2010

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Publication Details

Arjomandi, A, Valadkhani, A and Harvie, C, An Analysis of Productivity Changes in the Iranian banking Industry: a Bootstrapped Malmquist Approach, Working Paper 08-10, School of Economics, University of Wollongong, 2010, 26p.

University of Wollongong
Economics Working Paper Series 2010

http://www.uow.edu.au/commerce/econ/wpapers.html

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WP 08-10
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Abstract

This study employs various bootstrapped Malmquist indices and efficiency scores to investigate the effects of government regulation on the performance of the Iranian banking industry over the period 2003-2008. An alternative decomposition of the Malmquist index, introduced by Simar and Wilson (1998a), is also applied to decompose technical changes further into pure technical change and changes in scale efficiency. A combination of these approaches facilitates a robust and comprehensive analysis of Iranian banking industry performance. While this approach is more appropriate than the traditional Malmquist approach, for the case of banking efficiency studies, it has not previously been conducted for any developing country's banking system. The results obtained show that although, in general, the regulatory changes had different effects on individual banks, the efficiency and productivity of the overall industry declined after regulation. We also find that productivity had positive growth before regulation mainly due to improvements in pure technology, and that government ownership had an adverse impact on the efficiency level of state-owned banks. The bootstrap approach demonstrates that the majority of estimates obtained in this study are statistically significant.

Keywords: Regulation; Productivity; Banking; Data envelopment analysis; Bootstrap; Malmquist indices

JEL codes: C02, C14, C61; G21

1. Introduction

Over the last decade the Iranian banking industry has undergone many substantial changes, such as liberalization, government regulation and technological advances, which have resulted in extensive restructuring of the industry. These changes in policy have affected both government-owned banks (including commercial banks and specialized banks) and private banks. The former have been the most successful in acquiring market share, and it is mainly due to this reason that private banks are much newer than theses banks; they joined the market after 2001. However, it seems that government-owned banks were affected more noticeably after government regulation initiatives launched in 2005, which obliged all banks to reduce deposit and loan interest rates considerably. The government also imposed different interest rates and conditions on public and private banks, and imposed obligations on government-owned banks to assign higher priority in their lending operations to areas such as advanced technology projects, small and medium enterprises, and housing projects for low income earners. As a result, the level of non-performing loans (NPLs) of government-owned banks increased dramatically after 2006. According to the Central Bank of Iran, CBI, (2006), the annual growth rate of government-owned banks' NPLs was less than 30% before 2005, however this figure increased markedly to 129% in 2006. CBI (2006) also state that the highest share of the NPLs belongs to the "manufacturing and mining" (20.1%) and "construction" (19.5%) sectors. For these reasons in particular, this study investigates the effect of government policies on the productivity of the Iranian banking industry.

Fethi and Pasiouras (2010), in a comprehensive survey covering 196 studies which had applied operational research and artificial intelligence techniques in the assessment of bank performance, reveal that almost all studies that obtained estimates of total factor productivity growth employed a DEA[1]-type Malmquist index. This result demonstrates that the Malmquist index has widespread use in examining total factor productivity growth. Initially, Caves, Christensen and Diewert, (1982) introduced the Malmquist productivity index as a theoretical index. Färe et al. (1992) later merged Farrell's (1957) measurement of efficiency with Caves et al.'s (1982) measurement of productivity to develop a new Malmquist index of productivity change. Färe et al. (1992) subsequently demonstrate that the resulting total factor productivity (TFP) indices could be decomposed into efficiency change and technical change components. Färe, Grosskopf, Norris and Zhang (1994b) further decompose the efficiency change into pure technical efficiency change and changes in scale efficiency, a development which results in the Malmquist index becoming widely popular as an empirical index of productivity change.

However, Simar and Wilson (1998a) state that the FGNZ model does not provide a useful measure of technical change and their empirical results show that all the estimated means for technical change are insignificant: "many of the inaccuracies in FGNZ … may be attributed to their confusion between unknown quantities and estimates of these quantities"

[1] Data Envelopment Analysis (DEA) is one of the most popular non-parametric approaches in the literature that has been used widely in frontier efficiency and productivity methods.

(p. 4). Moreover, they conclude that "Without a statistical interpretation, it is not meaningful to draw inferences from results obtained with these methods as it is otherwise impossible to know whether the numbers reflect real economic phenomena or merely sampling variation" (p. 18). Instead, they propose an alternative decomposition of the Malmquist index. They estimate changes in technology by changes in the variable returns to scale (VRS) estimate, and further decompose the technical changes into pure technical change and changes in the scale of efficiency.

The DEA approach for estimating distance functions when constructing Malmquist indices is problematic. As DEA is a non-parametric approach, it does not allow for random errors and does not have any statistical foundation, hence making it inadequate for testing statistical significance of the estimated distance functions, or for conducting sensitivity analyses to examine their asymptotic properties; see Lovell (2000), Coelli et al. (2005), and Simar and Wilson (1998b, 1999, 2000). The inherent problem with mainstream DEA analysis is that distances to the frontier are underestimated if the most efficient firms within the population are not included in the sample. Analysis in this situation leads to biased frontier estimation from the sample and results in distances to all other units being measured relative to this biased frontier. Undoubtedly, uncertainty is carried through to parameters such as the Malmquist indices of TFP changes which are estimated from DEA distance functions.

