Eurasian Journal of Business and Economics 2014, 7 (13), 69-90

Robust Estimation of Productivity Changes in Japanese Shinkin Banks

Jianzhong DAI[*]

Abstract

This paper estimates productivity changes in Japanese shinkin banks during the fiscal years 2001 to 2008 using the Malmquist index as the measure of productivity change. Data envelopment analysis (DEA) is used to estimate the index. We also apply a smoothed bootstrapping approach to set up confidence intervals for estimates and study their statistical characteristics. By analyzing estimated scores, we identify trends in productivity changes in Japanese shinkin banks during the study period and investigate the sources of these trends. We find that in the latter half of the study period, productivity has significantly declined, primarily because of deterioration in technical efficiency, but scale efficiency has been significantly improved. Grouping the total sample according to the levels of competition reveals more details of productivity changes in shinkin banks.

Keywords: *Productivity, Banking, DEA, Smoothed Bootstrapping, Japan.*

JEL Code Classification*: C14, D24,G21*

[*] PhD candidate, Department of Economics, Kyushu University, Japan. Associate professor, School of Business, Nanjing University, China. E-mail: jianzhongdai@yahoo.com

1. Introduction

In this paper, we offer a robust estimation of the productivity changes in the Japanese shinkin banks from Fiscal Year (FY) 2001 to FY 2008. Shinkin banks are among the most important regional financial institutions in Japan. According to the "Shinkin Bank Act" published in June 1951, shinkin banks are regional, non-profit and mutual financial institutions, aimed at servicing small and medium enterprises (SMEs) and local inhabitants.

At the beginning of the 21st century, the Japanese economy struggled out from a "credit crunch" caused by the burst of the "bubble economy". In the first half of the 2000s, Japan enjoyed relatively high economic growth, but this trend was broken in the latter half of the 2000s. The environment of government supervision also changed. During this period, to strengthen the economy, the Japanese government significantly restructured the financial system. As the result, shinkin banks also experienced a lot of changes. Their permitted scope of business was widened. Many mergers and acquisition (M&A) cases occurred in the early 2000s. This scenario makes Japanese financial institutions in this period an interesting case for the analysis of the sources of productivity changes in the financial institutions. The analysis will not only contribute to the literature about the effects of environmental transformations on productivity changes, but also has meaningful illumination for policy makers in other countries considering financial restructuring.

This paper estimates productivity changes in shinkin banks by using a measurement called Malmquist index. The nonparametric data envelopment analysis (DEA) approach is used to estimate the index. By analyzing estimated scores, we examine trends in productivity changes in shinkin banks during the study period. We further decompose the estimated scores to inspect the sources of the trend. By comparing the productivity changes between different sub-periods and among different groups, we are able to deduce the effects of environmental transformations on the productivity changes in shinkin banks as a whole and the differences of the effect upon different kinds of shinkin banks.

Many papers have used the DEA approach to analyze the efficiency of financial institutions[1]. More recent papers include Rebelo and Mendes (2000) for the Portuguese banking, Kumar and Gulati (2008) for Indian public sector banks, Wheelock and Wilson (2008) for the U.S Federal Reserve check processing operations, Kao and Liu (2009) for the Taiwan commercial banks, Wheelock and Wilson (2009) for the U.S commercial banks, Nigmonov (2010) for Uzbekistan banks, Kaur and Kaur (2010) for the india banks, Behname (2012) for a sample of OPEC banks. Following Wheelock and Wilson (2009), we use the hyperbolic-oriented distance as the measure of efficiency. However, whereas they used the quantile estimation approach to deal with the stochastic characteristics of

[1] For an early literature survey in this area, see Berger and Humphrey (1997). For a more recent survey, see Fethi and Pasiouras (2010).

estimates, we use the smoothed bootstrapping method recommended also by Simar and Wilson (1999) to set confidential intervals for the estimated scores.

There are also some papers analyzing efficiency and productivity changes in Japanese financial institutions; Papers using the parametric approach include: McKillop et al. (1996), who analyzed the cost efficiencies of five giant Japanese city banks over the period 1978-1991 by estimating a composite cost function; Altunbas et al. (2000), who investigated the pure and scale efficiency for a sample of Japanese commercial banks between 1993 and 1996; The above analysis all focused on the periods of financial crisis and restructuring. On the contrary, Tadesse (2006) analyzed the scale economy and technical changes for a sample of Japanese banks during the period of 1974-1991, which is a period of relative stability and high growth. Meanwhile papers using DEA approaches include: Fukuyama (1993), who analyzed the efficiency of Japanese banks in FY 1991. Fukuyama (1996), who analyzed the technical and scale economy of Japanese credit associations in FY 1992. Fukuyama and Weber (2008), continued the study for the period of FY 2002-FY 2004. Drake and Hall (2003), who estimated the scale efficiency of Japanese banks in FY 1996. Drake et al. (2009), who used a slack based model (SBM) to estimate the efficiency of Japanese financial institutions during the period of 1995-2002 and compared the efficiency scores under different assumption of input and outputs. Horie (2010), who analyzed the sources of the efficiency and productivity changes in the Japanese shinkin banks during the period of FY 2005-FY2007. Among them Fukuyama (1996), Fukuyama and Weber (2008) and Horie (2010) are most closely related to the present paper. Fukuyama (1996), Fukuyama and Weber (2008) emphasized the importance of the choice of the direction of measurement. We follow the method used by Fukuyama and Weber (2008), but we use hyperbolic rather than directional distance as the measure of efficiency. Directional distance considers both the input and output efficiency, but it is not easy to decompose. Our choice of input and output is the same as Horie (2010). However, Horie (2010) divide the total sample into three sub-groups according to their “operational areas” and estimated a frontier for each group. In our case, we pool the sample together to estimate a single frontier. We do so for consideration of further regression analysis on the cause of productivity changes, in which “operational areas” may be one explanatory variable. Another difference is that Horie’s is deterministic in nature. Ours are stochastic.

This paper makes several contributions to the literature. First, we use the nonparametric bootstrapping approach suggested by Simar and Wilson (1999) to get robust estimates of the Malmquist index. To our knowledge, this is the first attempt of such kind in Japanese financial institutions. Second, we use the hyperbolical-oriented distance instead of input- or output-oriented Shephard distance as the measure of efficiency. This is also the first attempt of using this measurement for the case of Japanese financial institutions. Like the directional distance measurement which was used by Fukuyama and Weber (2008), hyperbolical-oriented distance considers both output and input efficiency, making it a very objective measurement of efficiency. With this measure, we avoid the problem of possible discrepancies between input- and output-oriented distances. Unlike directional distance, it can be decomposed. In addition, hyperbolic-oriented distance is closely linked to the concept of profit, which is the conventional measure of efficiency.

