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Technical Inefficiency and Firm Behavior: A Panel Study of Small and Medium Japanese Manufacturing Firms (Revised)

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The Research Institute of Economy, Trade and Industry https://www.rieti.go.jp/en/

Technical Inefficiency and Firm Behavior: A Panel Study of Small and Medium Japanese Manufacturing Firms*

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Abstract

This study examines the technical inefficiency of small and medium Japanese manufacturing firms by using panel data from the *Basic Survey on Small and Medium Enterprises* (2009-2018). We estimate the stochastic frontier production function with four production factors (regular workers, nonregular workers, capital stock and materials) and calculate the technical inefficiency of individual firms by applying a true random effects model that can distinguish technical inefficiency from firm heterogeneity.

We find that inefficient firms are smaller, rely more on nonregular workers, exhibit poorer firm performance, have a higher debt-asset ratio, pay a lower interest rate and are inactive in capital investment and R&D investment. We also find that inactive capital investment and a high debt-asset ratio are mainly responsible for causing technical inefficiency.

Keywords: technical inefficiency, stochastic frontier model, true random effects model,

investment, debt-asset ratio, non-regular workers

JEL Classification Number: D22, E22, E23, J24

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^{*} This study is conducted as a part of the Project "Study on Corporate Finance and Firm Dynamics" undertaken at Research Institute of Economy, Trade and Industry (RIETI). This study utilizes the micro data of "Basic Survey of Small and Medium Enterprises" which is conducted by Small and Medium Enterprise Agency. The author is grateful to Masazumi Hattori, Kaoru Hosono, Masayuki Morikawa, Hiroshi Ohashi, Ken-ichi Ueda, Iichiro Uesugi, Makoto Yano, two anonymous referees and Discussion seminar participants at RIETI for extremely helpful comments and suggestions. This research is financially supported by KAKENHI Grant-in-Aid for Scientific Research (C)#19K01596.

1. Introduction

Technical inefficiency in production is a major concern for firm managers and policy-makers. This is because improving the technical inefficiency of the firm might achieve better firm performance and gain competitiveness. Then, it is important to obtain an accurate estimate of technical inefficiency. In the past a number of studies attempted to estimate technical inefficiency, but the specified models share two common shortcomings. One is the time-invariant assumption of technical inefficiency. The models of Lee and Schmidt (1993) and Kumbhakar (1990) relax the assumption of time-invariant inefficiency, but remain a rigid structure.¹ The other shortcoming is to force cross firm heterogeneity into the same term that is used to capture technical inefficiency. Thus, measures of inefficiency in these models might be picking up firm heterogeneity in addition to or even instead of technical inefficiency. The confounding of the two effects has the potential seriously to distort the inefficiency measures.

The true random effects model overcomes these two shortcomings. The true random effects model, developed by Greene (2005a,b), is a special case of the random parameters model that preserves the central feature of the stochastic frontier model and accommodates time-variant heterogeneity. The purpose of this study is to obtain an accurate estimate of technical inefficiency of the Japanese manufacturing SMEs based on the true random effects model. Our study is the first to apply the true random effects model to Japanese manufacturing SMEs. It is frequently argued that SMEs are more inefficient than large firms in Japan, but there are no rigorous empirical studies that have examined the technical inefficiency of SMEs.² In this study we identify inefficient firms and compare the characteristics of inefficient firms and efficient firms by making use of panel data from the Basic Survey on Small and Medium Enterprises (BSSME) by the Small and Medium Enterprise Agency

¹ See Greene (2005b) for more detailed discussions.

² There are quite a few studies that examined the technical efficiency of Japanese banking firms. For example, see Fukuyama (1993), McKillop et al. (1996), Altunbas et al. (2000), Drake and Hall (2003), Assaf et al. (2011), and Fukuyama and Weber (2015), among others. Altunbas et al. (2000) use the SFM, while Assaf et al. (2015) calculate efficiency measures, using the Bayesian distance frontier approach. The other studies are based on data envelopment analysis (DEA). Ogawa (2020) examines the technical efficiency of Japanese rice farmers, using the SFM.

from 2009 to 2018, using the stochastic frontier model (SFM).³

We find that technical inefficiency was overestimated in the conventional stochastic frontier model which forces firm heterogeneity into the same term as technical inefficiency. Our study suggests that the conventional inefficiency term might include cross-firm heterogeneity in addition to technical inefficiency.

In addition to the main findings above, given the accurate estimates of technical inefficiency, we pin down the source of technical inefficiency by quantitatively comparing the effects of four candidates causing inefficiency, firm size, investment activities, firm's financial conditions and firm's labor conditions, on technical inefficiency. We find that inefficient firms are inactive in capital investment and R&D investment and inactive capital investment and a high debt-asset ratio are mainly responsible for creating technical inefficiency. Moreover, inefficient firm pays a lower borrowing interest rate, which helps inefficient firm survive by receiving evergreen loans from financial institutions. Our evidence implies that eliminating excessive debt helps inefficient firms correct the inefficient bank-firm relationship, start capital investment and escape the inefficiency trap.

This study is organized as follows. The next section reviews the past literature on technical inefficiency based on the SFM. Section 3 describes the dataset used for the analysis. In Section 4, a model for estimating technical inefficiency is formulated, and the estimated results thereof are indicated. In Section 5, the characteristics of efficient and inefficient firms, based on efficiency indices, are compared. In Section 6, we investigate the determinants of technical inefficiency and then discuss the measures to improve efficiency. Section 7 concludes this study.

2. Literature Review on Source of Technical Inefficiency and Econometric Issues

In this section we review the past studies that estimated the degree of technical inefficiency and examined the sources of technical inefficiency, using micro data of firms, from three viewpoints: targeted country, econometric methodology and determinants of technical inefficiency. Table 1 summarizes the past sixteen studies that adopted the stochastic frontier analysis to estimate the technical inefficiency of manufacturing firms and examine the sources of technical inefficiency in terms of targeted countries, sample period including data type, estimation method and the sources of technical inefficiency.

³ See Greene (1997) and Kumbhakar and Lovell (2000) for a comprehensive survey of the stochastic frontier model of technical and cost efficiency.

First, this is the first study to examine the technical inefficiency of Japanese manufacturing SMEs, using the firm-level panel data to the best of the author's knowledge. Almost all the studies investigate technical inefficiency and its causes of developing countries, such as India, Indonesia, Korea, Laos, Taiwan, Thailand and Vietnam. It is because those studies are concerned about lower productivity of manufacturing firms in developing countries possibly due to technical inefficiency.⁴ Our focus is to obtain precise estimates of technical inefficiency that is free from firm heterogeneity and examine the source of technical inefficiency.

Secondly, econometric methodology of the past studies is categorized into two groups. One group adopts the two-step procedure to identify the sources of technical inefficiency. In the first step the maximum likelihood estimates of technical inefficiency are obtained and in the second step the estimates of the technical inefficiency are regressed on possible candidates causing technical inefficiency. The other group follows Battese and Coelli (1995) where the non-negative technical inefficiency effects are assumed to be a function of firm-specific variables. We follow the two-step procedure to identify the sources of technical inefficiency, but in the first step we estimate the true random effect model that assumes time-varying technical inefficiency and distinguish firm's heterogeneity from technical inefficiency.

Thirdly, as was discussed in the introduction, we examine the source of technical inefficiency quantitatively. The determinants of technical inefficiency are categorized into four groups: firm size, firm's financial conditions, firm's labor conditions and investment activities. Therefore it is useful to discuss the effect of the four determinants on technical inefficiency in the past studies. Firm size is identified as a vehicle to increase the technical efficiency for Korea manufacturing firms (Kim (2003)) and Thai manufacturing SMEs (Amornkitvikai et al. (2013)). However, the effect of firm size on technical efficiency is mixed in Indonesian manufacturing sector depending on the industry (Margono and Sharma (2004)) and in Vietnam manufacturing SMEs (Minh et al. (2007) and Le and Harvie (2010)).