To solve this problem, Simar and Wilson (1998b, 2000) define a statistical model, the bootstrap simulation method, which allows for determining the statistical properties of the non-parametric estimators in the multi-input and multi-output case, and hence for constructing confidence intervals for DEA efficiency scores. In their later study, Simar and Wilson (1999) demonstrate that the bootstrap technique can also be employed to estimate confidence intervals for Malmquist indices. The most important practical implication of their conclusion is that statistical inference becomes possible for Malmquist indices. In this study, we employ the Simar and Wilson (1998a) approach to measure the Malmquist index and its components - changes in pure technical efficiency, changes in scale efficiency, pure changes in technology and changes in scale of technology - to provide a more inclusive and robust analysis of productivity and technical change in the banking industry of Iran. For the first time in the context of a developing country, we also employ the bootstrap simulation method (Simar & Wilson, 1998b; 2000) to determine whether the computed changes in productivity are real or not.

The remainder of this paper is structured as follows: Section 2 presents a literature review of the bootstrapped Malmquist indices. Sections 3 and 4 describe the methodology of Malmquist indices and the bootstrap technique, respectively. Section 5 explains the data and Section 6 discusses the results followed by some concluding remarks.

2. Literature Review of Bootstrapped Malmquist Studies

Despite a large body of literature surrounding the traditional (FGNZ) Malmquist index, there is little written about the usage of the bootstrapped Malmquist. Only a small number of studies have applied the statistical properties of the Malmquist estimates; see Hoff (2006), Galdeano-Gómez (2008), Balcombe et al. (2008), and Latruffe et al. (2008)[2]. The exception is Tortosa-Ausina et al. (2008) who use both the FGNZ model and the bootstrap technique to investigate the productivity of the Spanish banking system over the post-deregulation period 1992–1998. Their findings show that productivity growth occurred, and that this was mainly attributable to an improvement in production possibilities (technical changes). Their bootstrap analysis also revealed that productivity changes for most of the firms were not statistically significant.

Our study is, therefore, unique in the sense that the bootstrap technique has not previously been applied to the alternative decomposition of Malmquist indices in the evaluation of a developing country's banking system. Wheelock and Wilson (1999) and Gilbert and Wilson (1998) analyse the banking systems of developed countries, the US and Korean systems respectively. Wheelock and Wilson (1999), using the alternative decomposition of the Malmquist productivity index, show that the growing inefficiency of US banks in the period 1984-1993 can be largely attributed to the general failure of banks to adopt technological improvements. Gilbert and Wilson (1998) study the effect of deregulation on the productivity of Korean banks between 1980 and 1994. The index of changes in pure technology indicates that after deregulation Korean banks altered their mix of inputs and outputs considerably, leading to improvements in productivity. The index of change in the scale of technology suggested that the most efficient scale size was increasing over time. While it seems that in many empirical applications the bootstrap approach is more appropriate than the traditional

[2] Hoff (2006) applied bootstrapped Malmquist to the fisheries sector for assessing TFP changes for the fleet of Danish seiners operating in the North Sea and the Skagerrak. Galdeano-Gómez (2008) applied this technique in the field of marketing cooperatives. Balcombe et al. (2008) and Latruffe et al. (2008) estimated bootstrapped Malmquist indices for samples of Polish farms.

Malmquist, it has not been widely used in other applied studies, presumably due to the lack of user-friendly software. In this study we apply the FEAR package in R, which was introduced by Wilson (2006) to estimate technical efficiency, the different components of the Malmquist productivity index, and their confidence intervals.

3. Productivity Measurement Using the Malmquist Index

To measure productivity change between periods t_1 and t_2, consider N firms which produce q outputs using p inputs over T-time periods. A generic firm in period t_1 employs input x_{t_1} to produce output y_{t_1}, whereas in period t_2 quantities are x_{t_2} and y_{t_1}, respectively. The production possibilities set at time *t* is:

$$S_t = \{(x, y) \mid x \textit{ can produce } y \textit{ at time } t\}, \tag{1}$$

where *x* is an input vector, $x \in \mathbb{R}^n_+$, and *y* is an output vector, $y \in \mathbb{R}^m_+$, at time *t*. This can be described in terms of its sections. For example:

$$y_{t_2}(x_{it_1}) = \left\{ y \in \mathbb{R}^m_+ \middle| (x, y) \in S_t \right\} \tag{2}$$

that is its corresponding output feasibility set. Based on Shephard (1970), the output distance function for firm *i* at time t_1 is:

$$D^o_{it_1|t_2} \equiv \inf \left\{ \theta > 0 \;\middle|\; y_{it_1} / \theta \in y_{t_2}(x_{it_1}) \right\}. \tag{3}$$

The distance function $D^o_{it_1|t_2}$ measures the distance from the i-th firm's position in the input-output space at time t_1 to the boundary of the production set at time t_2, where inputs remain constant and θ is a scalar equal to the efficiency score. When t_1 and t_2 are equal, then it will be a measure of efficiency relative to technology at the same time, and $D^o_{it|t} \le 1$. When t_1 and t_2 are not equal, $D^o_{it_1|t_2}$ can be <,>, or =1.