The rest of this paper is arranged as follows: Section 2 conducts a brief literature review on the research methodology. Section 3 describes the data and the variables. Section 4 presents and analyzes the estimation results. Section 5 draws conclusions from the analysis. The technical details are presented in the appendix.

2. The Methodology

The approach we used in this study consists of three steps: In the first step we measure efficiency for each sample year using the nonparametric DEA approach. In the second step, we calculate and decompose the Malmquist index based on the efficiency measurement conducted in the first step. In the third step, we use a re-sampling technique called smooth bootstrapping to establish confidence intervals for the estimated Malmquist index and also do some tests.

2.1 Measurement of Efficiency

In this paper, efficiency is the relative performance of a decision making unit (DMU) compared to a standard of best practices. One of the widely used measures of efficiency is “Shephard distance”. Shephard distance can be estimated either along the direction of input or output. Under the constant return to scale (CRS) assumption, both input- and output-oriented measures of efficiency are the same for any DMU. Hence using either measure makes no difference. However, under the variable return to scale (VRS) assumption, results may significantly vary, especially for DMUs located at the extremes of the production set (Fukuyama, 1996).

There are still no theoretical foundations that can guide the choice between input and output orientations. Thus, to obtain an unbiased measure of efficiency, some papers have used other measures. One of these measures is the so called hyperbolic-oriented distance. Given an arbitrary production point, hyperbolic-oriented efficiency is defined as the proportion needed to reduce the input and increase the output simultaneously to push the point to the frontier.
Mathematically, we can define the production set Ψ^t at time *t* as

$$\Psi^t = \left\{(x,y)\Re^{N+M} \mid x \text{ can produce } y \text{ at time } t\right\} \tag{1}$$

Where $x \in \Re^N$ is the *N* dimension vector of input and $y \in \Re^M$ is the *M* dimension vector of output. The Shephard hyperbolic-oriented distance D_0 for a point (x_0, y_0) in the production set is defined as

$$D_0 = \sup\{\gamma > 0 \mid (x/\gamma, \gamma y) \in \Psi^t\} \tag{2}$$

Where γ is the scale that needed to decrease x_0 and increase y_0 simultaneously to push the point (x_0, y_0) to the efficient frontier $\partial^t Q(x, y)$ (the set that constituted by efficient DMUs, which are those points with $\gamma = 1$).
In the case of multiple input and output, parametric and nonparametric approaches have been developed to estimate radial production efficiency. Data envelopment analysis (DEA) is one of the most widely used nonparametric approaches. DEA identifies efficient DMUs through linear or non-linear programming. The production frontier is the convex combination of optimal points (see appendix for programming details).

Compared to the parametric approach, one advantage of DEA is that it does not assume any functional form for the production function ; thus it avoids the difficulty of specifying a correct functional form. Another strong point of DEA is that it does not require any information on the prices of output and input, which are sometimes difficult to gather or even does not exist (in our case, obtaining the prices of the labor input of shinkin banks is difficult because of the increasing importance of hiring temporary workers and outsourcing) .

However, the traditional DEA approach also has some shortcomings. Unlike the parametric approaches, the traditional DEA approach does not take into consideration random effects in models; because it assumes that there are no random factors that temporarily influence efficiency scores. Similarly, measurement errors are also ignored. It is also well known that nonparametric models like DEA are more sensitive to the outliers compared with the parametric models. More important, since traditional DEA models are deterministic in nature, it is impossible to test the significance of the DEA estimates statistically.

2.2 Measurement of the Productivity Changes and the Malmquist Index

Given a panel database, we can measure productivity changes over time besides estimating efficiency of DMUs for a fixed year. Productivity measures the ability of DMUs to turn inputs into outputs. From a static point of view, productivity and efficiency are almost the same. However, from a dynamic point of view, these two concepts are somewhat different. Over a given period, not only DMU efficiency but also the technology of the whole industry (i.e., the production potential) may be changed. Thus, compared with the static efficiency measurement, the measurement of productivity changes not only provides a dynamic view of the productivity, but also offers information on the changes in industrial technology.

In case of multiple outputs and inputs, economic and management analysts have used various approaches in measuring productivity changes. Among these approaches, Malmquist index is the most widely used. The Malmquist index can be estimated using the DEA approach; so no information on input and output prices is needed. Furthermore, the index can easily be decomposed to analyze sources of productivity changes. In this paper, we use the Malmquist index to measure productivity changes.

In the Malmquist index, Shephard distance is used as the measure of efficiency. Beside calculating the distance of DMU *i* in year *t* according to the frontier of year *t* as $D_i^{t,t}$, we can estimate the distance of DMU *i* in year *t+1* according to the frontier of year *t* as $D_i^{t,t+1}$. Similarly, we can calculate the distance of DMU *i* in year *t* and *t+1* both according to the frontier of year *t+1* as $D_i^{t+1,t}$ and $D_i^{t+1,t+1}$ respectively. The Malmqust index is the geometric average of the two ratios:

$$M_i = \left[\frac{D_i^{t,t+1}}{D_i^{t,t}} \times \frac{D_i^{t+1,t+1}}{D_i^{t+1,t}} \right]^{1/2} \tag{3}$$

The explanation of *M* depends on the method used to calculate the distance *D*. For input- or hyperbolic-oriented distance, a larger (smaller) value of *M* means deterioration (improvement) of productivity over time. On the other hand, for the output-oriented distance, a larger (smaller) value of *M* means an improvement (deterioration) in productivity over time.

To detect sources of the productivity changes, we need to decompose the Malmquist index into several components. We use a decomposition method called FGLS which was first proposed by Färe, Grosskopf, Lindgren and Roos (1992):

$$M = EC_v \times SC \times TC \tag{4}$$

Where

$$EC_v = \frac{D_v^{t+1,t+1}}{D_v^{t,t}};\ SC = \left(\frac{D_C^{t+1,t+1}}{D_V^{t+1,t+1}} \right) / \left(\frac{D_C^{t,t}}{D_V^{t,t}} \right) = \frac{SE^{t+1}}{SE^t}\ ;\ TC = \left[\frac{D_c^{t,t+1}}{D_c^{t+1,t+1}} \times \frac{D_c^{t,t}}{D_c^{t+1,t}} \right]^{1/2}$$

D is defined as in equation (2), except the low subscript *V* and *C* are distances calculated under the VRS and CRS assumptions, respectively.

EC_v is the change in pure technical efficiency. It also called the "catch up effects", since it measures the change in position of a given DMU to the current frontier between year *t* and *t+1* under the assumption of VRS. *SC* is the change in scale economy and the ratios SE^t and SE^{t+1} are indexes for scale economy in year *t* and *t+1* respectively. *SE* is the ratio of VRS distance to CRS distance. *TC* is the technological changes. It is the geometric average of two ratios. The first item is the ratio of the distances of a DMU *i* in time *t* to the frontier in *t* and in *t+1*, respectively. The second term is the ratio of the distances for the same DMU in time *t+1*. Because *TC* measures the productivity changes due to the movement of the CRS production frontier from time *t* to *t+1*, it is also called "frontier shift effects". Note unlike other components of the index, the distance in time *t* is in the numerator while the distance in time *t+1* is in the denominator. Therefore for a hyperbolic distance *TC* less than 1(larger than 1) means an outward (inward) shifts of the frontier (as other components are).

