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Abstract

This study investigates the efficiency of Japanese credit cooperatives using a stochastic directional distance function approach and compares the results obtained from a slack-based data envelopment analysis model (SBM). Moreover, it focuses on the differences in the four groups classified by a type of common bond in a membership and considers the validity of small financial cooperatives. The findings reveal that ethnic minority-owned cooperatives that experienced a drastic consolidation in the last two decades are more efficient than the other groups and those owned through an industry-based membership are less efficient. Although the results slightly differ among alternative measures, this paper emphasizes the potential merger effects of small financial cooperatives in Japan.

Keywords: Efficiency, Cooperative financial institutions, Consolidation.
JEL Classification Code: C67; G21; G34.

1. Introduction

Cooperative structured financial institutions play an important role particularly in retail banking around the world. Japan is no exception: cooperative financial institutions still hold more than a 30% share of both the deposit and the loan markets at the end of FY 2012. In the Japanese financial system, various types of cooperative-structured financial institutions exist. Among them, credit cooperatives are further divided into the following three groups according to the type of common bond in a membership: regional, industry based, and occupation based.[1] Approximately 80% of them are regional credit cooperatives owned by members who are local residents. Institutions comprising ethnic minority residents are commonly classified as a different type.[2] Thus, four groups of credit cooperatives are regarded to exist in Japan. Along with the numerous commercial banks, credit cooperatives have suffered from the problem of non-performing loans after the bubble burst in the 1990s. Consequently, failures and mergers reduced those numbers by more than 60% during the past two decades, from 408 at the end of FY 1990 to 157 at the end of FY 2012. In particular, ethnic minority-owned cooperatives drastically decreased, from 78 at the end of FY 1990 to 16 at the end of FY 2012.

The main purpose of this study is to empirically investigate whether the recent consolidation trend of Japanese credit cooperatives has influenced their performance and to examine the differences among the four groups of institutions. In particular, we focus on the validity of non-regional membership credit cooperatives. Among Japan's credit cooperatives, those belonging to the non-regional membership type group are relatively small in number and have a strong commitment to the principles of mutuality and cooperation. However, some non-regional membership credit cooperatives have maintained their independence, while others have chosen to increase their size through mergers in recent years. Indeed, the average asset size of non-regional membership credit cooperatives increased by more than 60% during the past two decades, from 52,058 million yen at the end of FY 1990 to 83,982 million yen at the end of FY 2012.[3] These changes suggest the severity of the business environment that many non-regional membership credit cooperatives have been facing. The current situation of non-regional membership credit cooperatives seems inconsistent with previous studies that found advantages in being a small bank for small business lending.[4]

1 Credit cooperatives (also known as Shinkumi banks) are organized under the Law for Small Business Cooperatives of 1949, and are principally based on the mutual support of owners and workers of small and medium-sized firms.

2 Almost all ethnic minority-owned cooperatives were owned by the Koreans, with the remainder owned by the Chinese.

3 Sample sizes are 153 and 60, respectively. Although 155 non-regional membership credit cooperatives exist, financial data on two of them were not disclosed.

4 Previous studies revealed that small banks have a competitive advantage in small business lending (see, Berger & Udell, 1996; Sapienza, 2002; Carter et al., 2004). Moreover, other studies also

Regarding the U.S. credit union studies, Frame et al. (2002) found significant differences in the performance of large credit unions with different types of common bonds. Specifically, they found that credit union membership expansion dilutes the information advantages associated with a tight common bond of association. Several studies examined the effects and impacts of mergers on credit union performance. Fried et al. (1999) found that credit unions that engage in acquisitions are more efficient than those that are acquired. However, Bauer et al. (2009) showed that the interest rates offered by credit unions making acquisitions are not significantly affected by mergers. Moreover, although mergers are not examined directly, Goddard et al. (2008) found that larger institutions are better able to diversify into non-traditional product lines, bringing about the reduction of the volatility of their earnings.

In contrast, researches investigating the effects of consolidation on financial institutions, including cooperative structured ones, often pay attention to the changes in performance after the consolidation. Until now, most research relied on data envelopment analysis (DEA), which measures how efficient an institution converts inputs into outputs.[5] However, as Fried et al. (2002) suggested, DEA has the disadvantage of measurement errors from assuming no statistical noise. In addition, because the number of efficient firms on the frontier tends to increase with the numbers of input and output variables, the results are likely to be biased toward efficiency.

In fact, Fukuyama et al. (1999) found that the ethnic minority-owned cooperatives were more efficient and experienced larger productivity growth during 1992–1996. The results seem inconsistent with the fact that many ethnic minority-owned cooperatives went bankrupt in the late 1990s. It is notable that the analysis was executed before the financial system crises, when poor disclosure standards hurt the credibility of financial statements of banks.[6] In this study, we employ stochastic frontier analysis (SFA) using a directional distance function approach that is expressed as a function of outputs and inputs.[7] Thus, similar to the standard DEA model, SFA is able to calculate efficiency by simultaneously using multiple outputs and inputs without input price variables. Furthermore, SFA can overcome the major drawback of DEA, which is assuming no statistical noise.

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showed that large banks may concentrate on larger firms and reduce the amount of lending to small businesses (see, Strahan & Weston, 1998; Peek & Rosengren, 1996).

5 See Fried et al. (1993), Fried and Lovell (1994), and Fried et al. (1999) for U.S. credit union studies.

6 Actually, the practice of window dressing was revealed as being widespread among many failed ethnic minority-owned cooperatives.

7 Regarding the literature on banking efficiency, previous studies using the distance function approach are very few compared with those using the production or cost function approaches. For instance, Cuesta and Orea (2002) employed this procedure for Spanish savings banks, Marsh et al. (2003) for U.S. commercial banks, and Koutsomanoli-Filippaki et al. (2009) for Central and Eastern European banks. In contrast, applications involving distance functions have become common in other recent literature on the public services industry (see, English et al., 1993; Fare et al., 1993; Coelli & Perelman, 1999; and Grosskopf et al., 1997).