Based on Färe et al. (1992) the Malmquist index between periods t_1 and t_2 can be defined as:

$$M^o_i(t_1, t_2) = \sqrt{\left(\frac{D^{oc}_{it_1|t_2}}{D^{oc}_{it_1|t_1}}\right)\left(\frac{D^{oc}_{it_2|t_2}}{D^{oc}_{it_2|t_1}}\right)} \tag{4}$$

which is a geometric mean of two Malmquist productivity indices for t_1 and t_2 as defined by Caves et al. (1982). If $M > 1$, then there has been positive total factor productivity change between periods t_1 and t_2. If $M < 1$, then there have been negative changes in the total factor productivity. $M = 1$ indicates no change in the productivity.

However, Simar and Wilson (1999) argue that the production possibility set S_t is never observed and consequently, all distances defined are unobserved. Hence the Malmquist productivity index and the distance functions mentioned above must be estimated. This, in sequence, requires estimation of the production set, $\widehat{S_t}$, and the output feasibility set, $\widehat{y}(x)$. Burgess and Wilson (1995) describe that the estimated production set can be written as:

$$\widehat{S_t} = \left\{ (x, y) \in \mathbb{R}_+^{m+n} \middle| y \le Y_t\gamma,\ x \ge X_t\gamma,\ \overline{1\gamma} = 1,\ \gamma \in \mathbb{R}_+^N \right\} \tag{5}$$

Where $Y_t = [y_{1t}, y_{2t}, ..., y_{Nt}]$ and y_{it} denotes $(m \times 1)$ vector of observed outputs, and $X_t = [x_{1t}, x_{2t}, ..., x_{Nt}]$ and x_{it} denotes $(n \times 1)$ vector of observed inputs. $\vec{1}$ and γ are vector of ones and intensity variables, respectively. Hence, the corresponding output feasibility sets can be described as:

$$\widehat{y_t^c}(x) = \left\{ y \in \mathbb{R}_+^m \middle| y \le Y_t\gamma,\ x \ge X_t\gamma,\ \gamma \in \mathbb{R}_+^N \right\} \text{, and} \tag{6}$$

$$\widehat{y_t^v}(x) = \left\{ y \in \mathbb{R}_+^m \middle| y \le Y_t\gamma,\ x \ge X_t\gamma,\ \overline{1\gamma} = 1,\ \gamma \in \mathbb{R}_+^N \right\}. \tag{7}$$

Substituting $\widehat{y_t^c}(x)$ and $\widehat{y_t^v}(x)$ for $y_t(x)$ in equation (2) leads to estimators of the distance functions which can be computed by solving the following linear programs:

$$(\widehat{D_{it_1|t_2}^{oc}})^{-1} = \max\left\{ \lambda \middle| \lambda y_{it_1} \le Y_{t_2}\gamma_i,\ x_{it_1} \ge X_{t_2}\gamma_i,\ \gamma_i \in \mathbb{R}_+^N \right\} \tag{8}$$

$$(\widehat{D_{it_1|t_2}^{ov}})^{-1} = \max\left\{ \lambda \middle| \lambda y_{it_1} \le Y_{t_2}\gamma_i,\ x_{it_1} \ge X_{t_2}\gamma_i,\ \overline{1\gamma} = 1,\ \gamma_i \in \mathbb{R}_+^N \right\} \tag{9}$$

where $\widehat{D_{it_1|t_2}^{oc}}$ features the assumption of constant returns to scale and $\widehat{D_{it_1|t_2}^{ov}}$ allows for variable returns to scale. Given estimates of the distance functions, estimates of the Malmquist index can be constructed by substituting the estimators for the corresponding true distance function values in (4):

$$\widehat{M}_i^o(t_1,t_2)=\sqrt{\left(\frac{\widehat{D_{it_1|t_2}^{oc}}}{\widehat{D_{it_1|t_1}^{oc}}}\right)\left(\frac{\widehat{D_{it_2|t_2}^{oc}}}{\widehat{D_{it_2|t_1}^{oc}}}\right)} \tag{10}$$

Alternatively, following Färe et al. (1992), this total factor productivity change can be decomposed into two components:

$$\widehat{M}_i^o(t_1,t_2)=\underbrace{\frac{\widehat{D_{it_2|t_2}^{oc}}}{\widehat{D_{it_1|t_1}^{oc}}}}_{\triangle Eff}\times\underbrace{\sqrt{\left(\frac{\widehat{D_{it_1|t_2}^{oc}}}{\widehat{D_{it_2|t_2}^{oc}}}\right)\left(\frac{\widehat{D_{it_1|t_1}^{oc}}}{\widehat{D_{it_2|t_1}^{oc}}}\right)}}_{\triangle Tech} \tag{11}$$

Where the term outside the square root sign, $\triangle Eff$, is an index of relative technical efficiency change, and shows how much closer (or farther away) a firm gets to the best practice frontier. It can be greater than, less than or equal to unity depending on whether the evaluated firm improves, stagnates, or declines. The second component, $\triangle Tech$, is the technical change component which measures how much the frontier shifts, and points out whether the best practice firm, relative to which the evaluated firm is compared, is improving, stagnating, or deteriorating. It can be greater than, less than or equal to unity depending on whether the technical change is positive, zero, or negative.