The effect of firm's financial conditions on technical inefficiency can be evaluated by external factors and internal factors. Typical measure of external factor is government financial assistance to firms, which has been a main concern for the studies focusing on developing countries. Amornkitvikai

⁴ Two papers focus on analyses of technical inefficiency for developed countries: Bottasso and Sembenelli (2004) for Italy and Dilling-Hansen et al. (2003) for Denmark.

et al. (2013) find that the firms receiving government assistance have higher technical efficiency than their counterparts that receive no government assistance for Thai manufacturing SMEs. In contrast Le and Harvie (2010) find a significantly negative effect of government credit assistance to firms on the technical efficiency of Vietnamese manufacturing SMEs. Sayavong (2021) finds that credit access is crucial in reducing technical inefficiency by mitigating financial constraint. We use the debt-asset ratio to measure the firm's internal financial condition since the debt-asset ratio of inefficient firms is significantly higher than that of efficient firms, as will be seen in the subsequent section.

As for the labor conditions, many studies point out the importance of labor quality in increasing technical efficiency. See Dinh et al. (2020), Charoenrat and Harvie (2013) and Sayavong (2021) for the evidence of Vietnamese small-scale enterprises, Thai manufacturing SMEs and Laos manufacturing industries, respectively. We also examine the effect of labor quality on technical inefficiency by using the ratio of regular workers in the firm's labor force as it has been argued that there is significant quality difference between regular workers and non-regular workers.

Investment activities have played a vital role to enhance the technical efficiency in the past studies. Aw and Batra (1998) shows that technical efficiency is positively correlated with R&D investments in the Taiwanese manufacturing firms. Dilling-Hansen et al. (2003) find that R&D-active Danish firms are significantly more efficient than other firms. Dinh et al. (2020) also states that Vietnamese smallscale enterprises can increase the technical efficiency by improving their technology. We measure investment activities for firms by two measures: size of capital investment and R&D investment.

3. Dataset and Characteristics

The data employed in the analysis are the panel data of the Basic Survey on Small and Medium Enterprises (*Cyusho Kigyo Jittai Kihon Chosa*) by the Small and Medium Enterprise Agency. The sample period covers 10 years, from 2009 to 2018. Our sample firms are manufacturing firms whose equity capital is less than 300 million yen or whose number of employees is less than 300 persons. The sample firms are divided into three subindustries: machinery industry, light industry and heavy industry. The machinery industry includes general-purpose, production and business-oriented machinery, electronic components and devices, electrical machinery, equipment and supplies, information and communication electronics equipment and transport equipment. The total number of observations of the machinery industry is 8,542. Light industry includes food products and beverages, textile products, timber, furniture, printing, rubber products, leather and other manufacturing industries. The total number of light industry is 20,585. Heavy industry includes pulp, paper and

paper products, chemicals, petroleum and coal products, nonmetallic mineral products, basic metal and fabricated metal products. The total number of observations of heavy industry is 9,332. The panel data are sparse in the sense that 89.2% of firms in the machinery industry, 87.5% of firms in light industry and 89.1% of firms in heavy industry stay in the panel data for only one year. Our dataset is an unbalanced panel data.

Now, an explanation is in order on the procedure of data construction. Most of the basic data are obtained from the balance sheets and profit-and-loss statements of individual firms. The real output (Y) is calculated by dividing sales by the output deflator of the System of National Accounts (SNA) corresponding to each industry.⁵ The labor input (N) has two components. One is the number of regular employees (NR), and the other is the number of nonregular employees (NNR), which includes part-time workers, temporary workers and seconded workers. The capital stock (K) is calculated by deflating the nominal tangible fixed assets of three types (buildings and structures, instruments, tools, vessels and vehicles, and machine equipment) by the corresponding price indices and summing them. We use the deflator of gross fixed capital formation (buildings and structures and machinery and equipment) in the SNA. The materials (M) are calculated by dividing the expenditure on nine types of items (cost of goods purchased, material costs, outsourcing costs, other costs of goods sold, cost of utilities, freight and packing costs, sales charges, advertisement expenses, other costs of sales expenses and administrative expenses) by the intermediate input deflator in the SNA and summing them.

Table 2 shows the descriptive statistics of the real output, four production factor inputs and other important firm attributes.⁶ The firm attributes include labor productivity, defined as real output divided by total employees, the ratio of regular employees to total employees, real total assets, defined as total assets divided by the output deflator, the debt-asset ratio, defined as the ratio of total debt to total assets, the operating profit ratio and the borrowing interest rate, defined as the interest and discount expenses divided by the sum of short-term borrowing, long-term borrowing and corporate bond debt. The means of real output, capital stock, material input and total assets are all above the medians and exhibit a right-skewed distribution. The mean ratio of regular employees is slightly below 50%, while the median ratio of regular employees hovers at approximately 50%. The mean debt-asset ratio is above 0.8 in all industries. The mean debt-asset ratio is notably high in light industry, above

⁵ The base year of the deflator is 2011.

⁶ We discard the observations that are less than the 2.5 percentile or more than the 97.5 percentile of the variables in each industry.

4. Identification and Estimation of Technical Inefficiency

We estimate the stochastic frontier production function, which comprises four production factors (regular workers, nonregular workers, capital stock and materials), and calculate technical inefficiency indices of production for individual firms. The index of inefficiency is calculated under two production functions, the Cobb-Douglas production function and translog production function, and the two specifications about technical inefficiency. In both specifications, we assume that the inefficiency term is a random variable. In one specification, we assume that technical inefficiency is a time-invariant random variable that is uncorrelated with the regressors. Then, we estimate the inefficiency parameters by generalized least squares (GLS).⁷

A drawback of this specification is that firm heterogeneity cannot be distinguished from technical inefficiency. That is, measured inefficiency might be picking up firm heterogeneity in addition to or even instead of technical inefficiency. The true random effects model, developed by Greene (2005a,b), overcomes this shortcoming. The true random model is a variant of the random parameters model, retaining the basic nature of the stochastic frontier model. The formulations of the true random model reinterpret the time invariant term as firm-specific heterogeneity due to omitted time invariant factors such as firms' organizational characteristics. Another virtue of the true random model is to relax the time invariancy of technical inefficiency and assume that technical inefficiency is a time-varying random variable.

In the conventional random effects model, the stochastic frontier production function is specified as

$$\ln Y_{it} = f(lnNR_{it}, lnNR_{it}, lnK_{it}, lnM_{it}) - u_i + v_{it}$$
(1)

where Y_{it} : output in year t

- NR_{it} : regular employees in year t
- NNR_{it} : non-regular employees in year t
- K_{it} : capital stock in year t
- M_{it} : material input in year t
- u_i : time invariant random variable representing inefficiency, $u_i \ge 0$
- v_{it} : disturbance term

0.95.

