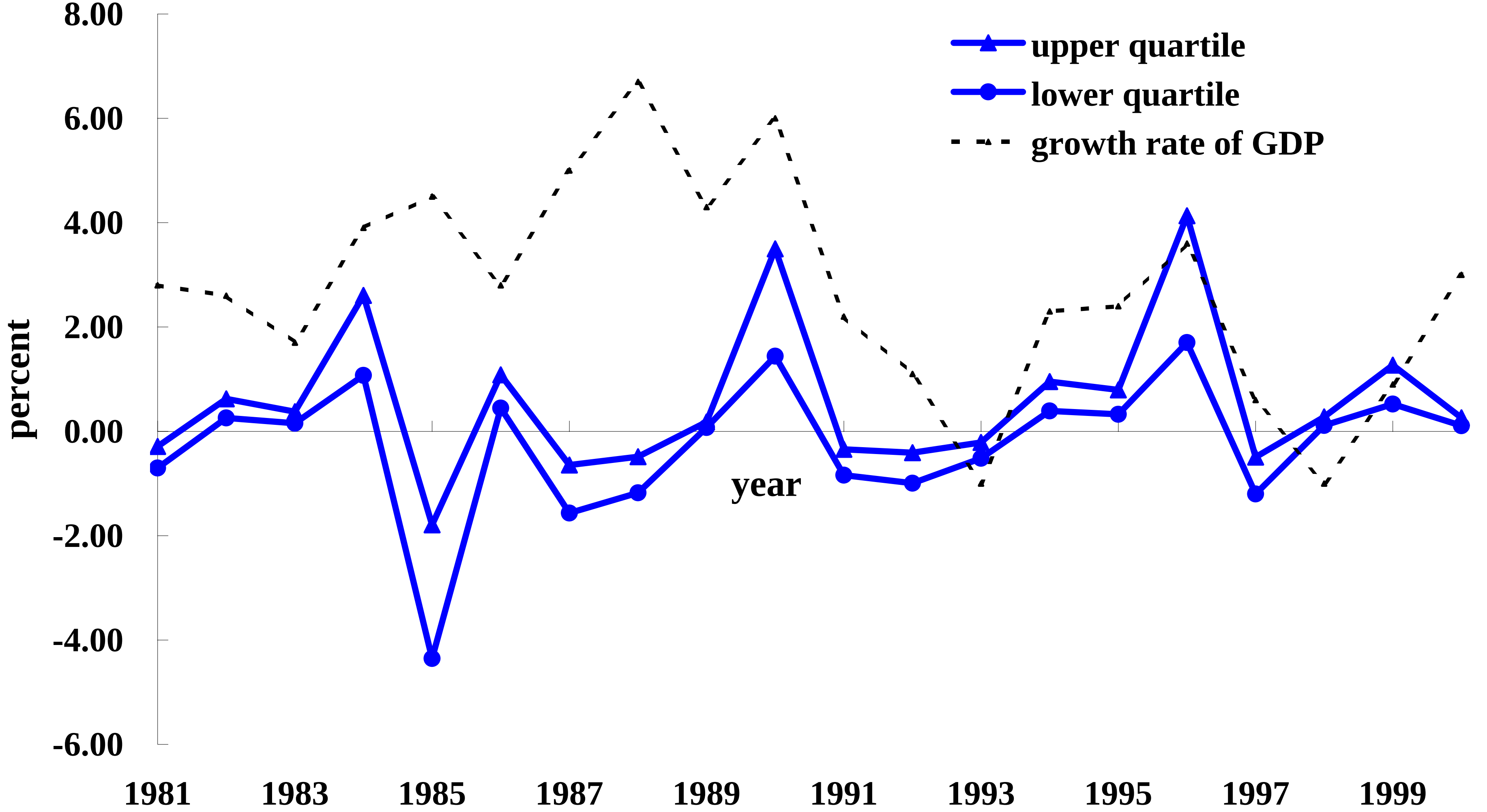

Fig. 4 The effects of efficiency change on productivity