Färe et al. (1994a) demonstrate that the technical change component can be decomposed into two factors: pure technical efficiency change and changes in scale efficiency;

$$\widehat{M}_i^o(t_1,t_2)=\underbrace{\left(\frac{\widehat{D_{it_2|t_2}^{ov}}}{\widehat{D_{it_1|t_1}^{ov}}}\right)}_{\triangle PureEff}\times\underbrace{\left(\frac{\widehat{D_{it_2|t_2}^{oc}}\,/\,\widehat{D_{it_2|t_2}^{ov}}}{\widehat{D_{it_1|t_1}^{oc}}\,/\,\widehat{D_{it_1|t_1}^{ov}}}\right)}_{\triangle Scale}\times\underbrace{\sqrt{\left(\frac{\widehat{D_{it_1|t_2}^{oc}}}{\widehat{D_{it_2|t_2}^{oc}}}\right)\left(\frac{\widehat{D_{it_1|t_1}^{oc}}}{\widehat{D_{it_2|t_1}^{oc}}}\right)}}_{\triangle Tech} \tag{12}$$

where $\triangle PureEff$ and $\triangle Scale$ are measures of pure efficiency change and change in scale efficiency, respectively, and $\triangle Eff = \triangle PureEff \times \triangle Scale$. $\triangle Tech$ remains unchanged from (11), and gives a measure of change in technology. While $\triangle Tech$ signifies that the Constant Returns to Scale (CRS) frontier shifts over time, pure efficiency change and scale efficiency change correspond to VRS frontiers from two different periods.

On the other hand, Simar and Wilson (1998a) state that if a generic firm's position in the input-output space remains fixed between time t_1 and t_2, and the only change that happens is in the VRS estimate of technology (e.g. shift upward), then the $\triangle Tech$ presented in (12) would be equal to unity, indicating no change in technology. The only way that the $\triangle Tech$ in equation (12) would show a change in technology is if the CRS estimate of the technology changes. Hence, it is concluded by the authors that in such a circumstance, the CRS estimate of the technology is statistically inconsistent. Since the VRS estimator is always consistent under the assumptions of Kneip et al. (1996), they propose an alternative decomposition of the Malmquist index to estimate changes in technology ($\triangle Tech$) by changes in the VRS estimate;

$$\widehat{M_i^o}(t_1,t_2)=\underbrace{\left(\frac{\widehat{D^{ov}_{it_2|t_2}}}{\widehat{D^{ov}_{it_1|t_1}}}\right)}_{\triangle PureEff}\times\underbrace{\left(\frac{\widehat{D^{oc}_{it_2|t_2}}\,/\,\widehat{D^{ov}_{it_2|t_2}}}{\widehat{D^{oc}_{it_1|t_1}}\,/\,\widehat{D^{ov}_{it_1|t_1}}}\right)}_{\triangle Scale}\times$$
$$\underbrace{\sqrt{\left(\frac{\widehat{D^{ov}_{it_1|t_2}}}{\widehat{D^{ov}_{it_2|t_2}}}\times\frac{\widehat{D^{ov}_{it_1|t_1}}}{\widehat{D^{ov}_{it_2|t_1}}}\right)}}_{\triangle PureTech}\times\underbrace{\sqrt{\left(\frac{\widehat{D^{oc}_{it_1|t_2}}\,/\,\widehat{D^{ov}_{it_1|t_2}}}{\widehat{D^{oc}_{it_2|t_2}}\,/\,\widehat{D^{ov}_{it_2|t_2}}}\times\frac{\widehat{D^{oc}_{it_1|t_1}}\,/\,\widehat{D^{ov}_{it_1|t_1}}}{\widehat{D^{oc}_{it_2|t_1}}\,/\,\widehat{D^{ov}_{it_2|t_1}}}\right)}}_{\triangle ScaleTech} \tag{13}$$

where $\triangle Tech$ is further decomposed into pure technical changes, $\triangle PureTech$, and changes in the scale of technology, $\triangle ScaleTech$, and $\triangle Tech = \triangle PureTech \times \triangle ScaleTech$. $\triangle PureTech$ measures pure changes in technology and is the geometric mean of two ratios which measure the shift in the VRS frontier estimate relative to the bank's position at time t_1 and t_2 . When $\triangle PureTech$ is greater than unity, it indicates an expansion in pure technology. Specifically, it shows an upward shift of the VRS estimate of the technology. $\triangle ScaleTech$ provides information regarding the shape of the technology by describing the change in returns to scale of the VRS technology estimate at two fixed points, which are the firm's locations at times t_1 and t_2 . When $\triangle ScaleTech$ is greater than unity, this indicates that the technology is moving farther from constant returns to scale and the technology is becoming more and more convex. When this index is less than unity it gives us an idea that the technology is moving toward constant returns to scale, and $\triangle ScaleTech$ equal to unity shows no changes in the shape of the technology.

A similar decomposition of the Malmquist index is also proposed by Ray and Desli (1997). They combine changes in the scale of efficiency and changes in the scale of technology into a single term (SCH). However, Simar and Wilson (1999) state that Ray and Desli's SCH confuses changes in the shape of the technology and changes in scale efficiency experienced by the production unit. Färe (1997), agrees that Ray and Desli's alternative decomposition of Malmquist incorrectly measures changes in scale efficiency. Other kinds of decompositions and components of the Malmquist index are described by Fried et al. (2008), who conclude that the choice of appropriate decompositions is dependent on the research question. Accordingly, in this study, the comprehensive decomposition of Simar and Wilson (1998a) is employed with the aim of providing additional insight into productivity and technical change in the banking industry in Iran.