2.3 Confidence Intervals and Hypothesis Testing for the Malmquist Index

As mentioned earlier, traditional DEA efficiency scores and the Malmquist index based on them are deterministic in nature. No random effects or errors are assumed. Recently some researchers have tried to overcome this weakness of the DEA approach. However, detailed asymptotic distribution of the DEA scores remains unknown.

When the exact form of the distribution of an estimator is unknown, bootstrapping becomes an appealing instrument for analyzing some statistical properties of the estimator. Simar (1992) was the first to introduce the bootstrapping method into the estimation of production frontiers.

In the case of the hyperbolic-oriented efficiency estimator $\hat{\gamma}$ and its corresponding Malmquist index $\hat{m}$, bootstrapping means generating *B* new samples of production sets $Q_{ij}^{*} = (x_{ij}^{*}, y_{ij}^{*}),\ i = 1 \cdots n,\ j = B$ by repeatedly generating new samples from the original sample *B* times (data generating process), and then calculating the corresponding hyperbolical-oriented distance for each DMU ($\hat{\gamma}_{ij}^{*},\ i = 1 \cdots n,\ j = 1, \cdots, B$) and the corresponding Malmquist index ($\hat{m}_{ij}^{*}, i = 1 \cdots n,\ j = 1, \cdots, B$). Through the distribution of $\hat{m}^{*}$, we obtain some of the statistical properties of $\hat{m}$. These properties enable us to draw some inferences about $\hat{m}$. In our case, we can calculate confidence intervals or test some hypothesis about $\hat{m}$.

2.3.1 Data Generation Process

The simplest way of bootstrapping is repeatedly drawing items with replacement uniformly from the original sample. The advantage of this simple (naïve) bootstrapping is that it does not require estimating the probability density function (p.d.f) of data, which simulations usually require. However, if we generate samples of the same size as the original sample, we will most likely generate samples which include certain items of the original sample more than once. In some situations, this may cause serious problems because the influence of the repeated items may be overly magnified.

To overcome the foregoing shortcoming, we utilize the smoothed bootstrapping approach recommended by Simar and Wilson (1999). This approach combines the advantages of simulation and bootstrapping. In smoothed bootstrapping, we need to define a p.d.f for the original sample. However, unlike in case of simulation, we need not estimate the exact p.d.f. We generate new samples using the naïve bootstrapping method and then perturb the new samples by some standard error σ of the defined p.d.f to get a “smoothed” sample.

Malmquist index estimation requires distance measure *D* in two periods, so a joint p.d.f smoothed bootstrapping is needed.

We also need to determine the number of bootstrapping samples *B*. To get more robust results, we choose *B*=2000.

For the technical details of the smooth bootstrapping approach used in this research, see Simar and Wilson (1999).

2.3.2 Confidence Interval and Hypothesis Testing for $\hat{m}$ Using Bootstrapping

Using $m_{ij}^*,\ i = 1 \cdots n,\ j = B$ generated from the smoothed bootstrapping process, we estimate the confidence interval for $\hat{m}$ at each point *i* in the sample. The distribution of m_{ij}^* is unknown, so we use a method called quantile approach to estimate the confidence intervals and arrange the *B* number of m_{ij}^* from the lowest to the largest:

$$m_{i1}^* \le m_{i2}^* \le \cdots \le m_{iB}^*$$

According to the principle of order statistics, the lower bound of m_i^* with p confidence level is the m_{ij}^* with order $l = N(1-p)$. On the other hand, the upper bound of m_i^* with p confidence level is the m_i^* with order $l = Np$ [2].

In a similar way, we can test hypotheses by using bootstrapping results. For example, if we are interested in whether, on average, productivity change in the first period ($\overline{m}_1$) is significantly different from that in the second period ($\overline{m}_2$), for each sample *j* generated from bootstrapping we can calculate its average $\overline{m}_{tj}^* = \frac{1}{N}\sum_{i=1}^{N} m_{ti}^*,\ t=1,2,\ i=1,\cdots,N;\ j=1,\cdots,B$. Thereafter, we can calculate the statistic $t_j = \overline{m}_{2j}^* - \overline{m}_{1j}^*,\ \ j=1,\cdots,B$. Using quantile approach, we can calculate the left-side significance level (*SL*) of the hypothesis $t_j < 0$ as

$$SL_{t_j<0} = \#(t_j < 0)/B,\ j=1,\cdots,B \tag{5}$$

[2] For example, if B=1000 and we want the lower bound of m_{ij}^* at 95% confidence level, we need only to find the m_{ij}^* whose order is 50 because the proportion of m_i^* that is smaller than m_{i50}^* is 5%. Following the same reasoning, if we want the upper bound of m_{ij}^* at 95% confidence level, we need only to find the m_{ij}^* whose order is 950 because the proportion of m_i^* that is higher than m_{i950}^* is also 5%.

Where $\#(t_j < 0)$ is the number of t_j which is less then 0. In a similar way we can also get the right-side significance level ($t_j > 0$)

3. Data

Our data consist of annual data from the income statements of the shinkin banks from FY 2001 to FY 2008. The data come from the database of Nikkei NEED[3].

In the estimation of productivity changes, one difficulty is the choice of time length. If the time length is too short, it is very likely that no significant changes in productivity will be detected. Besides, normally more than 2 years are needed for the effects of M&A to be fully exposed (Horie, 2010). For this reason, as well as for the purpose of balance, we choose a 3 year time length. This divides the entire study period into two 3 year periods (i.e., FY 2001 to FY 2004 and FY 2005 to FY2008) and results in two estimations of the Malmquist indexes.

M&A and shutdown cause discontinuity in the data for acquired or closed banks. In the case of acquiring banks or the merging banks (some with a new name), the operating environments are also significantly changed, making a simple comparison of these banks before and after the merging misleading. To avoid this problem, for each period we excluded all of those banks which have been involved in the M&A activities or have been closed down during the period. After so doing, for the period FY 2001-FY 2004, the sample is reduced from 303 to 232. However, the sample for the period FY 2005-FY 2008 is rebound to 261 because of the relatively few cases of M & A in the latter part of 2000s.

As mentioned above, one of the serious problems of the DEA analysis is its high sensitivity to outliers. Therefore, to get robust estimates, we need a technique to detect and delete outliers from samples. However, most outlier detection techniques are designed for parametric methods. Here we use the approach suggested by Wilson (1993), which is particularly designed for nonparametric frontier models[4]. By using this technique, 6 outliers are detected in the first period so the sample is further reduced to 226. In the second period, 5 outliers are detected, reducing the sample to 256.