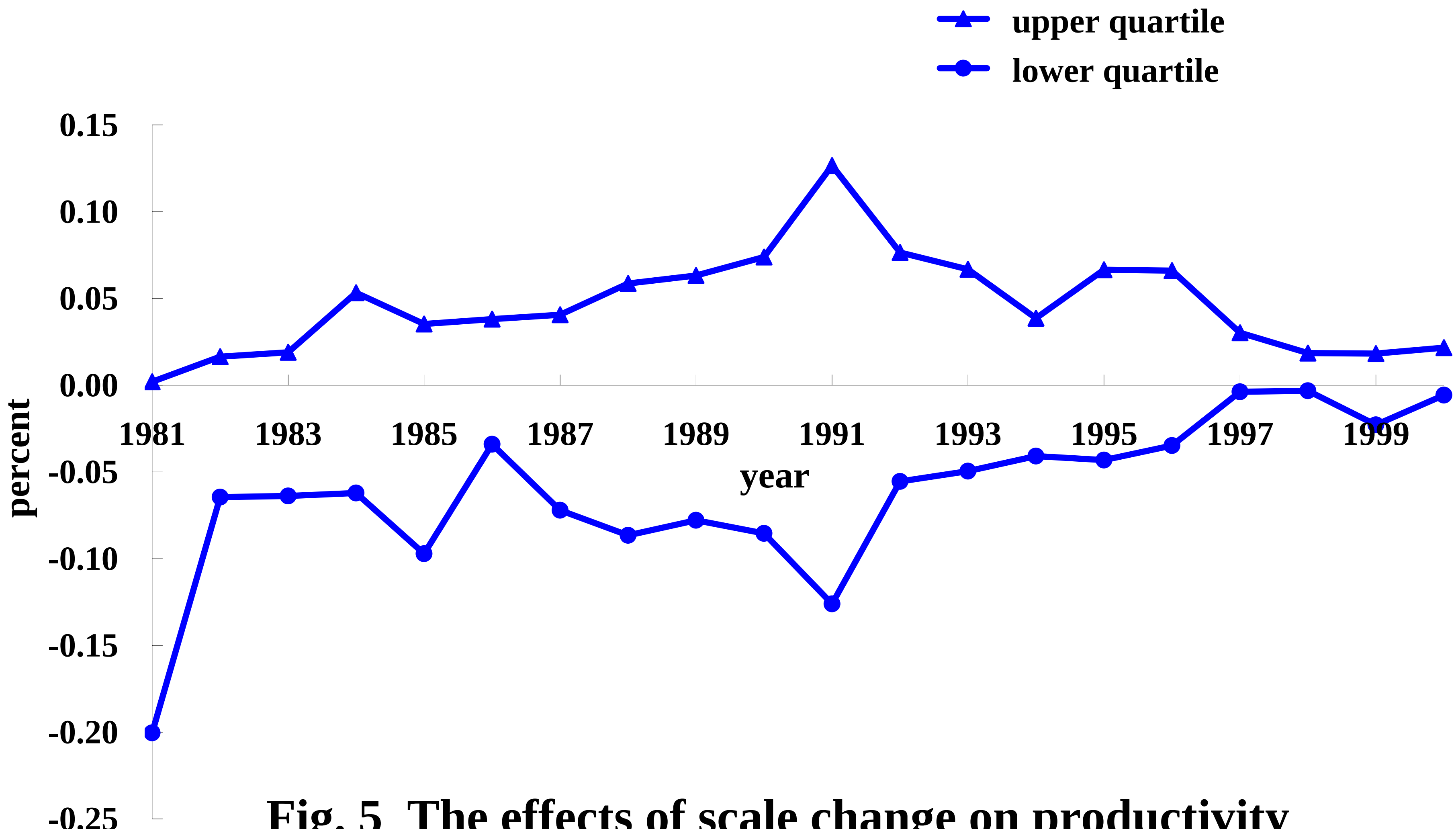

Fig. 5 The effects of scale change on productivity