4. Formulation of the Bootstrap

Simar (1992) and Simar and Wilson (1998b) are pioneers in using the bootstrap in frontier models to obtain non-parametric envelopment estimators. The idea behind bootstrapping is to approximate a true sampling distribution by mimicking the data-generating process. The procedure is based on constructing a pseudo sample and re-solving the DEA model for each DMU with the new data. Repeating this process many times enables us to build a good approximation of the true distribution. Simar and Wilson (1998b) show that the statistically consistent estimation of such confidence intervals very much depends on the consistent replication of a data-generating process (DGP). In other words, the most important problem of bootstrapping in frontier models relates to the consistent mimicking of the DGP.[3] They argued that this problem refers to the bounded nature of the distance functions. Since the distance estimation values are close to unity, re-sampling directly from the set of original data (the so-called naive bootstrap) to construct pseudo-samples will provide an inconsistent bootstrap estimation of the confidence intervals.

Hence, to overcome this problem, they propose a smoothed bootstrap procedure. They use a univariate kernel estimator of density of the original distance function estimates (for efficiency scores in that case), and then construct the pseudo data from this estimated density. However, to estimate the Malmquist indices, we have panel data instead of a single cross-section of data with the possibility of temporal correlation. Thus, Simar and Wilson (1999), in adapting the bootstrapping procedure for Malmquist indices, propose a consistent method using a bivariate kernel density estimate via the covariance matrix of data from adjacent years. However, the estimated distance functions $\widehat{D_{it_1|t_1}}$ and $\widehat{D_{it_2|t_2}}$ using a kernel estimator are bounded from above unity and it is noted by Simar and Wilson (1999) that a bivariate kernel

[3] See Simar and Wilson (2000) for a thorough analysis based on Monte Carlo evidence.

estimator value under this condition is biased and asymptotically inconsistent. To account for this issue, Simar and Wilson (1998b, 1999) adapt a univariate reflection method proposed by Silverman (1986).[4] Therefore, to achieve consistent replication of the DGP taking all of these features into account, one must use the smoothed bootstrap. Repeatedly re-sampling from the Malmquist indices via the smoothed bootstrap results in a mimic of the sampling distribution of the original distance functions (a set of bootstrap Malmquist indices), from which confidence intervals can be constructed. On the whole, this process can be summarized as follows:

1. Calculation of the Malmquist index $\widehat{M_i^o}(t_1,t_2)$ for each bank $(i=1,...,N)$ in each time (t_1 and t_2) by solving the linear programming models (8) and (9) and their reversals.
2. Construction of the pseudo data set $\left\{\left(x_{it}^*, y_{it}^*\right); i=1,...,N; t=1,2\right\}$ to create the reference bootstrap technology using the bivariate kernel density estimation and adaption of the reflection method proposed by Silverman (1986).
3. Calculation of the bootstrap estimate of the Malmquist index $\widehat{{}^*M_i^o}(t_1,t_2)$ for each bank $(i=1,...,N)$ by applying the original estimators to the pseudo sample attained in step 2.
4. Repeating steps 2 to 3 for a large number of B times (in this study B=2000) to facilitate B sets of estimates for each firm.
5. Construct the confidence intervals for the Malmquist indices.

The basic idea designed for construction of the confidence intervals of the Malmquist indices is that the distribution of $\widehat{M_i^o}(t_1,t_2) - M_i^o(t_1,t_2)$ is unknown and can be approximated by the distribution of $\widehat{{}^*M_i^o}(t_1,t_2) - \widehat{M_i^o}(t_1,t_2)$, where $M_i^o(t_1,t_2)$ is the *true* unknown index, $\widehat{M_i^o}(t_1,t_2)$ is the estimate of the Malmquist index, and $\widehat{{}^*M_i^o}(t_1,t_2)$ is the bootstrap estimate of the index. Hence, a_α and b_α defining the $(1-\alpha)$ confidence interval:

$$\Pr(b_\alpha \le \widehat{M_i^o}(t_1,t_2) - M_i^o(t_1,t_2) \le a_\alpha) = 1-\alpha \tag{14}$$

can be approximated by estimating the values a_α^* and b_α^* given by:

$$\Pr(b_\alpha^* \le \widehat{{}^*M_i^o}(t_1,t_2) - \widehat{M_i^o}(t_1,t_2) \le a_\alpha^*) = 1-\alpha \tag{15}$$

[4] This method is founded on the idea of "reflecting" the probability mass lying beyond unity where, in theory, no probability mass should exist.

Thus, an estimated $(1-\alpha)$ percentage confidence interval for the i-th Malmquist index is given by:

$$\widehat{M_i^o}(t_1,t_2)+a_\alpha^* \le M_i^o(t_1,t_2) \le \widehat{M_i^o}(t_1,t_2)+b_\alpha^* \tag{16}$$

A Malmquist index for the i-th firm is said to be significantly different from unity (which would indicate no productivity change), at the α % level, if the interval in Eq. (16) does not include unity.