Since the sample banks included in different periods are different, a necessary concern is the possible sample selection bias. However, we already picked out those banks which have over-significant influences on the results in each period. We also used bootstrapping techniques to test the significance of the results. We

[3] This database is offered by the Company "Japanese Economic News" (Nihon keizai Shimbon, Nikkei.) The database includes various kinds of financial and economic data. FY 2001 and FY 2008 are the beginning and end year of the database when the paper is written.

[4] The technique details of the method are not given in the paper due to the limitation of space, interested authors can refer to the paper by Wilson (1993).

believe after these treatments it is possible to compare the results of the two periods.

The choice of output and input is another important, but difficult task in DEA, especially in the case of financial institutions. There are two different definitions of financial institutions. The production approach treats financial institutions as organizations producing financial services. Meanwhile, the intermediation approach looks upon the financial institutions as a medium between debtors and creditors. A major difference between these two definitions of financial institutions lies in input selection. In the production approach, only direct physical input, such as employees and operational spaces are treated as input. Deposits are considered as products offered to customers. On the other hand, in the intermediation approach, medium outputs, such as deposits, are considered as input. For a detailed description of the strengths and weaknesses of these two controversial definitions and their effects on the estimation of the efficiency of the financial institutions, see Berger and Humphrey (1997).

As for the measurement of the scale of output and input, both quantities and values (income or net income for output and cost for input) may be used. There are too many different kinds of financial services that a financial institution may offer, and directly pooling different kinds of products up to a few major categories is usually not possible, so quantity is not an ideal measure of production scale for financial institutions. Meanwhile, in using value measurement, we should keep in mind that values may reflect pricing ability instead of productivity.

As in Horie (2010), the method we used is similar to the production approach. We use the value rather than the volume of output and input as the measures of scales. Since the scope of business of shinkin banks is not as wide as that of large financial institutions in Japan, we focus on credit services provided by shinkin banks, which account for more than 70% of the current incomes of most shinkin banks. In the income statement of shinkin banks, the credit activities are reflected under the entry “Income on funds managed”. We group items under this entry to form two products: A single item in the entry called “Interests from loans”, which is the interest incomes from loans, forms the first product. It is the largest source of interest income of shinkin banks. Meanwhile, other items in the entry, such as interest incomes from call loans, bonds, and deposits in other financial institutions, are aggregated to form the second product called “other interest income”.

Unlike most analysts, we use net income rather than total income as output. We subtract expenses on raising funds for a given credit from income originated from that credit. Using this method, we not only eliminate one input in the model but also avoid the difficult problem of treating deposits in the model. Interest earned from deposits is treated as income, whereas interest paid to depositors is treated as expenses incurred in the production of credit products

Unfortunately, there are no separate entries of interest expenses corresponding to each of the two products. All interest expenses are put under a single entry "Fund Raising Expenses". To get the corresponding expense for each of the two products, following Horie (2010), we break up this single entry into two entries. The equations for the two products are as follows:

$$NY_L = Y_L - \frac{Y_L}{Y_I} C_I \tag{6}$$

$$NY_{NL} = Y_{NL} - \frac{Y_{NL}}{Y_I} C_I \tag{7}$$

Where:

NY_L =net interest from loans;

NY_{NL} = net other interest income;

Y_L = total interest income from loans;

Y_{NL} = total other interest income;

$Y_I = Y_L + Y_{NL}$ = total interest income; and

C_I = total fund raising expenses.

In the input side, we also selected two inputs: One is the labor expenses. In the income statement of shinkin banks, they are recorded under the entry "Labor expenses"; however, this entry only includes the expenses on the formal employees. In recent years, like in other Japanese corporations, informal workers have accounted for an increasingly large proportion of the employees in the shinkin banks. Expenses on these employees are included in the entry called "General expenses", and they account for about one third of this entry (Horie 2010). Due to the lack of information, we cannot segregate expenses on informal employees from general expenses and add them to labor expenses. Thus we should keep in mind that labor expenses do not include all of the cost of labor inputs for shinkin banks.

Another input used in this research is fixed expenses. Roughly speaking, it is the capital input for shinkin banks. This input includes two expense entries in the income statement: "general expenses" and "expenses on service transactions". General expenses consist of rents for stores, depreciation, expenses on advertisements, deposit insurance fees, outsourcing expenses, and expense on informal employees, etc.. Expenses on service transactions are expenses on financial services by the shinkin banks for their financial activities. This entry is neither large enough to be considered as a separate input nor too small to be ignored. Since these expenses are similar to some of the general expenses (e.g., outsourcing expenses and expenses on informal employees), we added them to general expenses.

The data used in this research cover a long length of time; therefore we need to consider the inflation effect. We use the GDP deflator to deflate the data for each period respectively, with the beginning year of each period as 100.

Table 1 presents the descriptive statistics of the inputs and outputs for FY 2001 - FY 2004 and FY 2005 - FY 2008, respectively. Table 1 clearly shows that the scale of business of the shinkin banks significantly increased from the first period to the second period; however, the variance of scale among the banks also increased.

Table 1: Descriptive statistics for inputs and outputs (in million yen)

	y11	y12	x11	x12	y21	y22	x21	x22
FY2001 - FY 2004								
Min.	220	77	220	132	202	66	204	125
Median	2247	746.5	1658	1042	2093	618.5	1470	957.5
Mean	3643	1225	2423	1599	3521	1087	2196	1561
Max.	21010	9418	11970	9678	33100	9604	18990	13580
SD	3762	1337	2295	1617	4090	1294	2305	1737
FY 2005 - FY 2008								
Min.	397	63	354	202	287	136	303	212
Median	2902	998.5	1807	1314	2528	1079	1827	1297
Mean	4808	1475	2873	2161	4318	1666	2835	2178
Max.	31510	11880	18280	14030	26390	11050	17980	14220
SD	5478	1589	3001	2401	4936	1723	2948	2457

y11=Net interest from loans in the beginning year y21=Net interest from loans in the end year
y12= Net other interest income in the beginning year y22= Net other interest income in the end year
x11= Labor expenses in the beginning year x21= General expenses in the end year
x12= Labor expenses in the beginning year x22= General expenses in the end year
Min, Median, Mean, Max and SD are the minimum, median, mean, max, and standard error of the sample, respectively.

4. Results

We use a package of the software R called FEAR to estimate the data. It was designed by P. W. Wilson (2008) particularly for the purposes of DEA. We first analyze the results for the total sample and then decompose them according to the levels of market power to explore the relationship between market power and productivity change.

4.1 Results for the total sample

At first, we examine the descriptive statistics for estimations on FY 2001-FY 2004 and FY 2005-FY 2008. These are outlined in Table 2.