Similar to studies employing DEA, most previous studies employing the stochastic distance function approach assume either the output or input orientation approaches ex ante. However, very few studies investigated the efficiency of Japan’s credit cooperatives; thus, no definite choice of an appropriate orientation is available. For these reasons, this study employs an approach that estimates both output and input distance functions and compares the results with each other. Furthermore, to check for robustness, we compare the results with those obtained from DEA. Regarding the selection of a DEA model, we employ the slack-based DEA model (SBM) introduced by Tone (2001), which is a well-known non-radial efficiency measure in the DEA literature.

The remainder of this paper proceeds as follows. Section 2 presents the methodology adopted in this study to measure efficiency levels. Section 3 describes the data. Section 4 reports the results, and Section 5 concludes the paper.

2. Methodology

2.1 Stochastic distance function approach

The advantages of a directional distance function approach, which is employed in this study, include permitting the modeling of a multi-input, multi-output production process without price information.

As noted by Fare and Primont (1995), the output distance function is generally based on the following definition of the production technology of the firm. The output set expressed as $P(x)$ represents the set of all output vectors $y \in R_+^M$ that can be produced using the input vector $x \in R_+^K$. The production technology is assumed to satisfy the standard axioms, such as convexity and disposability. The output distance function $D_o(x, y)$ is then defined as follows:

$$D_O(x, y) = \min\{\theta > 0; \frac{y}{\theta} \in P(x)\}, \qquad (1)$$

where y and x are M outputs and K inputs, respectively. The output distance function is non-decreasing, positively linearly homogeneous, and convex in outputs but is decreasing in inputs. Thus, this function can be interpreted as the maximum radial expansion of outputs, holding the inputs constant.[8] The output distinction function D_o (x, y) takes a value that is less than or equal to 1 if each output is an element of the feasible production set, expressed as $P(x)$; thus, if all output

[8] See, Cornes (1992) for a more theoretical foundation of the distance function.

vectors are located on the upper boundary of the production set, the function has a value of unity. Therefore, the magnitude of $1/\theta$ in equation (1) represents a radial expansion of outputs that is required to attain the production frontier.

For the functional form of the distance function, the popular translog form is employed in this study. Further, following previous studies, a restriction of linear homogeneity in outputs is imposed on the function. Homogeneity implies that $D_o\ (x, \mu y) = \mu D_o\ (x, y)$, where $\mu > 0$; thus, if one of the outputs, such as the q^{th} output is arbitrarily selected, μ can be set to $1/y_q$. Accordingly, the translog output distance function is expressed as follows:

$$\ln(D_{Oi} / y_{qi}) = \alpha_0 + \sum_{j=1}^{K} \alpha_j \ln x_{ji} + \sum_{l=1}^{M-1} \beta_l \ln y_{li}^* + \frac{1}{2}\sum_{j=1}^{K}\sum_{k=1}^{K} \alpha_{jk} \ln x_{ji} \ln x_{ki}$$
$$+ \frac{1}{2}\sum_{l=1}^{M-1}\sum_{h=1}^{M-1} \beta_{lh} \ln y_{li}^* \ln y_{hi}^* + \sum_{j=1}^{K}\sum_{l=1}^{M-1} \rho_{jl} \ln x_{ji} \ln y_{li}^*, \quad i = 1, 2, \ldots, N, \qquad (2)$$

where $y_l^* = y_l/y_q$, and α, β, and ρ are the coefficients to be estimated. By restricting the linear homogeneity in outputs, the summations of all of the terms involving the q^{th} output become zero; thus, the summations involving the q^{th} output in the aforementioned expression are higher than M–1, but not higher than M. Based on Young's theorem, the symmetry conditions are also imposed on the second-order parameters in (2); that is, $\alpha_{jk} = \alpha_{kj}$ for all j and k, and $\beta_{lh} = \beta_{hl}$ for all l and h.

By using TL (.) to represent the translog function, this equation may be more concisely expressed as

$$\ln D_{Oi} - \ln(y_{qi}) = TL(x_i, y_i / y_{qi}, \alpha, \beta, \rho), \quad i = 1, 2, \ldots, N, \quad (3)$$

and hence

$$-\ln(y_{qi}) = TL(x_i, y_i / y_{qi}, \alpha, \beta, \rho) - \ln D_{Oi}, \quad i = 1, 2, \ldots, N, \quad (4)$$

Furthermore, by appending a symmetric error term v_i to account for the statistical noise and by rewriting ln D_{oi} as u_i, the following stochastic output distance function can be obtained:

$$\ln(y_{qi}) = -TL(x_i, y_i / y_{qi}, \alpha, \beta, \rho) + v_i - u_i, \quad i = 1, 2, \ldots, N, \qquad (5)$$

where v_i is the normally distributed error term and u_i is the one-sided inefficiency term that is assumed to take one of several distributional forms.

Similarly, the input distance function is defined. However, in contrast to the output distance function that assumes the input vector constant, the input distance function considers the amount by which the input vector may be proportionally decreased by holding the output vector constant. Using the input set expressed as $L(y)$, the input distance function can be expressed as follows:

$$D_I(x,y) = \max\{\rho > 0; \frac{x}{\pi} \in L(y)\}, \quad (6)$$

where the input set $L(y)$ represents the set of all input vectors $x \in R_+^K$ that can produce the output vector $y \in R_+^M$. The input distance function is non-decreasing, positively linearly homogeneous, and convex in inputs, but is also increasing in outputs. Thus, this function can be interpreted as the minimum radial reduction of inputs with the outputs held constant. The distinction function $D_I(x, y)$ takes a value that is greater than or equal to 1 if each input is an element of the feasible input set expressed as $L(y)$. The magnitude of $1/\pi$ in equation (6) represents a radial reduction of inputs required to reach the inner boundary of the input set.