It should be mentioned that using the calculated bootstrap value in step 4, we can also correct for any finite-sample bias in the original estimators of the Malmquist indices. We only need to apply a simple procedure outlined by Simar & Wilson (1999) as follows:

The bootstrap bias estimate for the original estimator $\widehat{M_i^o}(t_1,t_2)$ is:

$$\widehat{bias_B}\left[\widehat{M_i^o}(t_1,t_2)\right] = B^{-1}\sum_{b=1}^{B} {}^*\widehat{M_i^o}(t_1,t_2)(b) - \widehat{M_i^o}(t_1,t_2) \tag{17}$$

Thus, a bias-corrected estimate of $M_i^o(t_1,t_2)$ can be computed as:

$$\begin{aligned}\widetilde{M_i^o}(t_1,t_2) &= \widehat{M_i^o}(t_1,t_2) - \widehat{bias}_B\left[\widehat{M_i^o}(t_1,t_2)\right] \\ &= 2\widehat{M_i^o}(t_1,t_2) - B^{-1}\sum_{b=1}^{B} {}^*\widehat{M_i^o}(t_1,t_2)(b).\end{aligned} \tag{18}$$

However, as explained by Simar & Wilson (1999), this bias-corrected estimator may have a higher mean-square error than the original estimator, and hence it will be less reliable. Overall, the bias-corrected estimator should only be considered if the sample variance ${}^*s_i^2$ of the bootstrap values $\left\{{}^*\widehat{M_i^o}(t_1,t_2)(b)\right\}_{b=1,\ldots,B}$ is less than a third of the squared bootstrap bias estimate for the original estimator, that is;

$${}^*s_i^2 < \frac{1}{3}\left(\widehat{bias_B}\left[\widehat{M_i^o}(t_1,t_2)\right]\right)^2. \tag{19}$$

This procedure can be achieved using commands *malmquist.components* and *malmquist* in the FEAR software program.

The above methodology for Malmquist indices can be easily adapted to the efficiency scores. Only the time-dependence structure of the data which is taken into account for the Malmquist indices must be changed by replacing t_1 and t_2 with the period considered. The procedure can be done using command *boot.sw98* using FEAR.

5. The Data

To facilitate measurement of efficiency scores and productivity change, we initially had to specify sets of inputs and outputs for the banks in our sample. However, there is no consensus as to how to specify inputs and outputs. In this study, focusing on bank services, we employ the intermediation approach. Under this approach banks are viewed as financial intermediaries with outputs measured in dollar amounts, and with labour, capital, and various funding sources as inputs. This approach has several variants; *asset*, *value-added* and *user cost* views. Sealy and Lindley (1977) focus on the role of banks as financial intermediaries between depositors and final users of bank *assets*, and classify deposits and other liabilities, together with real resources (labour and capital), as inputs, and only bank assets such as loans as outputs. Berger, Hanweck and Humphrey (1987) classify loans and all types of deposits as "important" outputs since these balance sheet categories contribute to bank *value added*, and labour, capital, and purchased funds they classify as inputs. Alternatively, Aly et al. (1990) and Hancock (1991) implement a *user-cost* framework to determine whether a financial product is an input or an output owing to its net contribution to bank revenue. Utilising this approach a bank asset can be categorized as an output if the financial return on the asset exceeds the opportunity cost of the investment, and a liability can be categorized as an output if the financial cost of the liability is less than its opportunity cost.

As our measurement of productivity depends on a mutually exclusive distinction between inputs and outputs, following Aly et al. (1990), as well as Wheelock and Wilson (1999) and Burgess and Wilson (1995), we classify inputs and outputs on the basis of the user cost approach. We include three inputs: labour (x_1) measured by the number of full-time equivalent employees on the payroll at the end of each period, physical capital (x_2) measured by the book value of premises and fixed assets, and purchased funds (x_3) including all time and savings deposits and other borrowed funds (not including demand deposits). We include three outputs: total demand deposits (y_1), public sector loans (y_2) including loans for agriculture, manufacturing, mining and services, and non-public loans (y_3). All data were obtained from Iran's Central Bank archives (CBI 2005, and CBI 2008). We consider all banks operating in the Iranian banking industry except three banks that are not homogenous in input and output mixes. We have balanced panel data for 14 banks and 6 years (2003-2008).

6. Empirical Results

6.1 Estimated Output-Oriented Technical Efficiency Scores

To estimate output-oriented technical efficiency for the banks, the linear programming problems in equation (9) must be solved for each bank in each period, and the interpretation is simple. When $\widehat{D}^{ov}_{it|t}$ is equal to unity it indicates that the i-th firm lies on the boundary of the production set of period *t*, and accordingly is technically efficient. When $\widehat{D}^{ov}_{it|t}$ is below unity it indicates that the firm is positioned under the frontier and is technically inefficient. Table 1 summarizes annual mean efficiency for the banking industry over the period 2003-2008. Column 2 of Table 1 lists the mean efficiency estimates, and columns 3-6 list the bias-corrected estimates, bootstrap bias estimates, and the efficiency's lower and upper bounds for the 95% confidence intervals (annual means), respectively, for each year. Table 1 shows that although the industry is inefficient over all years, the industry efficiency level improves over the period 2003-2006, and declines considerably after 2006. Note that in all cases the mean of estimated efficiency lies to the right of the estimated confidence intervals; this result obviously reflects the theory behind the construction of the confidence intervals presented by Simar and Wilson (1998b).