Table 2: Descriptive Statistics of the Malmquist results

	Malm		Pure.eff		Tech		Scale	
	FY01/04	FY05/08	FY01/04	FY05/08	FY01/04	FY05/08	FY01/04	FY05/08
Min.	0.7859	0.9509	0.8373	0.9066	0.973	0.9867	0.8933	0.8937
Median	1.006	1.034	1	1.001	1.002	1.038	1.004	0.9939
Mean	1.011	1.035	1.002	1.01	1.006	1.037	1.004	0.9896
Max.	1.317	1.217	1.149	1.206	1.157	1.09	1.074	1.068
SD	0.052	0.046	0.046	0.048	0.025	0.02	0.052	0.046

Note: Malm = Malmquist index; Pure. eff = pure efficiency score; Tech = technical efficiency score; Scale = scale economy score

In both periods, the median is above 1, indicating less than half of the shinkin banks have improved their productivity. The mean of the Malmquist index is also above 1. Using the bootstrapping method described in Section 2.3, we cannot reject the hypothesis that in both periods the average of Malmquist index ($\overline{malm}^*_{1j}$ and $\overline{malm}^*_{2j}$) are above 1 with 91.3% and 99.93 confidence levels, respectively[5]. Thus we can conclude that productivity has decreased in both periods.

Table 3: Results of hypothesis test for total sample

statistic	definition	Null hypthesis	Significance level (%)
$\overline{malm}^*_{1j}$	Average Malmquist index in period 1is higher than period 1	$\overline{malm}^*_{1j}>1$	91.3
$\overline{malm}^*_{2j}$	average Malmquist index in period 2 is higher than in period 1	$\overline{malm}^*_{2j}>1$	99.93
d_{malm}	average Malmquist score in period 2 is higher than in period 1	$\overline{malm}^*_{2j}-\overline{malm}^*_{1j}>0$	100
d_{ME1}	Average pure efficiency score is higher than total score in period 1	$\overline{pure.eff}^*_{1j}-\overline{malm}^*_{1j}>0$	30.9
d_{MT1}	Average technical score is higher than total score in period 1	$\overline{tech}^*_{1j}-\overline{malm}^*_{1j}>0$	30.9
d_{MS1}	Average scale economy score is higher than total score in period 1	$\overline{scale}^*_{1j}-\overline{malm}^*_{1j}>0$	38.5
d_{ME2}	Average pure efficiency score is higher than total score in period 2	$\overline{pure.eff}^*_{2j}-\overline{malm}^*_{2j}>0$	0.15
d_{MT2}	Average technical score is higher than total score in period 2	$\overline{tech}^*_{2j}-\overline{malm}^*_{2j}>0$	41.6
d_{MS2}	Average scale economy score is higher than total score in period 2	$\overline{scale}^*_{2j}-\overline{malm}_{2j}>0$	0
d_{pure2}	Average pure efficiency score is higher in period 2 than in period 1	$\overline{pure}^*_{2j}-\overline{pure}^*_{1j}>0$	84
d_{tech}	Average technical score is higher in period 2 than in period 1	$\overline{tech}^*_{2j}-\overline{tech}^*_{1j}>0$	0.1
d_{scale}	Average scale economy score is higher in period 2 than in period1	$\overline{scale}^*_{2j}-\overline{scale}^*_{1j}>0$	8.05

[5] All the hypothesis test results are summarized in table 3.

All quantile statistics for the Malmquist index are higher in FY 2005-FY 2008 than in FY 2001 - FY 2004. With 100% confidence we cannot reject the hypothesis that on average the Malmquist index is higher in the second period than in the first period ($d_{malm} = \overline{malm}^*_{2j} - \overline{malm}^*_{1j} > 0, \quad j = 1 \cdots B$) .

Thus we conclude that from the first to the second period, productivity deterioration has worsened. However, the range and variance of the data (except for data on pure efficiency) are narrowed in the second period, indicating a tendency of convergence among shinkin banks.

Then the number of banks whose productivity has improved (with Malmquist indexes less than 1) in each period was examined. These data are listed in Table 4.

Table 4: Number of Banks with Improved Malmquist Results

	Malm		Pure. eff		Tech		Scale	
	score	Up95%	score	Up95%	score	Up95%	score	Up95%
FY2001-	104	91	105	57	102	0	95	2
FY2004	(46.02)	(40.27)	(46.46)	(25.22)	(45.13)	(0.00)	(42.04)	(0.88)
FY2005-	61	35	110	68	9	0	178	34
FY2008	(23.83)	(13.67)	(42.97)	(26.56)	(3.52)	(0.00)	(69.53)	(13.28)
Difference	-43	-56	5	11	-93	0	83	32
	(-22.19)	(-26.59)	(-3.49)	(1.34)	(-41.62)	(0.00)	(27.50)	(12.40)

Note: Score is the original results of the estimation
Up95% is the upper bound at 95% confidence level of the bootstrapping confidence interval
Data in bracket are ratios of the total sample

In FY 2001 - FY 2004, the productivity of 104 shinkin banks (46% of the total sample) has increased. Among them 91 banks (about 40% of the total sample) can be robustly assured with 95% confidence that their scores are below 1. Comparatively, in FY2005 to FY2008, the Malmquist indexes of 61 shinkin banks (about 24% of the total sample) were less than 1. Among them 35 banks (about 14% of the total sample) can be robustly assured with 95% confidence that their scores are below 1. Thus, from examining the number of banks whose productivity has been improved, we confirm the finding from the analysis of descriptive statistics.

Examining the components of the Malmquist index can shed light on the sources of the decline in productivity. From Table 2, we see that in the first period the mean and median of the three components are almost the same (all slightly above 1). Using the bootstrapping hypothesis testing method, we find that, on average, none of the component scores are significantly different from the Malmquist scores. The significance levels for the hypothesis that, on average, pure efficiency and technical efficiency scores are higher than the Malmquist scores ($d_{ME1} = \overline{pure.eff}^*_{1j} - \overline{malm}^*_{1j} > 0$ and $d_{MT1} = \overline{tech}^*_{1j} - \overline{malm}^*_{1j} > 0$, respectively) are both 30.9%. In the case of scale economy, the significant level for ($d_{MS1} = \overline{scale}^*_{1j} - \overline{malm}^*_{1j} > 0$) is 38.5%.

From table 4, we observe that in the first period, the number of banks with pure efficiency, technical efficiency, and scale efficiency scores less than 1 is also not much different from the number of banks with Malmquist indexes less than 1. Thus, from the estimates themselves, we find that the three components of the Malmquist index offer similar levels of contribution to the change of the index. However, when we consider the robustness of estimates, almost no shinkin banks' technical or scale efficiency score is robustly below 1.

Hence, we may conclude that in FY 2001-FY 2004, the major cause of the slight deterioration in the productivity of shinkin banks is the worsening of technical and scale efficiency. This worsening of scale economy is somewhat surprising, because in this period, the number of M&A cases is much larger than that in the later period. This may be because the effects of M&A cases occurred in the first period are reflected in the subsequent period.