After imposing linear homogeneity in inputs, which implies that $D_I(\omega x, y) = \omega D_I(x, y)$, where $\omega > 0$, the translog input distance function is similarly expressed.

$$\ln(D_{Ii}/x_{qi}) = \alpha_0 + \sum_{j=1}^{K-1}\alpha_j \ln x^*_{ji} + \sum_{l=1}^{M}\beta_l \ln y_{li} + \frac{1}{2}\sum_{j=1}^{K-1}\sum_{k=1}^{K-1}\alpha_{jk}\ln x^*_{ji}\ln x^*_{ki}$$
$$+ \frac{1}{2}\sum_{l=1}^{M}\sum_{h=1}^{M}\beta_{lh}\ln y_{li}\ln y_{hi} + \sum_{j=1}^{K-1}\sum_{l=1}^{M}\rho_{jl}\ln x^*_{ji}\ln y_{li}, \quad (7)$$

where $x_j^* = x_j/x_q$. Given the restriction of linear homogeneity in inputs, the summations of all of the terms involving the q^{th} input becomes zero. Following the steps similar to those previously explained, this equation may be more concisely expressed as

$$\ln D_{Ii} - \ln(x_{qi}) = TL(x_i/x_{qi}, y_i, \alpha, \beta, \rho), \quad i = 1,2,\ldots,N \quad (8)$$

and hence,

$$-\ln(x_{qi}) = TL(x_i/x_{qi}, y_i, \alpha, \beta, \rho) - \ln D_{Ii}, \quad i = 1,2,\ldots,N. \quad (9)$$

Furthermore, similar to the stochastic output distance function in equation (5), the stochastic input distance function can be described as follows:

$$\ln(x_{qi}) = -TL(x_i/x_{qi}, y_i, \alpha, \beta, \rho) + v_i + u_i, \quad i = 1,2,\ldots,N. \quad (10)$$

Now, the inefficiency term has changed from $-u_i$ to $+u_i$ given the difference in the definitions of each distance function.

In accordance with the stochastic frontier production or cost functions, these two models are also estimated through the maximum likelihood procedure. Moreover, they require a priori assumptions about the statistical distribution of the inefficiency terms. Although the half-normal assumption is the most common in the literature on banking efficiency, the distribution of inefficiency is specified as exponential in this study.[9] By employing the estimated values of the parameters, the predicted value for each efficiency is estimated as the negative exponent of the error term (i.e., exp($-u_i$)), which is not directly observable. We employed the representative point estimator developed by Battese and Coelli (1988).

2.2 Slack-based DEA

The standard DEA models are based on the proportional reduction or augmentation of input and the output vectors and do not account for slack. In this study, we employ a SBM introduced by Tone (2001). In contrast to the standard DEA models, the SBM has the advantage of generating a representative measure that is able to calculate the depth of inefficiency by reflecting nonzero slack in inputs and outputs when they are present.[10] The model formula that provides constant returns to scale (CRS) is expressed as follows:

$$
\begin{aligned}
\text{Min} \quad & \rho = \left(1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}\right) \Big/ \left(1 + \frac{1}{r}\sum_{i=1}^{r}\frac{s_i^+}{y_{ik}}\right) \\
\text{s.t.} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{ik} \qquad (i=1,2,\cdots,m) \\
& \sum_{j=1}^{n} y_{ij}\lambda_j - s_i^+ = y_{rk} \qquad (i=1,2,\cdots,r) \\
& \lambda_j,\ s_i^-,\ s_i^+ \geq 0 \qquad (j=1,2,\cdots,n), \qquad (11)
\end{aligned}
$$

where λ is a vector assigned to individual productive units and s_i^- and s_i^+ measure the distance of inputs $X\lambda$ and outputs $Y\lambda$ of a virtual unit from those of the unit evaluated.[11] The numerator and the denominator of the objective function in equation (11) measure the average distance of inputs and outputs, respectively, from the efficiency threshold. If we ignore the input slack s_i^- and specify the

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[9] We tested the half-normal distribution and confirmed that the log-likelihood value from the exponential model was higher than the half-normal model. Although we also tested the truncated-normal distribution, estimation results did not converge.

[10] DEA efficiency measures incorporating slack have been used in recent studies on the efficiency of financial institution. For instance, Avkiran (2009) employed this procedure for UAE banks and Fukuyama and Weber (2010) for Japanese banks.

[11] The efficiency measures of variable returns to scale (VRS) are obtained by adding the restriction that λ is summed to 1. However, the VRS efficiency scores are greater than or equal to the measures obtained from the CRS model. Because the efficiency variances are relatively small and it seems difficult for the VRS model to clearly distinguish among the four types of credit cooperatives, we employed the CRS model in this study.

numerator as 1, we obtain the output-oriented efficiency measures. Similarly, if we ignore the output slack s_i^+ and specify the denominator as 1, we obtain the input-oriented efficiency measures. The SBM efficiency measures are always lower or equal to those obtained from the standard DEA models, which do not take into account for non-radial slacks.

3. Data

With regard to output and input specification, we employ a standard intermediation approach that assesses credit cooperatives as financial intermediaries utilizing labor and capital to transform deposits into loans and other earning assets. Because credit cooperative activities are essentially controlled by members of cooperatives and are considered conservative—as opposed to that of commercial banks—the intermediation approach is best suited for an efficiency analysis. We consider three outputs: interest on loans and discounts (y_1), other interest income (y_2), and commissions and fees (y_3). We also consider three inputs: deposits (x_1), employees (x_2), and tangible fixed assets (x_3). Although the observed levels of balance sheet variables, such as loans and securities, is commonly used as bank outputs in the intermediation approach, the composition of assets—particularly the amount of securities—is diversified among credit cooperatives.[12] Therefore, we employ the values of income primarily generated from financial intermediation and non-interest activities as outputs.[13] All of the data were obtained from “Financial Statements of All Credit Cooperatives,” edited by Financial Book Consultants, Ltd. (Kin-yu Tosho Consultant Sha). Table 1 presents the basic statistics of these variables.