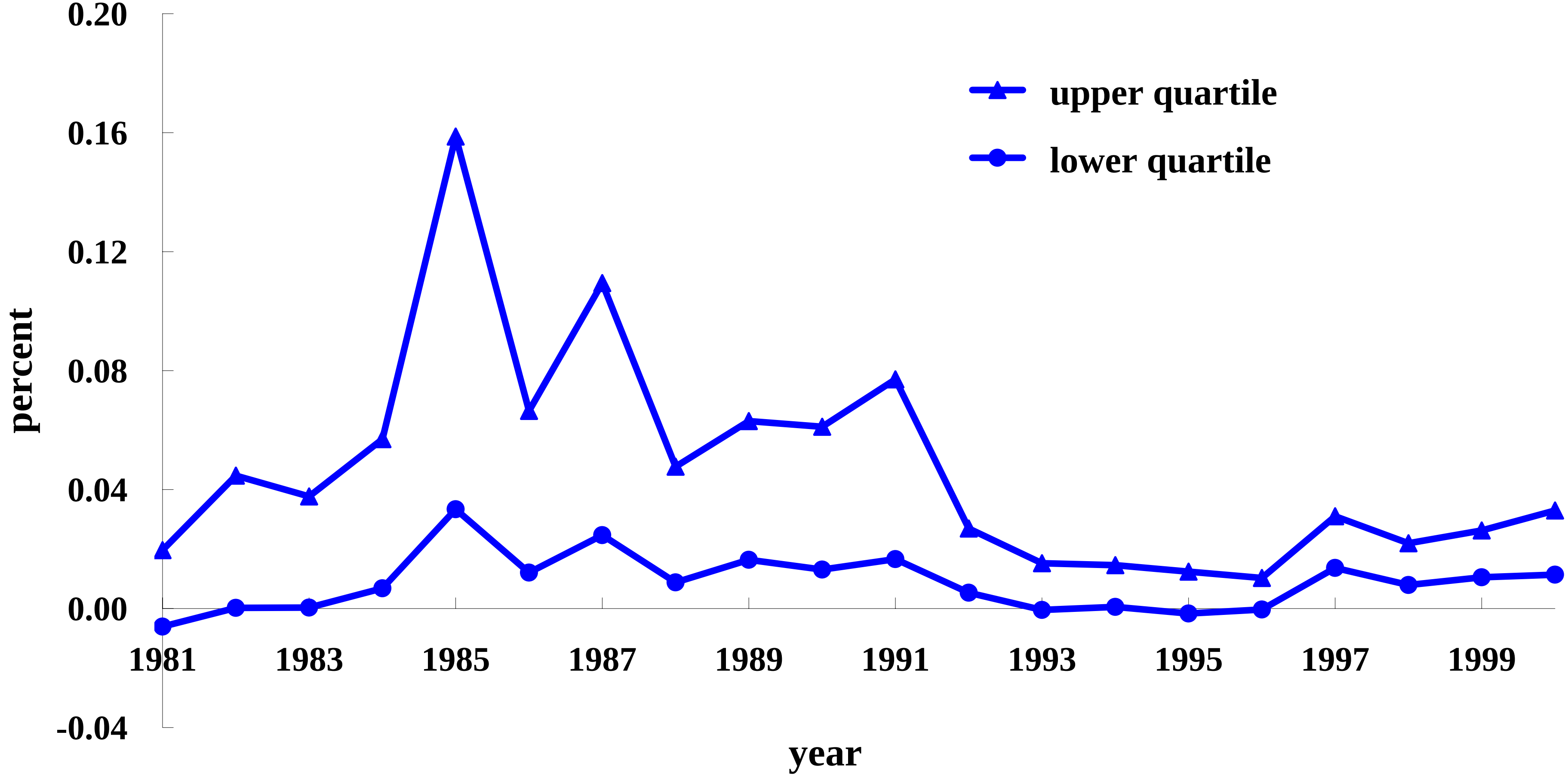

Fig. 6 The input and output mix effects on productivity