Table 1, Bootstrap estimates (Annual average)

Year	Estimated Eff	Bias-Corrected	Bias	Lower Bound	Upper Bound
2003	0.8940	0.8258	0.0681	0.4890	0.8908
2004	0.9542	0.9284	0.0258	0.8305	0.9542
2005	0.9793	0.9685	0.0107	0.9309	0.9793
2006	0.9911	0.9877	0.0033	0.9777	0.9911
2007	0.8928	0.8826	0.0103	0.8623	0.8926
2008	0.9382	0.9028	0.0354	0.6285	0.9378
Mean	0.9416	0.9160	0.0256	0.7865	0.9409

Source: Authors' calculations.

In addition, the estimates of technical efficiency differ from the bias-corrected estimates. In some periods this difference (the bias) is quite small. For instance, the difference was less than 0.03 between 2004 and 2007, while in 2003 the difference was about 0.07. The means of the estimated confidence intervals, which define statistical location of the true efficiency, were pretty narrow over 2005, 2006 and 2007. The minor bias of VRS estimates and the relatively smaller confidence intervals in these years imply that the results are relatively stable. However, results from this Table are very general and do not help us to distinguish between the performance of individual banks. Hence, the bootstraps of the efficiency scores for individual banks are displayed in three major categories of commercial, specialized and private banks in Tables 2 and 3. For the sake of brevity, only the bootstrap of efficiency scores for the years 2003 and 2008 are presented in these tables, respectively[5].

A comparison of Table 2 and Table 3 shows that the specialized banks are the most efficient banks in both years. The results are mixed for commercial and private banks. A number of banks show similar efficiencies in both periods, but a few banks show substantial disparities over the periods. For instance, among the commercial banks, National Bank and Trade Bank were efficient in both periods, whereas Bank Refah, which is quite inefficient in 2003, becomes efficient in 2008. On the other hand, the situation of Export Bank becomes worse in 2008, and its efficiency deteriorates from 0.95 in 2003 to 0.74 in 2008. Private banks also show similar disparities; Parsian Bank and EN Bank appear to be pretty efficient in both periods. Karafarin Bank improves its efficiency significantly in 2008 and reaches an efficiency score of 1.0, but Saman Bank's position perform exactly the opposite.

Table 2
Bootstrap of efficiency scores, 2003

Bank	Estimated Eff	Bias-Corrected	Bias	Lower Bound	Upper Bound
- Government-owned Banks:					
Commercial Banks:					
National Bank	1.0000	0.9155	0.0845	0.5082	0.9962
Bank Sepah	0.8995	0.8440	0.0555	0.7062	0.8965
Export Bank	0.9538	0.8972	0.0566	0.7382	0.9506
Trade Bank	0.8188	0.7727	0.0461	0.6212	0.8160
Bank Mellat	1.0000	0.9087	0.0913	0.5457	0.9954
Bank Refah	0.6665	0.6266	0.0399	0.5084	0.6639
Specialized Banks:					
Agricultural Bank	1.0000	0.9181	0.0819	0.5197	0.9962
Housing Bank	1.0000	0.9164	0.0836	0.0013	0.9971
Export development Bank (ED Bank)	1.0000	0.9102	0.0898	0.5745	0.9954
Bank of Industry and Mines (BIM)	1.0000	0.9221	0.0779	0.4090	0.9970
- Private Banks:					
Karafarin Bank	0.5122	0.4816	0.0307	0.3996	0.5108
Saman Bank	0.6651	0.6234	0.0417	0.4967	0.6629
Parsian Bank	1.0000	0.9116	0.0884	0.4200	0.9962
Bank Eghtesad Novin (EN Bank)	1.0000	0.9139	0.0861	0.3983	0.9970
Mean	0.8940	0.8258	0.0681	0.4891	0.8908

Source: Authors' calculations.

As stated by Simar and Wilson (1998b), relative comparisons of the performance among firms based on the estimated efficiency scores should be made with caution. Of special note, Housing Bank is efficient in both periods (as its estimated efficiency is 1.000 in both periods), and its estimated confidence intervals for 2003 and 2008 overlap. However the estimated lower bound in 2008 was much higher than that of 2003, suggesting that its true

[5] Results for all years are available from the authors upon request.

efficiency may have improved in 2008. In this case the bias-corrected efficiency scores can be very helpful in distinguishing between decision units. For instance, the bias-corrected efficiency of Housing Bank increases from 0.916 in 2003 to 0.958 in 2008, suggesting that this bank was not equally efficient in 2003 and 2008. The bias for some banks is very small; hence, their bias-corrected efficiency score is very close to the original estimate (e.g. Saman Bank in 2008), but a few banks show large differences (e.g. Bank Mellat in 2003). The bias estimates, in general, are higher for the most efficient banks (with the estimated efficiency of 1.000) in both years. There are also substantial dissimilarities between banks' confidence intervals; both Tables 2 and 3 show that a number of estimated confidence intervals are quite wide (e.g. Housing Bank and EN Bank in Table 2 and BIM and Parsian in Table 3), while others are rather narrow (e.g. Bank Refah and Karafarin Bank in Table 2 and Bank Refah and Saman Bank in Table 3). In general, the widths of confidence intervals appear to be narrower and the bias-corrected efficiencies tend to reach higher values in 2008.