In the stochastic distance function approach, we calculate individual technical efficiency using a pooled dataset comprising each financial institution from FY 2007 to FY 2012.[14] In contrast, each year of cross-sectional data is used in the slack-based DEA.

<Insert Table 1>

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12 Although Fukuyama et al. (1999) also employed the intermediation approach, they considered two representative stock measures as bank outputs: the value of loans and securities.

13 These outputs are consistent with the profit-oriented operating approach proposed by Drake et al. (2006) in the context of DEA. In this approach, banks are viewed as business decision-making units with the final objective of generating maximum revenue from the total cost incurred from running the business.

14 In this study, the pooled data are unbalanced because of the failure or the reorganization of sample banks.

4. Empirical results

4.1 Results of the stochastic distance function

Table 2 presents the empirical results for the estimated model. Before estimation, all monetary variables except input x_2 were deflated by the GDP deflator index. Further, in keeping with the characteristics of the translog functional form, each variable was divided by its mean value. The results in Table 2 pertain to the case in which linear homogeneity restrictions are imposed using output y_1 and input x_1 as a numeraire.[15] Regarding the results of the output distance function model, the terms ln σ_v^2 and ln σ_u^2 are statistically significant at the 1% level. In addition, the one-sided generalized likelihood ratio test rejects the null hypothesis of $\sigma_u = 0$ at the 1% level. Moreover, as revealed, all first-order coefficients and approximately half of the second-order coefficients indicate statistical significance suggesting that the estimated model is a good fit with the observed data. In addition, all elasticities possess the expected signs at the geometric mean. Therefore, at this point, the estimated output distance function fulfills the property of monotonicity (i.e., non-decreasing in outputs and decreasing in inputs).

The results of the input distance function model are similar. The terms ln σ_v^2 and ln σ_u^2 are also statistically significant at the 1% level and the one-sided generalized likelihood ratio test rejects the null hypothesis of $\sigma_u = 0$ at the 1% level. Moreover, in this case, the monotonicity property—non-decreasing in inputs and decreasing in outputs—of the estimated input distance function model is completely satisfied at the geometric mean. Therefore, the stochastic frontier approach based on both of the input and the output distance functions should be noted as being appropriate for examining the technical efficiency for Japanese credit cooperatives.

<Insert Table 2>

4.2 Summary of efficiency measures

Table 3 summarizes the efficiency results of the output distance function model. The estimated mean technical efficiency is found to be 0.9314 during 2008–2012. Comparisons between the types of ownership structures reveal that credit cooperatives owned by ethnic minority residents are the highest on average (0.9445). In contrast, credit cooperatives classified as an industry-based type are the lowest on average (0.9138). The Kruskal–Wallis test indicates that a significant difference exists

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[15] As a result of examining the cases in which other outputs and inputs are used as a numeraire, the robustness evidence, which states that the estimated values of each parameter are approximately consistent, has been obtained.

in the variances of the four groups at the 1% level (the χ^2 value is 38.2669).[16] In addition, the results of the Steel–Dwass pairwise comparisons demonstrate that significant differences exist between pairs of four groups, except for between the ethnic minority residential type and the occupation-based type. Thus, credit cooperatives classified as an industry-based type are significantly less efficient than those of other groups. Moreover, credit cooperatives owned by ethnic minority residents are significantly more efficient than those owned by regional domestic residents. The result is consistent with the findings of Fukuyama et al. (1999) that investigate the relative efficiency levels between domestic and foreign-owned credit cooperatives by using a DEA, whereas the periods are different. Regarding the temporal variation in the yearly mean efficiency, although the pattern is non-monotonic, it decreases from 0.9334 in 2008 to 0.9266 in 2012 for regional domestic residential credit cooperatives. A similar trend is also confirmed for credit cooperatives classified as a business type; the yearly mean technical efficiency decreases from 0.9283 in 2008 to 0.9024 in 2012. In contrast, this efficiency slightly increases for the ethnic minority residential credit cooperatives and remains almost unchanged for those classified as an occupation-based type.

<Insert Table 3>

Next, Table 4 summarizes the efficiency results of the input distance function model. The estimated mean technical efficiency is found to be 0.9299 during 2008–2012, which is slightly less than the results in Table 3. Consistent with the results of the output distance function model, credit cooperatives owned by ethnic minority residents are the highest on average (0.9433) and those classified as an industry-based type are the lowest on average (0.9113). The Kruskal–Wallis test indicates that a significant difference also exists in the variances between four groups of credit cooperatives at the 1% level (the χ^2 value is 34.4527). The results of the Steel–Dwass pairwise comparisons also show that significant differences exist between the pairs of four groups except for between ethnic minority residents and type of occupation. Thus, credit cooperatives owned by ethnic minority residents are significantly more efficient than those owned by regional domestic residents, and those classified as an industry-based type are remarkably inefficient. The temporal variation in the yearly mean efficiency is also consistent with the previous results summarized in Table 3.

<Insert Table 4>

Table 5 summarizes the efficiency results from the output-oriented SBM. The constant returns to

[16] Because the homogeneity of the variances was rejected, we employed the Kruskal–Wallis non-parametric test. The same approach applies hereafter.

scale (CRS) model has the property that all observed production combinations can be scaled up or down proportionally. Because the number of fully efficient units having a value of 1 is small in the CRS model, the variance (standard deviation) in the calculated efficiencies is generally large. Table 5 clearly shows these properties. Furthermore, the yearly mean efficiency scores fall much below those derived from the output distance function model. However, interestingly, the temporal variation in the yearly mean efficiency is consistent with the results in Table 3 and decreases from 0.5892 in 2008 to 0.5039 in 2012. In contrast, distinctive dissimilarities are observed in the comparisons between the four groups of ownership structures. Credit cooperatives owned by ethnic minority residents are the lowest on average except for FY 2008, and those classified as industry-based type are the highest on average for FY 2011 and FY 2012. However, the Kruskal–Wallis test leads to no significant difference in variances between four groups of credit cooperatives for every year. In addition, the Steel–Dwass pairwise comparisons also show no significant differences between all pairs of the four groups.