In the second period (FY 2005-FY 2008), the hypothesis that, on average, pure efficiency and scale economy scores are higher than the Malmquist scores ($d_{ME2} = \overline{pure.eff}^{*}_{2j} - \overline{malm}^{*}_{2j} > 0$ and $d_{MS2} = \overline{scale}^{*}_{2j} - \overline{malm_{2j}} > 0$) can be rejected at 0.15% and 0% confidence levels respectively. This means pure efficiency and scale economy both behave better than the total scores in the second period. But the corresponding confidence level for technical efficiency ($d_{MT2} = \overline{tech}^{*}_{2j} - \overline{malm}^{*}_{2j} > 0$) is 41.6%. It is not significantly different from Malmquist scores.

During the second period, the number of shinkin banks with pure efficiency scores less than 1 is 110. Among them, the number of banks whose upper bounds of 95% confidence intervals are below 1 is 68. Both are more than twice the corresponding level for the Malmquist index in the same period. For the scale efficiency component, 178 shinkin banks have scores less than 1, the number is almost thrice the number of banks with Malmquist indexes less than 1, but only 34 banks have scores robustly below 1. On the other hand, only 9 banks have technical component less than 1. None of them is robust at 95% confidence level. From these findings, we may conclude that in FY 2005-FY 2008, the major cause of the deterioration in the productivity changes of the shinkin banks is the worsening of technical efficiency. Pure efficiency and scale efficiency play positive roles in the trend of productivity changes.

Comparing the two periods, the results of the bootstrapping hypothesis testing show that the significance level is 84% for the statistic $d_{pure2} = \overline{pure}^{*}_{2j} - \overline{pure}^{*}_{1j} > 0$, 0.1% for the statistic $d_{tech2} = \overline{tech}^{*}_{2j} - \overline{tech}^{*}_{1j} > 0$ and 8.05% for the statistic $d_{scale} = \overline{scale}^{*}_{2j} - \overline{scale}^{*}_{1j} > 0$. Thus only the hypothesis that, on average, the trend of technical efficiency growth has been deteriorated in the later period cannot be rejected with 0.1% confidence level.

From FY 2005-FY 2008 to FY 2001- FY 2004, the proportion of shinkin banks with pure efficiency scores less than 1 decreased by 3.49%. However, if considering the robustness of the results at 95% confidence level, the ratio increased by 1.34%. The proportion of banks with technical scores less than 1 drastically dropped by 42%. However, as in the first period, none of the results are robust at 95% confidence level. The ratio of shinkin banks with scale efficiency scores less than 1 has significantly increased by 27.5%. The ratio of banks with scores robustly less than 1 increased by 12.4%.

Thus from the analysis of the components, we may also conclude that there is a significant deterioration in the productivity of shinkin banks from the period of FY 2001-FY 2004 to the period of FY 2005-FY 2008. The major cause for this decline of productivity growth is the worsening of technical efficiency. However, we also see that scale efficiency has significantly improved, probably because the large number of M&A cases happened at the beginning of the century has gradually manifested its effects. Scale efficiency is the only component that has shown significant improvement.

4.2 Results for the Sub-Groups

For a more detailed examination of the trend in productivity changes of sinkin banks during the 2000s, we further divide the total sample into subgroups to investigate results of the estimation. Most analysts divide the total sample according to the scale of the financial institutions being analyzed. However, for regional financial institutions like shinkin banks, regional environmental conditions are more important to productivity than scale. Here we only divide the sample according to an indicator reflecting the level of competition in areas where shinkin banks operate. We are especially interested in the effects of M&A peaks at the beginning of the 21st century, so we only analyze results for FY 2005-FY 2008.

Because we measure Malmquist index in value terms, so the resulting scores reflect not only real productivity changes, but also the changes in price fixing ability of the banks. There are no clear theoretical assumptions on the influence of market power on productivity changes measured in value terms. Shinkin banks located in highly competitive areas may benefit from improvement in pure and technical efficiency because of intense competition (market competition hypothesis). On the other hand, shinkin banks located in less competitive areas may benefit from high price fixing ability and improved economy of scale (market power hypothesis).

I use “city, town or village” (shi, mura or machi) as the unit of area. Many shinkin banks operate over more than one unit of area, so following Horie (2010), we use the weighted average of regional statistics of the *share* as the indicator of market power:

$$Q_i = \sum_{j=1}^{M} w_{ij} share_{ij} \qquad i = 1, 2, \cdots N,$$

where :

Q_i is the weighted average of *share* for shinkin bank *i*, in year *t* (for the reason of simplicity, *t* is omitted in the subscript);

w_{ij} is the weight given to bank *i*, which is the ratio of the number of branches owned by bank *i* in area *j* to its total number of branches in year *t*;

$share_{ij}$ is the market power indicator defined above of shinkin bank *i* in area *j*.

We divide the sample into three groups. Banks belonging to the first and fourth quantile of the *share* distribution compose the first and the third group, respectively. Those between them created the second group. Table 5 shows the descriptive statistics of the Malmquist results for the subgroups:

Table 5: Descriptive Statistics of the Malmquist Results for Subgroups

	Malm	Pure.eff	Technical	Scale
Min				
1st Group	0.954	0.910	0.998	0.894
2nd Group	0.998	0.975	1.024	0.973
3rd Group	0.955	0.907	0.998	0.931
Median				
1st Group	1.036	1.000	1.028	0.996
2nd Group	1.033	1.004	1.039	0.994
3rd Group	1.034	0.999	1.049	0.991
Mean				
1st Group	1.037	1.014	1.028	0.995
2nd Group	1.035	1.011	1.038	0.987
3rd Group	1.034	1.003	1.043	0.989
Max				
1st Group	1.166	1.185	1.067	1.068
2nd Group	1.217	1.206	1.090	1.059
3rd Group	1.196	1.118	1.083	1.038
SD				
1st Group	0.047	0.047	0.018	0.027
2nd Group	0.046	0.050	0.019	0.027
3rd Group	0.043	0.044	0.020	0.023

Note: see Table 2.

Table 5 shows that in FY 2005 to FY 2008, on average, the higher the *share* group a shinkin bank belongs to, the slower is its decline in productivity. Shinkin banks with larger market shares experience slower declines in productivities compared with banks with smaller market shares. Note also that shinkin banks in the first group vary more widely in productivity changes than other groups.

Using the bootstrapping hypothesis testing method[6], the hypothesis that, on average, the Malmquist index of the second group is significantly larger than that of

[6] All the hypothsis test results in sub-group analysis are summarized in table 6.

the first group ($d_{M21} = \overline{malm}^*_{22} - \overline{malm}^*_{21} > 0$) cannot be rejected at 99.65% confidence level. But the hypothesis ($d_{M32} = \overline{malm}^*_{32} - \overline{malm}^*_{22} > 0$) can be rejected at 0.55% confidence level. Therefore, we may conclude with confidence that the second group has the highest rate of decline in productivity. This appears quite confusing and inconsistent with inferences from the original scores.