⁷ See Schmidt and Sickles (1984) for the details of estimation.

i is an index of individual firm

In the true random effects model, the stochastic frontier production function is specified as

$$\ln Y_{it} = f(lnNR_{it}, lnNR_{it}, lnK_{it}, lnM_{it}) + w_i - u_{it} + v_{it}$$
(2)

where Y_{it} : output in year t

 NR_{it} : regular employees in year t

 NNR_{it} : non-regular employees in year t

- K_{it} : capital stock in year t
- M_{it} : material input in year t
- w_i : time invariant random variable representing firm heterogeneity
- u_{it} : time-varying random variable representing inefficiency, $u_{it} \ge 0$

 v_{it} : disturbance term

For the specification of the production function, the Cobb-Douglas function is written as

 $f(lnNR_{it}, lnNR_{it}, lnK_{it}, lnM_{it}) = \alpha_R lnNR_{it} + \alpha_N lnNNR_{it} + \alpha_K lnK_{it} + \alpha_M lnM_{it}$ (3) When the production function is the translog type, it is written as

$$f(lnNR_{it}, lnNNR_{it}, lnK_{it}, lnM_{it}) = \alpha_R lnNR_{it} + \alpha_N lnNNR_{it} + \alpha_K lnK_{it} + \alpha_M lnM_{it} + \alpha_{RR}(lnNR_{it})^2 + \alpha_{RN}(lnNR_{it})(lnNNR_{it}) + \alpha_{RK}(lnNR_{it})(lnK_{it}) + \alpha_{RM}(lnNR_{it})(lnM_{it}) + \alpha_{NN}(lnNNR_{it})^2 + \alpha_{NK}(lnNNR_{it})(lnK_{it}) + \alpha_{NM}(lnNNR_{it})(lnM_{it}) + \alpha_{KK}(lnK_{it})^2 + \alpha_{KM}(lnK_{it})(lnM_{it}) + \alpha_{MM}(lnM_{it})^2$$
(4)

We assume that u_{it} is distributed as exponential in the true random effects model. It is assumed that the disturbance term (v_{it}) is i.i.d. normal as $N(0, \sigma_v^2)$. The parameter estimates of the true random effects model are obtained by simulated maximum likelihood technique. The year dummies and subindustry dummies also are added to the explanatory variables. Table 3 shows the results of the stochastic frontier production function. First, let us compare the estimation results of the Cobb-Douglas production function with those of the translog production function. Significantly positive values are obtained for all the coefficient estimates of the Cobb-Douglas production function, irrespective of industry. On the other hand, the estimation results of the translog production function are not entirely satisfactory, since many of the coefficient estimates are not significant due to multicollinearity. It is straightforward to test the validity of the Cobb-Douglas production function by the Wald test. The null hypothesis is that all the coefficients of the quadratic terms are zero. Table 4 shows the test statistics. It is evident that the null hypothesis is decisively rejected in all industries. Therefore, the production behavior of Japanese manufacturing SMEs is well characterized by the translog production function. Table 5 shows the mean elasticity of regular workers, nonregular workers, capital and material input calculated from the translog production function. Surprisingly, the output elasticity with respect to factor inputs calculated from the parameter estimates of the translog production function are quite close to those obtained under the Cobb-Douglas production function, although the Cobb-Douglas production function is rejected as the specification of production technology. It also should be noted that there are close similarities of the output elasticity with respect to factor inputs across industries. The material input elasticity takes the largest value, ranging from 0.65 (machinery industry) to 0.71 (light industry). Regular worker elasticity takes the second-largest value and ranges from 0.20 (light industry) to 0.10 (light industry). Capital elasticity takes the smallest value and is in the narrow range of 0.01 to 0.02.

Now, we compare the technical inefficiency estimates of the time-invariant random effects model with those of the true random effects model. We calculate the technical inefficiency measure of Jondrow et al. (1982) for individual firms based on the coefficient estimates of the production function as follows.

For the time-invariant random effects model,

$$E[u_i | \varepsilon_{it}]$$
(5)
where $\varepsilon_{it} \equiv v_{it} - u_i$
m effects model,

For the true random effects model,

$$E[u_{it} | \varepsilon_{it}]$$
(6)
where $\varepsilon_{it} \equiv v_{it} - u_{it}$

Table 6 shows the mean of the technical inefficiency estimates and degree of technical efficiency under two different random effects models.⁸ The estimates of technical inefficiency of the time-invariant random effects model are much larger than those of the true random effects model, irrespective of industry. When the production technology is specified as the Cobb-Douglas type, the

⁸ Degree of technical efficiency is calculated as $exp(-\epsilon)$, where ϵ is the technical inefficiency measure.

technical efficiency varies from 23.05% to 33.84% in the time-variant random effects model, while the technical efficiency varies from 90.58% to 94.08% in the true random effects model. When the production technology is specified as the translog production function, the technical efficiency varies from 37.57% to 46.71% in the time-variant random effects model, while the technical efficiency varies from 88.34% to 90.51% in the true random effects model. It is clear that measured inefficiency might be picking up firm heterogeneity in addition to technical inefficiency in the time-invariant random effects model. Our estimation results suggest that measured inefficiency is overestimated in the timeinvariant random effects model.

Technical inefficiency under the misspecified production function

It might be argued that technical inefficiency arises from the existence of nonregular workers who might have lower productivity than regular workers. When regular workers and nonregular workers have different marginal effects on production, the use of total workers, rather than the separate use of regular workers and nonregular workers, as an explanatory variable of the production function might create misspecification bias in the parameter estimates and thus lead to fallacious statistical inferences of technical inefficiency. To gauge the effect of this misspecification on the estimates of technical inefficiencies, we estimate the production function with three input factors (total workers, capital stock and materials) and calculate technical inefficiency indices for individual firms. The estimates of technical inefficiency under the misspecified production function in the true random effects model are shown in Table 7. The estimates of technical inefficiency under the misspecified model are larger than those under the correctly specified model, irrespective of industry. Thus, the misspecification of production technology in which the output elasticity of nonregular workers is identical to that of regular workers might create upward biases of technical inefficiency.

Based on the above results, we conclude that technical inefficiency is precisely estimated by the translog production function in the true random effects model. Therefore, the subsequent analysis is based upon the estimates of the technical inefficiency obtained by the translog production function in the true random effects model.⁹

⁹ The analysis in the subsequent sections is almost entirely unaffected even if we use the inefficiency indices that are obtained under the assumption of the Cobb-Douglas production function in the true random effects model.

5. Comparison of Characteristics between Efficient Firms and Inefficient Firms

Based on the median of the inefficiency measures of the stochastic frontier model estimated in the preceding section, manufacturing firms are divided into an efficient firm group and an inefficient firm group, and the characteristics of their behaviors are examined. We compare the behavioral characteristics of the efficient and inefficient firms based on the following 16 items:

- 1) Real output
- 2) Number of workers
- 3) Capital stock
- 4) Material input
- 5) Total assets
- 6) Labor productivity
- 7) Ratio of regular workers
- 8) Operating profit rate
- 9) Debt-asset ratio
- 10) Borrowing interest rate
- 11) Proportion of firms that made capital investment
- 12) Investment rate
- 13) Marginal q
- 14) Proportion of firms that made R&D investment
- 15) R&D investment rate
- 16) Proportion of firms that have patents

Some explanation is in order on the above variables. Items 1 to 5 compare the firms' production activities as well as the firm size. Items 6 to 10 provide information on the firms' performance and financial conditions. Items 11 to 16 compare the firms' investment behaviors. The driving force of investment activities is marginal q (Mq), the present discounted value of the maximized profit rate divided by the investment goods price. In other words, the marginal q is defined as:

$$Mq_{t} = \frac{1}{p_{t}^{I}} E_{t} \Big[\sum_{j=0}^{\infty} \beta_{t+j} (1-\delta)^{j} \pi_{t+j} \Big]$$
(7)
where p_{t}^{I} : price of investment goods in period t
 $\beta_{t+j} = \prod_{i=1}^{j} (1+r_{t+i})^{-1}, \quad (j = 1, 2, \cdots), \quad \beta_{t} \equiv 1$

 r_{t+i} : borrowing interest rate in period t+i δ : depreciation rate π_{t+j} : profit rate, defined as the maximized profit divided by the capital stock at the end of t+j-1 period $E_t[\cdot]$: expectation operator conditional on the information set available

for the firm in period t

In constructing the marginal q series, special attention should be given to the stochastic property of the two underlying factors: borrowing interest rate (r_t) and profit rate (π_t) . The profit rate is defined as the ratio of operating profit to the beginning-of-period capital stock. It is assumed that the borrowing interest rate and the profit rate follow random walks independently. In other words,

$$r_{t+1} = r_t + u_{t+1}$$
(8)

$$\pi_{t+1} = \pi_t + v_{t+1}$$
(9)
where u_{t+1}, v_{t+1} : stationary white noise

Then, it can be shown that the marginal q is simply written as

$$Mq_t = \frac{\pi_t}{p_t^l} \frac{1}{r_t + \delta} \tag{10}$$

We use the median of the depreciation rate for each industry. That is, the depreciation rates are 18.22%, 16.53% and 18.29% for machinery industry, light industry and heavy industry, respectively.