<Insert Table 5>

Finally, Table 6 summarizes the efficiency results from the input-oriented SBM. Consistent with the results in Table 5, the yearly mean efficiency scores fall much below those derived from the input distance function model. However, the mean efficiency scores are larger than those in Table 5 for every year. Regarding the comparison between the types of ownership structures, credit cooperatives classified as the occupation-based type have the highest average efficiency for every year. In contrast, domestic residential credit cooperatives have the lowest average efficiency for every year. As a possible reflection of these distinctive differences, the Kruskal–Wallis tests indicate that significant differences exist in the variances between four groups of credit cooperatives at the 1% level for every year. In addition, the results of the Steel–Dwass pairwise comparisons show significant differences between pairs of domestic residential credit cooperatives and the other three groups. Therefore, the domestic residential credit cooperatives are significantly less efficient than the other types of ownership structures.

<Insert Table 6>

4.3 Correlation between different efficiency measures

We now conduct a correlation analysis between the efficiency scores computed from each approach. Table 7 summarizes the Kendall's rank correlation coefficients between each yearly efficiency score.[17] First, regarding the correlation between the same directional measures, the coefficients of the output-oriented measures (Output-DF vs. Output-SBM) are larger than those of the input-oriented measures (Input-DF vs. Input-SBM) for every year. However, each correlation coefficient is not very large: the largest value of the former is 0.5326 in 2009 and that of the latter is 0.4308 in 2008. In contrast, with regard to the correlation between the same measurement methods, interesting results are found. Although a strong correlation—higher than 0.80—exists for the stochastic distance function approach (Output-DF vs. Input-DF), a weak correlation—lower than 0.34—exists for the SBM (Output-SBM vs. Input-SBM). The latter coefficients are lower than those between the pairs of unrelated measures for every year (Output-DF vs. Input-SBM and Input-DF vs. Output-SBM).

These results further indicate that the differences in methodologies and orientations of computing efficiency may lead to inconsistent outcomes. Thus, when examining a causal relationship between efficiency measures and other variables for Japanese credit cooperatives, the choice of efficiency measure is a critical issue, particularly when considering policy implications. To verify these problems, in the next subsection we apply regression analysis to investigate the determinants of each efficiency score.

<Insert Table 7>

4.4 Sensitivity analysis of efficiency measures

In the literature on banking efficiency, investigating the determinants of efficiency using regression analysis is popular. Because the efficiency scores obtained from SFA and DEA range between 0 and 1, employing Tobit regressions in the second stage analysis is common. However, we employ both the Tobit and the OLS regression models to check the robustness of the results because no clear agreement exists on the appropriate methodology.[18] Additionally, to compare the regression results across alternative efficiency measures, we pool the DEA measures on the basis of yearly cross-section data. Following previous studies, we consider several factors as explanatory variables in the regression analysis. We employ capital adequacy ratios (CAR) and ratios of non-performing loans (NPL) as measures of bank health that affect the efficiency level. Moreover, the

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17 The Spearman's rank correlation coefficients were also calculated, and we confirmed the robustness of the results summarized in Table 7. Typically, the Spearman's rank correlation has smaller values than Kendall's rank correlation.

18 McDonald, (2009) argued that the use of the censored regression was considered inappropriate in the second stage analysis and suggested the use of OLS as the most appropriate.

loan-to-deposit ratio (LDR) is considered to investigate the willingness to meet loan demand by reducing investments in securities for each credit cooperative. The logarithm of total assets (TAST) is considered to account for differences in bank size. In accordance with previous studies that report a decline in efficiency directly following a merger, a dummy variable for credit cooperatives that experienced a merger in each fiscal year (MADM) is also included. Indeed, to confirm the previous results between four different types of credit cooperatives, we include three dummy variables ($TYDM_j$). We define the type of domestic residents as the basis for comparison.

Table 8 presents the results of the regression using output-oriented efficiency measures. For the Output-DF measures (as shown on the left side of Table 8), the estimates of bank health variables (CAR and NPL) are statistically significant, suggesting that a poor financial condition appears to be less efficient. Moreover, the LDR results show that the willingness to meet loan demands positively influence efficiency measures. Additionally, consistent with findings from previous studies, mergers lead to declines in efficiency. Regarding the dummy variable estimates for each credit cooperative type, the dummy for ethnic minority residents ($TYDM_2$) is statistically significant and positive, suggesting that credit cooperatives owned by ethnic minority residents are more efficient than the domestic residents type. The dummy for industry-based type ($TYDM_3$) is also statistically significant but negative, suggesting that industry-based credit cooperatives are less efficient than the domestic residents type. These findings are consistent with the previous results of the Steel–Dwass pairwise comparisons in Table 3. No remarkable differences are found between the Tobit and the OLS estimates. In contrast, the results for the Output-SBM measures (as shown on the right side of Table 8) reveal that almost all of the estimates are insignificant without the bank health variables. In particular, all of the dummy variables' estimates for each credit cooperative type are insignificant for the Tobit and OLS results. These extremely divergent results are reminders of the difficulties and problems in selecting efficiency analysis methods when considering policy implications.