Table 6: Results of hypothesis test for sub- groups

Test	definition	hypothesis	Significance (%)
d_{M21}	average Malmuist index of group 2 is larger than that of group 1	$\overline{malm}^*_{22} - \overline{malm}^*_{21} > 0$	99.65
d_{M32}	average Malmuist index of group 3 is larger than that in group 2	$\overline{malm}^*_{32} - \overline{malm}^*_{22} > 0$	0.55
d_{pure21}	average pure efficiency of group 2 is larger than that in group 1	$\overline{pure}^*_{22} - \overline{pure}^*_{21} > 0$	51.25
d_{pure32}	average pure efficiency of group 3 is larger than that of group 2	$\overline{pure.eff}^*_{1j} - \overline{malm}^*_{1j} > 0$	1.15
d_{tech21}	average technical score of group 2 is larger than that in group 1	$\overline{tech}^*_{22} - \overline{tech}^*_{21} > 0$	80.85
d_{tech32}	average technical score of group 3 is larger than that of group 2	$\overline{tech}^*_{23} - \overline{tech}^*_{21} > 0$	92.25
$d_{scale21}$	Average scale economy score of group 2 is larger than that of group 1	$\overline{scale}^*_{22} - \overline{scale}^*_{21} > 0$	14.05
$d_{scale32}$	average scale economy score in group 3 is larger than that in group 2	$\overline{scale}^*_{23} - \overline{scale}^*_{21}$	69.03

Analyzing the descriptive statistics of the components can help us find the sources of the foregoing confusing results. We observe from Table 5 that in FY 2005 to FY 2008, for original results similar conclusions can be drawn for pure efficiency and scale economy. On the contrary, the trend of technical efficiency is different from the trends of the two other components. On average, the higher the share group a shinkin bank belongs to, the faster is its decline in technical efficiency. This contradiction may have caused the confusing result of the robust analysis described above. These findings are in accordance with the market competition theory.

Using the bootstrapping hypothesis testing method, the hypothesis that, on average, the pure efficiency score of the first group is significantly less than that of the second group ($d_{pure21} = \overline{pure}^*_{22} - \overline{pure}^*_{21} > 0$) cannot be rejected only at 51.25% confidence level. Therefore the two groups are not significantly different from each other. On the other hand, the hypothesis that on average the pure efficiency score of the third group is larger than that of the second group ($d_{pure32} = \overline{pure}^*_{23} - \overline{pure}^*_{22} > 0$) can be rejected at 1.15% confidence level. Similarly, the hypothesis $d_{tech21} = \overline{tech}^*_{22} - \overline{tech}^*_{21} > 0$ cannot be rejected only at 80.85% level.

Whereas, the hypothesis $d_{tech32} = \overline{tech}^*_{23} - \overline{tech}^*_{21} > 0$ cannot be rejected at 92.25% level. For scale economy scores, the hypothesis $d_{scale21} = \overline{scale}^*_{22} - \overline{scale}^*_{21} > 0$ cannot be rejected only at 14.05% significance level. Whereas, the hypothesis $d_{scale23} = \overline{scale}^*_{23} - \overline{scale}^*_{21} > 0$ cannot be rejected at 69.03% confidence level. This means that, on average, the change in both technical and scale efficiency is not significantly different across the three groups.

Second, we examine the number of banks whose productivity has improved for each group. These data are listed in Table 7.

Table 7: Number of Banks with Improved Malmquist Results for the Sub-Groups

	Malm		Pure. Eff		Tehnical		Scale	
	score	Up95%	score	Up95%	score	Up95%	score	Up95%
1st	14	9	26	13	5	0	38	7
	(21.88)	(14.06)	(40.63)	(20.31)	(7.81)	(0)	(59.38)	(10.94)
2st	33	16	52	36	3	0	95	19
	(25.78)	(12.5)	(40.63)	(28.13)	(2.34)	(0)	(74.22)	(14.84)
3rd	14	10	32	19	1	0	45	8
	(21.88)	(15.63)	(50)	(29.69)	(1.56)	(0)	(70.31)	(12.5)

Note: see Table 3.

In FY 2005- FY 2008, the second group has the largest proportion of banks with improved productivities. However, after considering the robustness of the estimation, the third group now emerges with the largest proportion (this may partly explain the difference between the original scores and hypothesis testing). Pure efficiency and scale economy show a similar trend for original scores. Considering robust results, now the first group has a significantly smaller proportion of banks with improved pure and scale efficiency compared with the other groups. For technical efficiency, the picture is different. Higher groups have smaller proportions with improved productivity, and the differences are quite significant. However, since none of the results are statistically significant. The findings are without much meaning. These conclusions are consistent with inferences from the original scores.

In summary, we can conclude that in FY 2005-FY 2008, shinkin banks which located in least competitive areas have experienced the least decline in productivities. But this result is not robust. When we decompose the scores, banks located in least competitive areas also declined least in the pure efficiency. This result is robust. The results are in accordance with the market power hypothesis. In contrast, for technical efficiency, banks located in more competitive areas perform significantly better than those in less competitive areas, indicating that these banks benefit more from technological progress. This finding is in agreement with the theory of market competition. The contradiction between the two scores may have caused ambiguity in the influence of market power on the productivity if we consider the robustness of the estimation. There are no significant differences in scale efficiency across the three groups.

5. Conclusion

This paper tries to use a more robust approach than other related papers to estimate the productivity changes of the Japanese shinkin banks during the 2000s. From the results of this paper's analysis, we can clearly see that in the first half of the 2000s there is no significant change of productivities. However, in the latter half of the period, productivity has significantly declined. The major source of this trend is the down turn of the technology efficiency (the inward shift of the production frontier). This finding is in accord with the deteriorating of the economic environment in the latter half of the 2000s. However, in the second period, scale economy of the shinkin banks have been notably improved, which partly offset the deterioration of the environments. This may originate from the lag effects of active M&A in the early 2000s.

Using a bootstrapping technique enables us to have a clearer picture about the sources of the productivities changes. For example, in the first period, a large proportion of shinkin banks have their technical efficiency improved; yet if we consider the robustness of these results, the contribution of technical efficiency will be drastically reduced.

Grouping banks in the total sample according to the level of competition reveals the relationship between market power and productivity changes. From the original scores, we find that banks located in the least competitive areas experience the least declines in productivity, but this result is not robust. Checking the components, we observe that banks located in the least competitive areas experienced the slowest declines in pure efficiency. However, banks located in highly competitive areas are more successful in their efforts of slowing down the decline in technical efficiency. This compensates for their weakness in pure efficiency and makes the results less clear.