Table 8 shows the mean difference as well as its standard error of the 16 items described above between the efficient and inefficient firm groups. We observe the following differences in firm characteristics between efficient firms and inefficient firms, irrespective of industry.

- The efficient firm is significantly larger than the inefficient firm in terms of real output, number of workers, capital stock, material input and total assets.¹⁰
- 2) For the composition of workers, the proportion of regular workers is significantly higher for the

¹⁰ There is no statistical difference in capital stock between the efficient firms and the inefficient firms of the machinery industry.

efficient firm.

- 3) The efficient firm exhibits better performance in terms of labor productivity and operation profit rate.
- 4) Regarding financial conditions, the efficient firm has a lower debt-asset ratio but pays a higher borrowing interest rate.¹¹ Lower borrowing costs for inefficient firms suggest that banks make evergreen loans to zombie SMEs for the procrastination of nonperforming loans. Our evidence is consistent with the findings of Imai (2016).
- 5) The investment behavior of the efficient firm is more active than that of the inefficient firm. The proportion of firms that make capital investments as well as R&D investments is significantly higher for the efficient firm group. The capital investment rate is higher for the efficient firm group, which might reflect higher profitability of investment, measured by marginal q. In fact, the marginal q is below unity for the inefficient firm group, irrespective of industry. The proportion of firms that have patents also is higher for the efficient firm groups of the machinery and light industries.

6. Technical Inefficiency and Investment Behavior

We compared the characteristics of inefficient firms with those of efficient firms in the previous section. Given the differences in firm characteristics between efficient firms and inefficient firms, we make further investigation into the source of technical inefficiency. We categorize the determinants of technical inefficiency into four groups: firm size, firm's financial conditions, firm's labor conditions and investment activities. Then, we make a quantitative comparison of the effects of each variable on improving technical inefficiency.

Determinants of technical inefficiency

Firm size is identified as a vehicle to increase the technical efficiency through easy access to technology, market and external finance. Moreover, large firms might attain economies of scale. We measure firm size by the logarithm of real total assets (*LSIZE*).

The effect of firm's financial conditions on technical inefficiency can be evaluated by external factors and internal factors. Typical measure of external factor is government financial assistance to firms, which might play an important role in affecting the firms in developing countries. We pay

¹¹ There is no statistical difference in the borrowing interest rate between the efficient firms and the inefficient firms of heavy industry.

special attention to the internal factor of the firm. We measure the firm's internal financial condition by the debt-asset ratio (*DEBT*) for the following reason. The firm with excessive debt is mainly concerned with solving debt problem rather than positive activities of increasing productivity. Moreover, as was seen in the previous section, the situation gets worsened by evergreen lending practice, which might deprive firms of incentive to decrease excessive debt and thus aggravate technical inefficiency

Firm's labor conditions affect the technical efficiency mainly through labor quality of the firm. The firm with low quality of labor will suffer from technical inefficiency. Therefore, improving labor skill will contribute to increasing technical efficiency. We measure the firm's labor condition by the ratio of regular workers in the firm's labor force (*REGEMP*) since regular workers can acquire labor skills by receiving more training.

Investment activities play a vital role to enhance the technical efficiency. There are two important investment activities for firms: capital investment and R&D investment. The state-of-the-art technology is often embodied in new equipment and production plant, thus improving technical efficiency. R&D investment also improves technical efficiency by inventing new products and/or developing new cost-saving method of production. We specify a firm's investment activities by binary variables and quantitative variables. In the binary specification, investment activities are represented by two dummy variables. One is whether a firm made current capital investment or not, denoted by *INVDUM*. The other is whether a firm made current R&D investment, denoted by *RDINVDUM*. In the quantitative specification, we use the investment rate (*IK*), the ratio of current investment to capital stock, for capital investment, and the ratio of R&D investment to sales (*RDINVSALES*) for R&D investment.

We estimate the technical inefficiency function by using the four types of explanatory variables described above. The dependent variable is the technical inefficiency measure (*INEFFICIENCY*) obtained under the translog production function estimated by the true random model. Specifically, the following technical inefficiency equation is estimated by the random effects panel model.¹²

 $(INEFFICIENCY)_{it} = \alpha_0 + \alpha_1 (LSIZE)_{it} + \alpha_2 (INVDUM)_{it} + \alpha_3 (RDINVDUM)_{it} + \alpha_4 (DEBT)_{it} + \alpha_5 (REGEMP)_{it} + \varepsilon_{it}$

¹² The year dummies and subindustry dummies also are added as explanatory variables. The coefficient estimates of the year dummies and subindustry dummies are omitted.

(11)

$$(INEFFICIENCY)_{it} = \alpha_0 + \alpha_1(LSIZE)_{it} + \alpha_2(IK)_{it} + \alpha_3(RDINVSALES)_{it} + \alpha_4(DEBT)_{it} + \alpha_5(REGEMP)_{it} + \varepsilon_{it}$$

(12)

where INEFFICIENCY: technical inefficiency measure

LSIZE: logarithm of real total asset

- *INVDUM*: dummy variable that takes unity when a firm made current capital investment and zero otherwise
- *RDINVDUM*: dummy variable that takes unity when a firm made current R&D investment and zero otherwise

IK: ratio of capital investment to capital stock

RDINVSALES: ratio of R&D investment to sales

DEBT: debt-asset ratio

REGEMP: proportion of regular workers out of total workers

 ε : disturbance term

The estimation results are shown in Table 9. Firm size has a significantly negative effect on technical inefficiency. That is, a larger firm is more technically efficient. The debt-asset ratio has a significantly positive effect on technical inefficiency.¹³ This implies that firms with excessive debt suffer from technical inefficiency. As seen in the previous section, inefficient firms tend to have a higher debt-asset ratio but pay a lower borrowing interest rate. This evidence hints that an inefficient firm with a high debt-asset ratio survives partly by evergreen lending from financial institutions. Hiring more regular workers significantly mitigates technical inefficiency.

¹³ It might be argued that improvement in technical inefficiency enables the firms to earn more profit, increase internal funds and thus lower the debt-asset ratio. It implies that improvement in technical inefficiency causes the debt-asset ratio, not the other way around. The causality between a change in technical inefficiency and an improvement of firms' financial condition might be tested rigorously by panel VAR analysis, but the sparse nature of our panel data, in which only a few firms provide more than one-year observations, prevents us from estimating a panel VAR model.

For investment activities, activating capital investment significantly enhances technical efficiency, but increasing R&D investment does not improve technical inefficiency. Capital investment accompanies the acquisition of new plants or machines that embody advanced technology, which immediately contributes to enhancing technical efficiency, but there is always some uncertainty regarding whether R&D investment will show successful results and increase efficiency.

It is an interesting exercise to quantitatively compare the effects of each explanatory variable of the inefficiency equation on improving technical inefficiency. Specifically, we calculate the extent to which technical inefficiency decreases when the logarithm of firm size, debt-asset ratio, proportion of regular workers out of total workers or investment rate changes from the mean value of inefficient firms to that of efficient firms. For the effect of the start of capital investment on decreasing technical inefficiency, we simply calculate how much technical inefficiency decreases when a firm starts capital investment.¹⁴ ¹⁵ Table 10 shows the effects of each variable on improving technical inefficiency in percentage terms.