<Insert Table 8>

Next, Table 9 presents the results of the regression using input-oriented efficiency measures. For the Input-DF measures (as shown on the left side of Table 9), similar to the previous results for the Output-DF measures, the estimates of CAR, NPL, LDR, and MADM are statistically significant and possess the same sign. The estimates of the logarithm of total assets (TAST) are negative and statistically significant at the 10% level. The dummy variables for ethnic minority residents ($TYDM_2$) are positive but statistically significant only for the OLS results. In addition, the dummy variables for the industry-based type ($TYDM_3$) are statistically significant and negative. The implications for these estimates are consistent with the previous results of the Steel–Dwass pairwise comparisons in Table 4. The results for the Input-SBM measures regarding the estimates of the explanatory variables except for the three credit cooperative type dummies (as shown on the right side of Table 9) are quite similar to those for the Input-DF measures. Interestingly, in sharp contrast to the previous results for the Output-SBM measures in Table 8, all dummy variable estimates for each credit cooperative type are statistically significant. However, the signs of $TYDM_3$ and $TYDM_4$ are the reverse of those of the results for the Input-DF measures. Thus, according to the results of the Input-SBM measures, domestic residential credit cooperatives are significantly less efficient than the other types of ownership structures, supporting the previous results of the Steel–Dwass pairwise comparisons in Table 6.

<Insert Table 9>

In summary, at least for the ethnic minority-owned cooperatives, superior efficiency results are confirmed regardless of the differences in efficiency measures. These results are very consistent with the previous findings of Fukuyama et al. (1999), although the periods are different.[19] Given the abrupt changes in ethnic minority-owned cooperatives during the last two decades, our findings suggest that consolidation has a beneficial effect on efficiency gains.[20] As previously described, nearly 80% of the ethnic minority-owned cooperatives disappeared through consolidation during this period. In contrast, the validity of small financial cooperatives was not supported. In particular, the credit cooperatives classified as the industry-based type are statistically less efficient than those owned by domestic residents for the Output-DF and Input-DF measures. These results suggest the difficulties in expanding business operations for the industry-based type given their membership constraints.[21] Indeed, membership expansion is not necessarily beneficial to improve the efficiency of financial cooperatives.[22] However, it is probably apparent that the principle of cooperation

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[19] Elyasiani and Mehdian (1992) also found that minority-owned banks are significantly superior to non-minority-owned banks.

[20] Regarding the efficiency effects of mergers among cooperative financial institutions, the results were mixed. For instance, Garden and Ralston (1999) and later Ralston et al. (2001) found that mergers did not increase the technical or allocative efficiency of Australian credit unions relative to their unmerged counterparts. In contrast, as previously described, Fried et al. (1999) found the opposite results for U.S. credit unions.

[21] At the end of FY 2012, 21 out of 27 industry-based type credit cooperatives were owned by medical service workers(i.e., mainly medical practitioners). In addition to total asset size, the number of members is significantly smaller for this type of credit cooperative. Moreover, the number of industry-based type credit cooperatives owned by medical service workers remained about the same during the last two decades; 22 out of 42 industry-based type credit cooperatives are owned by medical service workers at the end of FY 1990.

[22] In U.S. credit union studies, Leggett and Strand (2002) found that agency problems grow as credit unions add membership groups and members, and contribute to worsening performance. Additionally, Frame et al. (2002) showed that credit union membership expansion dilutes the information advantages associated with a tight common bond of association.

restricts the ability of industry-based credit cooperatives to aggressively seek profits.

5. Conclusion

This study investigates the validity of small Japanese financial cooperatives by estimating the technical efficiency during 2008–2012. We first employ a stochastic directional distance function approach to estimate the technical efficiency for each credit cooperative and compare the results with those obtained by the non-parametric SBM. Thereafter we perform statistical tests to compare the efficiency of four groups classified by the nature of the owners' characters. Finally, to confirm the robustness of the results, we use regression analysis and verify the determinants of the differences in efficiency.

The results from the stochastic directional distance functions show significant differences in the variances between the four groups of credit cooperatives for both the output- and input-oriented measures. Moreover, consistent with the previous findings of Fukuyama et al. (1999), credit cooperatives owned by ethnic minority residents are significantly more efficient than those owned by regional domestic residents. In contrast, the results of the SBM measures are quite different, and no significant differences in variances between the four groups are found for the output-oriented scores. However, superior efficiency results of ethnic minority-owned cooperatives are confirmed for the input-oriented scores. Such apparent inconsistent outcomes between the alternative efficiency measures are verified as the weak rank correlations. The regression results also reveal that industry-based credit cooperatives are significantly less efficient than regional membership cooperatives with respect to the measures derived from stochastic directional distance functions.

To summarize, although we cannot conclude the validity of small credit cooperatives, the robustness results of the ethnic minority-owned cooperatives suggest the possibility of positive effects from further consolidation. Certainly, the consolidations among financial institutions seem to weaken the relationships between borrowers and lenders. However, the fact that increasing the number of memberships for small credit cooperatives is difficult without consolidation still prevails, and the tendency is stronger for the industry-based type, thus limiting the scope of the membership. In contrast, our results should be carefully considered because the chosen method of measuring efficiency has some influence over the results. Nevertheless, very little literature exists on the comparison of efficiency measures, particularly on Japan's credit cooperative data. Furthermore, because this study is the first attempt to employ a stochastic directional distance function approach, our findings may provide new insights into Japan's current credit cooperatives.