This paper also leaves some questions unanswered. This paper only analyzes the effects of competition on the production process. Further research is needed to analyze the influence of other external factors which do not directly involve in the production process, but may also influence the productivity.

References:

Altunbas, Y., Liu, M.-H., Molyneux, P. & Seth, R. (2000) "Efficiency and risk in Japanese banking." Journal of Banking & Finance 24(10): 1605-1628.

Behname, M. (2012) "The Compare of Concentration and Efficiency in Banking Industry: Evidence from the OPEC Countries." Eurasian Journal of Business and Economics, 5 (10), 15-24.

Berger, A. N. & Humphrey, D. B. (1997) "Efficiency of financial institutions: International survey and direction for future research." European Journal of Operational Research 98(2):

175-212.

Drake, L. and Hall, M. (2003) "Efficiency in Japanese banking: An empirical analysis." Journal of Banking & Finance 27(5): 891-917.

Drake, L., Hall, M. J. B. & Simper, R. (2009) "Bank modelling methodologies: A comparative non-parametric analysis of efficiency in the Japanese banking sector." Journal of International Financial Markets, Institutions and Money 19(1): 1-15.

Fare, R., Grosskopf S., Lindgren, B. & Roos, P. (1992) "Productivity Changes in Swedish Pharmacies 1980-1989: A Non-parametric Malmquist Approach." Journal of Productivity analysis 3(1-2): 85-101.

Fethi, M. D. & Pasiouras, F. (2010) "Assessing Bank Efficiency and Performance with Operational Research and Artificial Intelligence Techniques: A Survey." European Journal of Operational Research 204(2): 189-198.

Fukuyama, H. (1993) "Technical and Scale Efficiency of Japanese Commerical Banks: a Non-parametric Approach." Applied Economics 25(8): 1101-1112.

Fukuyama, H. (1996) "Return to Scale and Efficiency of Credit Associations in Japan：A Nonparametric Frontier Approach." Japan and World Economy 8: 259-277.

Fukuyama, H. & Weber, W. (2008) "Japanese Banking Inefficiency and Shadow Pricing." Mathematical and Computer Modelling 48(11-12): 1854-1867.

Nigmonov, A. (2010) "Bank Performance and Efficiency in Uzbekistan." Eurasian Journal of Business and Economics, 3 (5): 1-25.

Harimaya, K. (2004) "Measuring the Efficiency in Japanese Credit Associations." Review of Monetary and Financial Studies 21: 92-112. In Japanese.

Horie, Y. (2010) "The Operation Area and The Efficiency of The shinkin Banks." Economics Research 76: 7-40. In Japanese.

Kao, C. & Liu, S. (2009) "Stochastic Data Envelopment Analysis in Measuring the Efficiency of Taiwan Commercial Banks." European Journal of Operational Research 196(1): 312-322.

Kaur, P. & Kaur G. (2010) "Impact of Mergers on the Cost Efficiency of Indian Commercial Banks." Eurasian Journal of Business and Economics 3 (5): 27-50.

Kumar, S. & Gulati, R. (2008) "An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis" Eurasian Journal of Business and Economics 1 (2): 33-69.

McKillop, D. G., Glass, j. C. & Morikawa, Y. (1996) "The Composite Cost Function and Efficiency in Giant Japanese Banks." Journal of Banking & Finance 20(10): 1651-1671.

Rebelo, J. & Mendes, V. (2000) "Malmquist Indices of Productivity Change in Portuguese Banking: The Deregulation Period." International Advances in Economic Research 6(3): 531-543.

Simar, L. & Wilson, P. W. (1999) "Estimating and Bootstrapping Malmquist Indices." European Journal of Operational Research 115(3): 459-471.

Simar, L. (1992) "Estimating Efficiencies from Frontier Models with Panel Data: A Comparison of Parametric, Non-Parametric and Semi-Parametric Methods with Bootstrapping." Journal of Productivity Analysis, 3: 171-203.

Tadesse, S. (2006) "Consolidation, Scale Economies and Technological Change in Japanese Banking." Journal of International Financial Markets, Institutions and Money 16(5): 425-445.

Wheelock, D. C. & Wilson, P. W. (2009) "Robust Non-parametric Quantile Estimation of Efficiency and Productivity Change in U.S. Commercial Banking." Journal of Business and Economic Statistics 27(3): 354-368.

Wilson, P. (2008) "FEAR: A Software Package for Frontier Efficiency Analysis with R." Socio-Economic Planning Sciences 42(4): 247-254.

Wilson, P. W. (1993) "Detecing Outliers in Deterministic Nonparametric Frontier Models." Journal of Business & Economic Statistics 11(3): 319-323.

Appendix: DEA efficiency score estimation

Here we only present the DEA model in relation to hyperbolic-oriented measurement. Suppose we observe a production sample $Q_n = (x_i, y_i),\ i = 1 \cdots n$ from the production set Ψ defined as in Section 2. For this sample, if we assume a constant return to scale (CRS), we can calculate the hyperbolic-oriented efficiency score for a fixed point (x_0, y_0) by solving the following programming (the CCR model):

$$\begin{aligned} &(Hyperbolic_0) \qquad \max_{\eta,\lambda} \quad \gamma_{CRS} \\ &\text{Subject to} \quad x_0 / \gamma_{CRS} \geq X\lambda \\ &\qquad \gamma_{CRS} y_0 \leq Y\lambda \\ &\qquad \lambda \geq 0 \end{aligned} \tag{8}$$

Where λ is a vector of real number. Solving the above programming problem results in a radial efficiency measure for a fixed point $\gamma_{CRS}(x_0, y_0)$. By calculating γ_{CRS} for every point in the sample, we obtain an efficient production frontier $\partial^t Q(x,y)$, which is the combination of the points with γ equal 1, and the estimated attainable production set Ψ^*_{CRS}:

$$\Psi^*_{CRS} = \left\{ (x,y)\Re^{p+q} \mid y \leq Y\lambda, x \geq X\lambda,\ \lambda \geq 0 \right\} \quad .$$

DEA efficiency scores can also be calculated under the assumption of variable returns to scale (VRS) assumption. The only difference between the CRS model and the VRS model is that the latter model include a new constraint $e\lambda = 1$ (*e* is a N dimension vector of 1).

Unlike traditional input- or output-oriented models, the programming in the case of hyperbolic-oriented distance is not linear. In the case of CRS, the input- and output-oriented distances are the same, so it is easy to prove that: $\gamma_{CRS} = \theta^{1/2}_{CRS} = \eta^{1/2}_{CRS}$, where θ_{CRS} and $\eta^{1/2}_{CRS}$ are the input- and output-oriented DEA efficiency scores, respectively (Fare, 1985); therefore by estimating the input- or output-oriented distance we can easily get the γ_{CRS}. The case of VRS is much complex to solve. However, with the help of computer, the programming may also be solved using numerical algorithm (Wheelock and Wilson, 2009).