The start of capital investment has the largest effect on reducing technical inefficiency. Technical inefficiency is reduced by 7.5% in the machinery industry, 7.55% in heavy industry and 9.83% in light industry. The large effect of starting capital investment is contrasted with the smaller effect of marginally increasing capital investment for firms that already made capital investments. The effect of increasing capital investment for firms that already made capital investments on reducing technical inefficiency is less than 1%, irrespective of industry. Our analysis shows that the start of capital investment (extensive margin) is more effective in improving technical efficiency than a marginal increase in existing investment projects (intensive margin).

A decrease in the debt-asset ratio, which exhibits the second-largest effect on improving technical efficiency, decreases technical inefficiency by 4.86% in the machinery industry and 5.81% in heavy industry. Other measures, such as the expansion of firm size and hiring more regular workers, have limited impacts on improving technical efficiency, since the effects on reducing technical inefficiency are less than 1%.

¹⁴ We do not calculate the effects of R&D investment on technical efficiency, since most of the coefficient estimates are statistically insignificant or do not take the sign expected by the theory.
¹⁵ See Table 8 for the mean values of firm size, debt-asset ratio, proportion of regular workers out

of total workers and the investment rates for the efficient firms and the inefficient firms.

What motivates firms to start capital investment?

Our evidence above shows that the start of capital investment is effective in improving technical efficiency. Now, we discuss the measures to obtain a firm that started on capital investment by estimating a binary investment model. Note that the proportion of firms that made capital investments is 29.9% in light industry, 35.7% in the machinery industry and 38.7% in heavy industry, as shown in Table 2. Therefore, we use the random effects probit model to estimate the parameter estimates of the investment function. The specification of the investment function is a standard one that includes the profitability of investment or marginal q (Mq) and debt-asset ratio (DEBT), measures of the financial conditions of the firm. The dependent variable (INVDUM) is a dummy variable that takes a value of one when a firm made current capital investment and zero otherwise.

Table 11 shows the estimation results of the investment function. In all industries, marginal q has a significantly positive effect on the probability that capital investment is positive. On the other hand, debt-asset ratio has a significantly negative effect on the probability that capital investment is positive, irrespective of industry. Now, we calculate the marginal effect of marginal q and the debt-asset ratio on the probability that capital investment is positive. When marginal q increases from the mean value of the inefficient firms to that of the efficient firms, the probability that capital investment is positive rises by only 1.95%, 1.74% and 1.60% for the machinery industry, light industry and heavy industry, respectively. However, when the debt-asset ratio decreases from the mean value of inefficient firms, the probability that capital investment is positive rises by 5.10%, 3.98% and 5.29% for the machinery industry, light industry and heavy industry, respectively. Combining the estimation results of the investment function with the evidence above, getting rid of excessive debt is quite effective in gaining technical efficiency by correcting the inefficient bank-firm relationship and starting capital investment.

7. Concluding Remarks

This study examined the technical inefficiency of Japanese small and medium manufacturing firms by using panel data from the *Basic Survey on Small and Medium Enterprises* collected by the Small and Medium Enterprise Agency from 2009 to 2018.

We estimated the stochastic frontier production function with four production factors (regular workers, nonregular workers, capital stock and materials) and calculated the technical inefficiency of individual firms by applying a true random effects model that can distinguish technical inefficiency from firm heterogeneity.

Our estimation results suggest that measured inefficiency is overestimated in the time-invariant random effects model, implying that measured inefficiency might be picking up firm heterogeneity in addition to technical inefficiency in the conventional time-invariant random effects model. Our study contributed to the literature of technical inefficiency by obtaining more precise estimates of technical inefficiency.

Moreover, we found that investment activities and lowering debt-asset ratio decreases technical inefficiency to a large extent. Some of the past studies found that R&D-active firms are more technically efficient.¹⁶ However, our study reveals that the start of capital investment is more effective than R&D investment in enhancing technical efficiency. The finding that getting rid of excessive debt leads to a rise in technical efficiency is also a new contribution to the literature. We pointed out that inefficient firms with a high debt-asset ratio might survive in the market by receiving evergreen lending at lower interest rate from financial institutions, which implies that bank lending does not necessarily improve technical inefficiency.

There are also limitations of our study. That is endogeneity problem of the SFM which is not dealt with in our study. Endogeneity might arise in the SFM for a number of reasons. In particular we pin down the factors creating technical inefficiency, which are inactive capital investment and a high debtasset ratio. If the SMEs know that these two factors are responsible for the technical inefficiency, then it might affect the SMEs input decision. There are two remedies to overcome this endogeneity. Straightforward way to avoid endogeneity is to devise appropriate econometric estimator.¹⁷ The other way, albeit more challenging, is to formulate the mechanism through which endogeneity is created. In our context inefficient firms have excessive debt and pay lower borrowing costs. Lower borrowing costs for inefficient firms suggest that banks make evergreen loans to zombie SMEs for the procrastination of nonperforming loans. Therefore, modelling the loan market for SMEs might be a promising avenue to solve endogeneity problem explicitly.

¹⁶ See Aw and Batra (1998) and Dilling-Hansen et al. (2003) for the positive effects of R&D investment on technical efficiency.

¹⁷ See Amsler et al. (2016) for a survey of existing econometric procedures to handle endogeneity in the SFM.

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Table 1 Micro-data studies on techincal inefficiency of manufacturinmg firms: literature survey

	country	sample period	estimation method	deterrminants of technical efficiency
Minh et al. (2007)	Vietnam	2000-2003 (panel)	ML estimation (normal distribution)	firm size
Tran et al. (2008)	Vietnam	1996 and 2001 (cross-section)	Battese and Coelli (1995)	use of family labor, location
Pham et al. (2010)	Vietnam	2003 (cross-section)	ML estimation (normal, exponential distribution) , two-step approach	export orientation, trade openness
Le and Harvie (2010)	Vietnam	2002, 2005, 2007 (cross-section)	Battese and Coelli (1995)	firm age, firm size, location, ownership, subcontracting, cooperation with a foreign partner, product innovation, competition and government assistance
Vu (2016)	Vietnam	2009-2013 (cross-section)	ML estimation (normal), two-step approach	net revenue per labor, firm age, export activities
Dinh et al. (2020)	Vietnam	2019 (cross-section)	ML estimation (normal, exponential distribution)	technology, employee quality, initiative of input materials
Aw and Batra (1998)	Taiwan	1986 (cross-section)	ML estimation (normal distribution)	R&D investments, informal contacts with foreign purchasers through export sales
Sheu and Yang (2005)	Taiwan	1996-2001 (panel)	Battese and Coelli (1995)	equity ownership of top officers
Amornkitvikai et al. (2013)	Thailand	2007 (cross-section)	Battese and Coelli (1995)	firm size, firm age, foreign ownership, location, government assistance
Charoenrat and Harvie (2013)	Thailand	2007 (cross-section)	ML estimation (normal distribution)	skilled labor, location, ownership
Kim (2003)	Korea	1980-1993 (panel)	Battese and Coelli (1995)	firm size
Sayavong (2021)	Laos	2012/13 (cross-section)	ML estimation (normal distribution), two-step approach	accounting system, skills of labor (education of managers), international trade activities
Margono and Sharma (2004)	Indonesia	1993 to 2000 (panel)	ML estimation (normal distribution), two-step approach	ownership, location, firm size, firm age
Goldar et al.(2004)	India	1990-91 to 1999-20 (panel)	Battese and Coelli (1995)	foreign ownership
Bottasso and Sembenelli (2004)	Italy	1978-93 (panel)	Battese and Coelli (1995)	foreign ownership (subsidiaries of foreign multinationals)
Dilling-Hansen et al. (2003)	Denmark	1995, 1997 (cross-section)	Battese and Coelli (1995), two-step approach	R&D activities, legal form of ownership