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Table 1. Descriptive statistics of variables used in the efficiency analysis (2007-2012)

(Unit：Person，Yen [in Million]）

Variables	Mean	Std. Dev.	Min	Max
Interest on loans and discounts (y_1)	1,690	2,388	18	19,131
Other interest and dividend income (y_2)	516	840	6	8,560
Fees and commissions (y_3)	108	197	0	2,076
Deposits (x_1)	108,760	148,177	3,080	1,205,405
Employees (x_2)	136	167	4	1,429
Tangible fixed assets (x_3)	1,727	2,535	0.27	17,323
Observaions			794	

Table 2. Parameter estimates of distance function

Parameter	Output distance function			Input distance function		
	Coefficient		Std. Err.	Coefficient		Std. Err.
const	-0.0987	***	0.0150	0.0901	***	0.0143
α_1				-0.5031	***	0.0138
α_2	0.3740	***	0.0082	-0.3569	***	0.0091
α_3	0.1133	***	0.0130	-0.1092	***	0.0128
β_1	-0.8155	***	0.0202			
β_2	-0.1498	***	0.0245	0.1711	***	0.0229
β_3	-0.0450	***	0.0114	0.0232	**	0.0109
α_{11}				-0.0266	***	0.0067
α_{12}				0.0777	***	0.0135
α_{13}				-0.0226	***	0.0070
α_{22}	0.0413	***	0.0064	-0.0479	***	0.0076
α_{23}	-0.0085		0.0074	-0.0099		0.0092
α_{33}	0.0187	***	0.0047	0.0092	***	0.0029
β_{11}	-0.1109	***	0.0228			
β_{12}	0.1710	***	0.0534			
β_{13}	0.0016		0.0123			
β_{22}	-0.0077		0.0366	0.0271		0.0295
β_{23}	-0.0343	*	0.0187	0.0295	*	0.0170
β_{33}	-0.0007		0.0039	0.0013		0.0037
δ_{12}				-0.0433	**	0.0206
δ_{13}				0.0142	**	0.0069
δ_{21}	0.0680	***	0.0188			
δ_{22}	-0.0465	*	0.0249	-0.0355		0.0255
δ_{23}	-0.0136	*	0.0070	0.0251	***	0.0081
δ_{31}	-0.0008		0.0148			
δ_{32}	-0.0189		0.0220	-0.0448	**	0.0185
δ_{33}	0.0122	**	0.0061	-0.0142	***	0.0049
DM_{v09}	0.0316	**	0.0151	-0.0272	*	0.0145
DM_{v10}	0.0884	***	0.0154	-0.0807	***	0.0148
DM_{v11}	0.1382	***	0.0158	-0.1252	***	0.0151
DM_{v12}	0.1656	***	0.0162	-0.1485	***	0.0156
$\ln\sigma_v^2$	-4.2486	***	0.0986	-4.3933	***	0.1012
$\ln\sigma_u^2$	-5.3058	***	0.2971	-5.1635	***	0.2511
LL	437.01			471.28		
LR-test	12.65	***		21.47	***	
Observations	794			794		

Notes: *, **, and *** denote a significant estimator at the 10%, 5%, and 1% levels, respectively.

Table 3. Descriptive statistics on efficiency scores derived from the output distance function

	Total samples			Type of ownership structures											
				Regional domestic residents			Ethnic minority residents			Industry-based			Occupation-based		
	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.
2008	0.9343	0.0323	162	0.9334	0.0362	101	0.9421	0.0157	16	0.9283	0.0268	27	0.9413	0.0257	18
2009	0.9356	0.0254	159	0.9375	0.0185	99	0.9415	0.0165	16	0.9217	0.0426	27	0.9407	0.0257	17
2010	0.9316	0.0361	158	0.9327	0.0307	98	0.9429	0.0126	16	0.9120	0.0576	27	0.9456	0.0227	17
2011	0.9292	0.0444	158	0.9303	0.0340	98	0.9475	0.0142	16	0.9047	0.0790	27	0.9447	0.0202	17
2012	0.9263	0.0544	157	0.9266	0.0543	97	0.9486	0.0183	16	0.9024	0.0722	27	0.9414	0.0257	17
All	0.9314	0.0398	794	0.9321	0.0365	493	0.9445	0.0155	80	0.9138	0.0588	135	0.9427	0.0237	86

Table 4. Descriptive statistics on efficiency scores derived from the input distance function

	Total samples			Type of ownership structures											
				Regional domestic residents			Ethnic minority residents			Industry-based			Occupation-based		
	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.
2008	0.9327	0.0388	162	0.9331	0.0400	101	0.9414	0.0175	16	0.9226	0.0465	27	0.9379	0.0323	18
2009	0.9347	0.0306	159	0.9374	0.0196	99	0.9409	0.0183	16	0.9204	0.0545	27	0.9354	0.0367	17
2010	0.9302	0.0400	158	0.9316	0.0313	98	0.9417	0.0172	16	0.9091	0.0685	27	0.9456	0.0266	17
2011	0.9278	0.0483	158	0.9285	0.0380	98	0.9461	0.0192	16	0.9041	0.0846	27	0.9438	0.0254	17
2012	0.9241	0.0593	157	0.9239	0.0592	97	0.9466	0.0241	16	0.9006	0.0791	27	0.9415	0.0284	17
All	0.9299	0.0445	794	0.9310	0.0398	493	0.9433	0.0191	80	0.9113	0.0677	135	0.9408	0.0297	86

Table 5. Descriptive statistics on efficiency scores derived from the slack-based output-oriented DEA model

	Total samples			Type of ownership structures											
				Regional domestic residents			Ethnic minority residents			Industry-based			Occupation-based		
	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.
2008	0.5892	0.2282	162	0.6001	0.1398	101	0.5315	0.1465	16	0.5259	0.3547	27	0.6746	0.3855	18
2009	0.5939	0.2266	159	0.5855	0.1356	99	0.5461	0.2209	16	0.5935	0.3709	27	0.6880	0.3362	17
2010	0.5725	0.2366	158	0.5644	0.1392	98	0.5214	0.2146	16	0.5941	0.3699	27	0.6327	0.3984	17
2011	0.5207	0.2303	158	0.5192	0.1444	98	0.4839	0.2324	16	0.5468	0.3376	27	0.5230	0.3941	17
2012	0.5039	0.2333	157	0.4862	0.1395	97	0.4697	0.2353	16	0.5571	0.3467	27	0.5528	0.3952	17