	mac	chinery indu	ıstry	1	ight industi	y	h	eavy indust	ry
	mean	median	standard deviation	mean	median	standard deviation	mean	median	standard deviation
Real output (ten thousand yen) ¹⁾	47,825.2	10,295.2	88,338.4	41,585.1	7,163.8	83,668.1	57,356.9	13,005.7	98,911.1
Number of regular employees (persons)	18.5	5.0	28.9	14.4	3.0	25.2	19.1	5.0	29.3
Number of nonregular employees (persons)	8.5	4.0	11.7	8.1	4.0	11.4	8.1	4.0	10.9
Capital stock (ten thousand yen) ²⁾	7,927.8	1,303.6	16,608.1	7,041.3	835.1	16,057.0	9,697.2	1,505.9	19,145.9
Material input (ten thousand yen) ³⁾	31,758.3	5,121.7	65,382.0	28,347.9	3,500.9	62,317.4	39,825.7	6,737.3	74,154.4
Labor productivity (ten thousand yen/person) ⁴⁾	1,223.2	990.3	939.6	1,127.4	829.9	964.0	1,474.9	1,104.3	1,184.5
Ratio of regular employees (%)	49.4	55.6	28.1	42.1	50.0	28.6	49.2	56.0	28.1
Total asset (ten thousand yen) ⁵⁾	44,524.4	8,775.1	82,786.6	36,839.9	5,155.3	77,110.0	52,637.9	9,874.5	94,434.6
Debt-asset ratio	0.8614	0.7398	0.6699	0.9589	0.8139	0.7376	0.8446	0.7498	0.6430
Operating profit ratio (%)	0.35	1.05	9.14	-0.54	0.00	8.02	0.52	0.78	7.74
Borrowing interest rate (%)	1.54	1.48	1.14	1.45	1.36	1.18	1.52	1.43	1.15
Proportion of firms that made capital investment (%)	35.7	0.0	47.9	29.9	0.0	45.8	38.7	0.0	48.7
Investment rate (%)	7.2	0.0	17.4	5.8	0.0	15.6	7.9	0.0	17.5
Marginal q	1.81	1.17	5.94	1.10	0.79	5.71	1.58	1.08	5.10
Proportion of firms that made R&D investment (%)	10.3	0.0	30.4	7.4	0.0	26.1	8.9	0.0	28.5
R&D investment rate (%)	0.03	0.00	0.16	0.02	0.00	0.13	0.03	0.00	0.15
Proportion of firms that have patents (%)	11.3	0.0	31.6	11.2	0.0	31.5	10.8	0.0	31.0

Table 2Descriptive Statistics of Major Variables

Notes: $1 \sim 5$ real values in 2011 price

Source: The Small and Medium Enterprise Agency, Basic Survey on Small and Medium Enterprises

	(1)	(2)	(3)	(4)
	random effects mod	lel (GLS)	true random effect	ts model
lnNR	0.2362 ***	1.1978 ***	0.2398 ***	1.2524 ***
	(55.36)	(29.63)	(58.30)	(32.64)
lnNNR	0.0872 ***	0.5056 ***	0.0880 ***	0.5050 ***
	(21.99)	(14.28)	(22.77)	(14.96)
lnK	0.0166 ***	-0.0127	0.0174 ***	-0.0068
	(6.50)	(-0.53)	(6.99)	(-0.30)
lnM	0.6592 ***	-0.5753 ***	0.6507 ***	-0.6933 ***
1	(182.22)	(-13.69)	(183.77)	(-17.21)
$(\ln NR)^2$	1	0.0652 ***		0.0706 ***
N	1	(20.69)		(23.43)
(lnNR)(lnNNR)	1	-0.0192 ***		-0.0228 ***
	1	(-4.31)		(-5.36)
(lnNR)(lnK)	1	-0.0083 ***		-0.0074 ***
	1	(-2.93)		(-2.74)
(lnNR)(lnM)	1	-0.0994 ***		-0.1063 ***
	1	(-24.47)		(-27.24)
(lnNNR) ²	1	0.0195 ***		0.0204 ***
, ,	1	(6.41)		(7.10)
(lnNNR)(lnK)	1	0.0079 ***		0.0069 ***
	1	(2.90)		(2.68)
(lnNNR)(lnM)	1	-0.0452 ***		-0.0438 ***
	1	(-11.90)		(-12.04)
$(\ln K)^2$	1	0.0038 ***		0.0055 ***
	1	(3.21)		(4.96)
(lnK)(lnM)	1	-0.0028		-0.0061 ***
` · · ·	1	(-1.14)		(-2.68)
$(\ln M)^2$	1	0.0680 ***		0.0745 ***
`	1	(28.34)		(32.40)
Constant term	3.6857 ***	9.3582 ***	3.8668 ***	10.1221 ***
1	(96.49)	(42.79)	(99.39)	(48.39)
$\sigma_{\rm u}$	0.2075	0.1816	0.0989	0.1239
$\sigma_{\rm v}$	0.1485	0.1424	0.1843	0.1445
Number of	6790	6790	6790	6790
observations	0790	0790	0790	0790

Table 3 Estimation Results of Stochastic Frontier Production Function: Machinery industry

Notes: The coefficient estimates of year dummies are suppressed.

The values in parhenthesis are t-values.

*,**, *** significant at 10%, 5% and 1% level, respectively

NR: regular workers NNR: non-regular workers K: capital stock M: material input

 $\sigma_{\!u}\!:$ standard deviation of inefficieny distribution

 $\sigma_{\!v}\!:$ standard deviation of disturbance distribution

	(1)	(2)	(3)	(4)
	random effects mod	lel (GLS)	true random effect	s model
lnNR	0.2029 ***	1.2538 ***	0.2177 ***	1.3295 ***
	(60.73)	(42.91)	(64.78)	(49.04)
lnNNR	0.0978 ***	0.5935 ***	0.1031 ***	0.6246 ***
	(30.58)	(22.75)	(31.91)	(24.52)
lnK	0.0118 ***	-0.0244	0.0076 ***	-0.0819 ***
	(5.69)	(-1.39)	(3.72)	(-4.71)
lnM	0.7121 ***	-0.5804 ***	0.7032 ***	-0.6813 ***
	(236.33)	(-18.39)	(232.58)	(-22.66)
$(\ln NR)^2$		0.0664 ***		0.0687 ***
		(28.88)		(31.95)
(lnNR)(lnNNR)		-0.0043		-0.0045
		(-1.36)		(-1.46)
(lnNR)(lnK)		-0.0023		-0.0082 ***
		(-1.12)		(-4.17)
(lnNR)(lnM)		-0.1135 ***		-0.1150 ***
		(-36.40)		(-39.86)
(lnNNR) ²		0.0197 ***		0.0208 ***
		(8.45)		(9.14)
(lnNNR)(lnK)		-0.0005		-0.0009
		(-0.25)		(-0.45)
(lnNNR)(lnM)		-0.0471 ***		-0.0497 ***
		(-16.23)		(-17.65)
$(\ln K)^2$		0.0037 ***		0.0056 ***
		(4.30)		(6.73)
(lnK)(lnM)		-0.0021		0.0007
		(-1.13)		(0.38)
$(\ln M)^2$		0.0709 ***		0.0738 ***
		(39.01)		(42.68)
Constant term	3.0689 ***	9.0328 ***	3.2355 ***	9.9617 ***
	(100.90)	(55.07)	(98.64)	(61.96)
$\sigma_{\rm u}$	0.2126	0.1833	0.0605	0.0996
$\sigma_{\rm v}$	0.1024	0.0916	0.1552	0.1035
Number of observations	8624	8624	8624	8624

Notes: The coefficient estimates of year dummies are suppressed.

The values in parhenthesis are t-values.

*,**, *** significant at 10%, 5% and 1% level, respectively

NR: regular workers NNR: non-regular workers K: capital stock M: material input

 $\sigma_{\!u}\!:$ standard deviation of inefficieny distribution

 $\sigma_{\!v}\!:$ standard deviation of disturbance distribution

	(1)	(2)	(3)	(4)
	random effects mod	lel (GLS)	true random effec	ts model
lnNR	0.2401 ***	1.4340 ***	0.2496 ***	1.4827 ***
	(59.39)	(44.11)	(63.25)	(48.34)
lnNNR	0.0797 ***	0.4939 ***	0.0875 ***	0.5097 ***
	(20.57)	(16.33)	(22.33)	(17.21)
lnK	0.0154 ***	0.0169	0.0132 ***	0.0071
	(6.28)	(0.87)	(5.44)	(0.38)
lnM	0.6733 ***	-0.7827 ***	0.6618 ***	-0.9182 ***
	(195.74)	(-23.15)	(194.22)	(-27.87)
$(\ln NR)^2$		0.0758 ***		0.0781 ***
		(28.49)		(30.99)
(lnNR)(lnNNR)		-0.0111 ***		-0.0112 ***
		(-2.82)		(-2.91)
(lnNR)(lnK)		-0.0043 *		-0.0073 ***
		(-1.85)		(-3.30)
(lnNR)(lnM)		-0.1259 ***		-0.1277 ***
		(-35.48)		(-37.24)
$(\ln NNR)^2$		0.0194 ***		0.0184 ***
× ,		(6.77)		(6.73)
(lnNNR)(lnK)		0.0021		0.0048 *
		(0.85)		(1.95)
(lnNNR)(lnM)		-0.0402 ***		-0.0430 ***
		(-11.82)		(-13.00)
$(\ln K)^2$		0.0025 **		0.0039 ***
~ /		(2.52)		(4.16)
(lnK)(lnM)		-0.0030		-0.0044 **
		(-1.44)		(-2.18)
$(\ln M)^2$		0.0782 ***		0.0840 ***
()		(39.24)		(43.30)
Constant term	3.5248 ***	10.2221 ***	3.7413 ***	11.2169 ***
	(103.13)	(58.70)	(104.60)	(65.82)
$\sigma_{\rm u}$	0.2222	0.1871	0.0790	0.1164
σ	0.1115	0.0981	0.1945	0.1477
Number of	71/2	71/5		
observations	/165	/165	/165	/165

Table 3 (continued) Estimation Results of Stochastic Frontier Production Function: Heavy industry

Notes: The coefficient estimates of year dummies are suppressed.

The values in parhenthesis are t-values.

*,**, *** significant at 10%, 5% and 1% level, respectively

NR: regular workers NNR: non-regular workers K: capital stock M: material input

 $\sigma_{\!u}\!\!:$ standard deviation of inefficieny distribution

 σ_v : standard deviation of disturbance distribution

	machinery industry	light industry	heavy industry
Conventional random effects model	1422.1 (0.00)	2690.7 (0.00)	2663.9 (0.00)
The true random effects model	1789.6 (0.00)	3383.3 (0.00)	3289.4 (0.00)

Table 4 The Wald test of the Cobb-Douglas Production function

Notes: The values in parenthesis are p-value.

	Conventional random effects model					
	machinery industry		light industry		heavy industry	
	The Cobb-Douglas production function	The translog production function	The Cobb-Douglas production function	The translog production function	The Cobb-Douglas production	The translog production function
regular worker	0.2362	0.2285	0.2059	0.1901	0.2401	0.2206
nonregular worker	0.0872	0.0864	0.0978	0.1050	0.0797	0.0794
capital	0.0166	0.0263	0.0118	0.0204	0.0154	0.0271
material input	0.6592	0.6649	0.7121	0.7153	0.6733	0.6875

Table 5 The mean	elasticity of	f regular worke	r. nonregular worker	. capital and	material input
			-,	, r	r

		The true random effects model					
	machinery industry		light industry		heavy industry		
	The Cobb-Douglas production function	The translog production function	The Cobb-Douglas production	The translog production function	The Cobb-Douglas production	The translog production function	
regular worker	0.2398	0.2306	0.2177	0.1980	0.2496	0.2268	
nonregular worker	0.0880	0.0871	0.1031	0.1056	0.0875	0.0856	
capital	0.0174	0.0298	0.0076	0.0202	0.0132	0.0284	
material input	0.6507	0.6497	0.7032	0.7006	0.6618	0.6681	

Table 6 Comparison of the mean of the technical inefficiency estimates

		(1) machine	ing muusuy		
	The Cobb-Douglas pr	oduction function	The translog production function		
	time-invariant random effects model	The true random effects model	time-invariant random effects model	The true random effects model	
techincal inefficiency measure	1.0836	0.0989	0.7613	0.1240	
degree of technical efficiency	0.3384	0.9058	0.4671	0.8834	

(1) machinery industry

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	The Cobb-Douglas pr	oduction function	The translog production function		
	time-invariant random effects model	The true random effects model	time-invariant random effects model	The true random effects model	
techincal inefficiency measure	1.2156	0.0610	0.8198	0.0997	
degree of technical efficiency	0.2965	0.9408	0.4405	0.9051	

(3) heavy industry

		()			
	The Cobb-Douglas pr	oduction function	The translog production function		
	time-invariant random effects model	The true random effects model	time-invariant random effects model	The true random effects model	
techincal inefficiency measure	1.4676	0.0862	0.9789	0.1166	
degree of technical efficiency	0.2305	0.9174	0.3757	0.8899	

Notes: Degree of technical efficiency is calculated as exp(- ε) where ε is technical inefficiency measure.

Table 7 The technical inefficiency estimates for the translog production functionwith three factor inputs (total workers, capital stock and materials)

	The Cobb-Douglas p	production function	The translog production function		
	Four factor inputs	Three factor inputs	Four factor inputs	Three factor inputs	
techincal inefficiency measure	0.0989	0.1197	0.1240	0.1348	
degree of technical efficiency	0.9058	0.8872	0.8834	0.8739	

(1) machinery industry

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	The Cobb-Douglas	production function	The translog production function		
	Four factor inputs	Three factor inputs	Four factor inputs Three factor inj		
techincal inefficiency measure	0.0610	0.0768	0.0997	0.1083	
degree of technical efficiency	0.9408	0.9261	0.9051	0.8974	

(3)	heavy	industry	,
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	The Cobb-Douglas p	production function	The translog production function		
	Four factor inputs	Three factor inputs	Four factor inputs	Three factor inputs	
techincal inefficiency measure	0.0862	0.0879	0.1166	0.1317	
degree of technical efficiency	0.9174	0.9159	0.8899	0.8766	

Notes: Degree of technical efficiency is calculated as $exp(-\varepsilon)$ where ε is technical inefficiency measure.

	(1) machinery industry				
	inefficient	efficient	mean difference		
	firms	firms			
Real output (ten thousand yen) ¹⁾	42,800	57,726	-14,926*** (-8.03)		
Number of regular workers (persons)	21.3	23.4	-2.11*** (-3.04)		
Number of nonregular workers (persons)	9.2	9.6	-0.44 (-1.58)		
Capital stock (ten thousand yen) ²⁾	9,072	9,313	-241 (-0.62)		
Material input (ten thousand yen) ³⁾	31,567	35,618	-4,051*** (-2.90)		
Labor productivity (ten thousand yen/person) ⁴⁾	1,115	1,523	-408*** (-19.17)		
Ratio of regular employees (%)	56.18	59.88	-3.70*** (-7.12)		
Total asset (ten thousand yen) ⁵⁾	41,983	56,113	-14,130*** (-7.66)		
Debt-asset ratio	0.9217	0.6871	0.2346*** (16.81)		
Operating profit ratio (%)	-2.55	3.66	-6.21*** (-27.41)		
Borrowing interest rate (%)	1.65	1.70	-0.05* (-1.84)		
Proportion of firms that made capital investment (%)	35.84	46.38	-10.54*** (-8.87)		
Investment rate (%)	6.12	9.55	-3.43*** (-7.76)		
Marginal q	0.35	3.54	-3.19*** (-22.02)		
Proportion of firms that made R&D investment (%)	8.75	13.32	-4.56*** (-6.02)		
R&D investment rate (%)	0.03	0.04	-0.02*** (-4.28)		
Proportion of firms that have patents (%)	10.14	15.26	-5.12*** (-6.36)		

Table 8 Comparison of Characteristics between Efficient and Inefficient Firms

Notes: 1)~5) real values in 2011 price

*, **, *** significant at 10%, 5%, 1% level, respectively. The values in parenthesis are t-values of the mean difference.