Table 6. Descriptive statistics on efficiency scores derived from the slack-based input-oriented DEA model

	Total samples			Type of ownership structures											
				Regional domestic residents			Ethnic minority residents			Industry-based			Occupation-based		
	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.	Mean	Std Dev.	Obs.
2008	0.6065	0.1875	162	0.5316	0.1384	101	0.6569	0.1080	16	0.7094	0.2100	27	0.8274	0.1957	18
2009	0.6337	0.1917	159	0.5493	0.1348	99	0.7221	0.1227	16	0.7570	0.2239	27	0.8463	0.1750	17
2010	0.6251	0.1972	158	0.5527	0.1438	98	0.6842	0.1536	16	0.7583	0.2359	27	0.7750	0.2332	17
2011	0.5904	0.1890	158	0.5201	0.1415	98	0.6695	0.1420	16	0.7023	0.2261	27	0.7438	0.2105	17
2012	0.5945	0.1985	157	0.5138	0.1432	97	0.6627	0.1505	16	0.7238	0.2316	27	0.7855	0.2043	17

Table 7. Correlation coefficients of the efficiency scores

		Output-DF	Input-DF	Output-SBM	Input-SBM
2008	Output-DF	−	−	−	−
	Input-DF	0.8034	−	−	−
	Output-SBM	0.5296	0.5378	−	−
	Input-SBM	0.4726	0.4308	0.3339	−
2009	Output-DF	−	−	−	−
	Input-DF	0.8237	−	−	−
	Output-SBM	0.5326	0.5067	−	−
	Input-SBM	0.3954	0.3466	0.3390	−
2010	Output-DF	−	−	−	−
	Input-DF	0.8297	−	−	−
	Output-SBM	0.4065	0.3712	−	−
	Input-SBM	0.4236	0.3780	0.3179	−
2011	Output-DF	−	−	−	−
	Input-DF	0.8160	−	−	−
	Output-SBM	0.4492	0.3266	−	−
	Input-SBM	0.4679	0.4063	0.2556	−
2012	Output-DF	−	−	−	−
	Input-DF	0.8112	−	−	−
	Output-SBM	0.4673	0.3491	−	−
	Input-SBM	0.4483	0.4203	0.3177	−

Notes: Each score is computed as the Kendall's rank correlation coefficients.

Table 8. Determinants of output-oriented efficiency scores

Variable	Dependent Variable							
	Output-DF Efficiency				Output-SBM Efficiency			
	Tobit		OLS		Tobit		OLS	
	Coefficient	Std. Error.	Coefficient	Std. Error.	Coefficient	Std. Error.	Coefficient	Std. Error.
Constant	0.8816***	0.0252	0.8822***	0.0275	0.2161	0.1839	0.2160	0.1729
CAR	0.0010***	0.0002	0.0010***	0.0002	0.0051***	0.0015	0.0041***	0.0016
NPL	-0.0006**	0.0002	-0.0006***	0.0002	-0.0041**	0.0018	-0.0036***	0.0012
LDR	0.0003***	0.0001	0.0003***	0.0001	0.0007	0.0007	0.0006	0.0008
TAST	0.0016	0.0013	0.0016	0.0015	0.0155	0.0097	0.0158*	0.0086
MADM	-0.1340***	0.0165	-0.1339*	0.0800	-0.0222	0.1202	-0.0397	0.1215
$TYDM_2$	0.0104**	0.0047	0.0104***	0.0028	-0.0205	0.0337	-0.0293	0.0246
$TYDM_3$	-0.0265***	0.0049	-0.0265***	0.0063	-0.0195	0.0359	-0.0363	0.0364
$TYDM_4$	0.0007	0.0052	0.0007	0.0035	0.0528	0.0383	0.0180	0.0435
Pseudo R^2	-0.0475				0.0858			
Adj R^2			0.1490				0.0253	
Observations	794							

Notes: ***, **, and * stand for significance at the 1%, 5%, and 10% levels, respectively. White heteroskedasticity adjusted standard error for OLS.

Table 9. Determinants of input-oriented efficiency scores

Variable	Dependent Variable											
	Input-DF Efficiency						Input-SBM Efficiency					
	Tobit			OLS			Tobit			OLS		
	Coefficient		Std. Error.	Coefficient		Std. Error.	Coefficient		Std. Error.	Coefficient		Std. Error.
Constant	0.9540	***	0.0283	0.9540	***	0.0302	0.4064	***	0.1261	0.4110	***	0.1167
CAR	0.0010	***	0.0002	0.0010	***	0.0002	0.0063	***	0.0011	0.0054	***	0.0010
NPL	-0.0009	***	0.0003	-0.0009	***	0.0002	-0.0057	***	0.0012	-0.0053	***	0.0009
LDR	0.0005	***	0.0001	0.0005	***	0.0001	0.0026	***	0.0005	0.0024	***	0.0006
TAST	-0.0029	*	0.0015	-0.0029	*	0.0017	-0.0012		0.0067	-0.0008		0.0055
MADM	-0.1370	***	0.0185	-0.1370		0.0846	-0.0374		0.0817	-0.0467		0.1229
$TYDM_2$	0.0084		0.0052	0.0084	***	0.0031	0.1475	***	0.0231	0.1401	***	0.0158
$TYDM_3$	-0.0294	***	0.0055	-0.0295	***	0.0065	0.1635	***	0.0246	0.1501	***	0.0264
$TYDM_4$	-0.0050		0.0058	-0.0050		0.0041	0.2243	***	0.0264	0.1951	***	0.0247
Pseudo R^2	-0.0494						1.8603					
Adj R^2				0.1457						0.3301		
Observations	794											

Notes: ***, **, and * stand for significance at the 1%, 5%, and 10% levels, respectively. White heteroskedasticity adjusted standard error for OLS.