	(2) light lifedsu y		
	inefficient	efficient	mean difference
	firms	firms	
Real output (ten thousand yen) ¹⁾	39,318	57,541	-18,223*** (-10.87)
Number of regular workers (persons)	17.7	19.9	-2.21*** (-4.03)
Number of nonregular workers (persons)	9.5	10.6	-1.10*** (-4.21)
Capital stock (ten thousand yen) ²⁾	8,502	9,675	-1,173*** (-3.30)
Material input (ten thousand yen) ³⁾	29,698	39,438	-9,740*** (-7.50)
Labor productivity (ten thousand yen/person) ⁴⁾	1,089	1,507	-418*** (-20.51)
Ratio of regular employees (%)	50.9	54.07	-3.18*** (-6.59)
Total asset (ten thousand yen) ⁵⁾	37,233	53,804	-16,571*** (-10.17)
Debt-asset ratio	1.0017	0.7839	0.2178*** (15.59)
Operating profit ratio (%)	-3.08	2.41	-5.49*** (-31.01)
Borrowing interest rate (%)	1.56	1.63	-0.07*** (-2.88)
Proportion of firms that made capital investment (%)	31.7	42.9	-11.15*** (-10.77)
Investment rate (%)	5.05	8.38	-3.33*** (-9.37)
Marginal q	-0.03	2.69	-2.71*** (-22.50)
Proportion of firms that made R&D investment (%)	6.94	9.81	-2.87*** (-4.82)
R&D investment rate (%)	0.02	0.03	-0.00 (-0.96)
Proportion of firms that have patents (%)	13.18	14.68	-1.50** (-2.02)

 Table 8 (continued) Comparison of Characteristics between Efficient and Inefficient Firms

 (2) light industry

Notes: 1)~5) real values in 2011 price

*, **, *** significant at 10%, 5%, 1% level, respectively. The values in parenthesis are t-vaules of the mean difference.

	(5) neavy industry		
	inefficient	efficient	mean difference
	firms	firms	
Real output (ten thousand yen) ¹⁾	48,266	73,249	-24983*** (-12.14)
Number of regular workers (persons)	20.7	22.9	-2.16*** (-3.35)
Number of nonregular workers (persons)	8.5	9.1	-0.59** (-2.37)
Capital stock (ten thousand yen) ²⁾	11,270	12,097	-827* (-1.84)
Material input (ten thousand yen) ³⁾	42,932	50,103	-7,171*** (-4.20)
Labor productivity (ten thousand yen/person) ⁴⁾	1,363	1,889	-526*** (-19.76)
Ratio of regular employees (%)	56.3	59.12	-2.82*** (-5.72)
Total asset (ten thousand yen) ⁵⁾	52,029	68,283	-16,254*** (-7.76)
Debt-asset ratio	0.9242	0.6874	0.2368*** (17.61)
Operating profit ratio (%)	-1.81	3.60	-5.42*** (-29.26)
Borrowing interest rate (%)	1.61	1.66	-0.05 (-1.61)
Proportion of firms that made capital investment (%)	39.25	51.01	-11.76*** (-10.07)
Investment rate (%)	6.62	11.03	-4.41*** (-10.02)
Marginal q	0.28	3.13	-2.84*** (-23.70)
Proportion of firms that made R&D investment (%)	7.91	10.50	-2.60*** (-3.81)
R&D investment rate (%)	0.03	0.03	-0.00 (-1.12)
Proportion of firms that have patents (%)	11.03	12.26	-1.23 (-1.62)

 Table 8 (continued) Comparison of Characteristics between Efficient and Inefficient Firms

 (3) heavy industry

Notes: 1)~5) real values in 2011 price

*, **, *** significant at 10%, 5%, 1% level, respectively. The values in parenthesis are t-values of the mean difference.

Table 9	The Determinants	of technical	inefficiency
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(1) use of investment dummy	
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	constant	investment dummy	R&D investment dummy	log size	debt	regemp	R-squared Number of observations
machinery industry	0.1609***	-0.0093***	0.0068*	-0.0041***	0.0269***	-0.0210***	0.0678
	(13.96)	(-3.77)	(1.88)	(-4.41)	(13.41)	(-3.65)	6,535
light industry	0.1045***	-0.0098***	-0.0001	-0.0010	0.0226***	-0.0234***	0.073
	(13.29)	(-5.66)	(-0.02)	(-1.57)	(17.05)	(-6.02)	8,262
heavy industry	0.1788***	-0.0088***	0.0081**	-0.0057***	0.0286***	-0.0259***	0.0836
	(15.74)	(-3.95)	(2.15)	(-6.47)	(13.96)	(-4.55)	6,917

(2) use of investment ratio

	constant	investment rate	R&D investment sales ratio	log size	debt	regemp	R-squared Number of observations
machinery industry	0.1684***	-0.0255***	-0.9937	-0.0051***	0.0257***	-0.0158***	0.0756
	(15.76)	(-4.36)	(-1.64)	(-6.10)	(13.37)	(-2.83)	6,058
light industry	0.1129***	-0.0218***	0.2270	-0.0020***	0.0224***	-0.0241***	0.0735
	(14.50)	(-4.64)	(0.40)	(-3.25)	(16.66)	(-6.11)	7,928
heavy industry	0.1790***	-0.0257***	0.0523	-0.0061***	0.0275***	-0.0235***	0.0878
	(16.70)	(-4.94)	(0.08)	(-7.48)	(13.83)	(-4.22)	6,541

Notes: The numbers in parenthesis are t-values.

*,**,*** significant at the 10%, 5% and 1% level.

	(%)				
	investment dummy firm size		debt-asset ratio	proportion of regular workers out of total workers	
machinery industry	-7.50	-0.96	-5.09	-0.63	
light industry	-9.83	-0.37	-4.94	-0.74	
heavy industry	-7.55	-1.33	-5.81	-0.63	

Table 10 Which factor is effective in decreasing technical inefficiency? Quantitaive evaluation

(2) use of investment ratio

(2) use of investment ratio				
investment rate	firm size	debt-asset ratio	proportion of regular workers out of total workers	
-0.71	-1.19	-4.86	-0.47	
-0.73	-0.74	-4.89	-0.77	
-0.97	-1.42	-5.58	-0.57	
	(2) use of investment investment rate -0.71 -0.73 -0.97	(2) use of investment ratioinvestment ratefirm size-0.71-1.19-0.73-0.74-0.97-1.42	(2) use of investment ratioinvestment ratefirm sizedebt-asset ratio -0.71 -1.19 -4.86 -0.73 -0.74 -4.89 -0.97 -1.42 -5.58	

	machinery i	ndustry	light ind	ustry	heavy industry		
marginal q	0.0061***	^c (6.09)	0.0064***	(7.20)	0.0056***	(4.79)	
debt-asset ratio	-0.2173***	(-19.10)	-0.1828***	(-20.75)	-0.2236***	(-19.66)	

Table 11 Marginal effects on the probability that capital investment is positiv