Table 3
Bootstrap of efficiency scores, 2008

Bank	Estimated Eff	Bias-Corrected	Bias	Lower Bound	Upper Bound
- Government-owned Banks:					
Commercial Banks:					
National Bank	1.0000	0.9603	0.0397	0.5574	0.9997
Bank Sepah	0.9097	0.8796	0.0301	0.7794	0.9093
Export Bank	0.7382	0.7153	0.0229	0.6177	0.7380
Trade Bank	0.9617	0.9341	0.0275	0.8150	0.9613
Bank Mellat	1.0000	0.9583	0.0418	0.6862	0.9995
Bank Refah	1.0000	0.9589	0.0411	0.5616	0.9995
Specialized Banks:					
Agricultural Bank	1.0000	0.9574	0.0426	0.8045	0.9994
Housing Bank	1.0000	0.9584	0.0416	0.7654	0.9994
Export development Bank (ED Bank)	1.0000	0.9794	0.0206	0.5642	0.9991
Bank of Industry and Mines (BIM)	1.0000	0.9592	0.0408	0.4282	0.9996
- Private Banks:					
Karafarin Bank	1.0000	0.9571	0.0429	0.5071	0.9910
Saman Bank	0.5252	0.5085	0.0167	0.4349	0.5250
Parsian Bank	1.0000	0.9554	0.0446	0.4749	0.9993
Bank Eghtesad Novin (EN Bank)	1.0000	0.9576	0.0424	0.8026	0.9990
Mean	0.9382	0.9028	0.0354	0.6285	0.9371

Source: Authors' calculations.

6.2 The Decomposition of the Malmquist Index

Concentrating only on efficiency estimates can provide an incomplete view of the performance of banks over time. It is for this reason that changes in distance function values over time could be caused by either 1) movement of banks within the input-output space (efficiency changes), or 2) progress/regress of the boundary of the production set over time (technological changes). The decomposition of the Malmquist index, as explained in section 2, makes it possible to distinguish changes in productivity, efficiency and technological change.

Table 4 reports various estimates of productivity changes for banks in the three categories over five pairs of years between 2003 and 2008. Almost all of the estimates are significantly different from unity at the 90% or 95% level of significance. Only BIM is insignificantly different from unity for one pair of years (2007/2008). Over 2003-2004 - the period after the private banks came into existence – of all 14 estimates of productivity changes only 5 banks show productivity gains. In this period, two of the specialized banks, Agricultural Bank and Housing Bank, had the highest levels of productivity losses. On average, the industry showed an 11% productivity loss (i.e. 0.98 productivity changes). The results for the three pairs of years, however, were quite the opposite.

During the period 2004-2005 all of the banks (with two exceptions) show moderate gains and all specialized banks show productivity expansions. In the period 2005-2006 the results indicate significant gains for ten banks, and significant decreases in productivity for four banks (two specialized banks and two private banks). All commercial banks show rather large productivity gains over this period. During the period 2006-2007 the industry showed a significant increase in productivity; about 28% on average. All banks but one showed productivity gains, and among these banks two of the specialized banks (i.e. ED Bank and BIM), demonstrated massive productivity advances of 2.29 and 2.67, respectively. The results for 2007-2008, however, were largely different. Most of the banks experienced large productivity losses and none of the commercial banks were productive. BIM, which showed the highest level of productivity gain in 2006-2007, exhibited a 33% productivity loss in 2007-2008. This pattern was also true for some of the commercial and private banks (Export Bank, Trade Bank, Bank Mellat and EN Bank). Using the four components explained in section 2, we can now trace the main causes of the productivity changes over the sample period. Tables 5-6 present estimates of the changes in pure efficiency, scale efficiency, pure technology and scale of technology, respectively.

Table 4
Estimates of Malmquist indexes (changes in productivity)

Bank	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008
- Government-owned Banks:					
Commercial Banks:					
National Bank	0.8208*	1.0740*	1.1795*	1.1426*	0.9083*
Bank Sepah	0.6920**	1.0804*	1.3003*	1.0548*	0.7610*
Export Bank	1.1310*	0.7633*	1.0915*	1.2199*	0.7202*
Trade Bank	0.8487*	1.0972*	1.0695*	1.2057*	0.8988*
Bank Mellat	0.6510*	1.1616*	1.2716*	1.2565*	0.9020*
Bank Refah	1.0179*	1.0818*	1.2881*	1.0993*	0.7688*
Specialized Banks:					
Agricultural Bank	0.5847*	1.1201*	1.1231*	1.0357*	0.9371*
Housing Bank	0.4532*	1.2940*	1.3102*	1.1968*	1.1560*
Export development Bank (ED Bank)	0.8865*	1.0110*	0.6927*	2.2992*	1.2269*
Bank of Industry and Mines (BIM)	1.3221*	1.0966*	0.8645*	2.6721*	0.6755
- Private Banks:					
Karafarin Bank	1.2538*	1.0707*	1.1854*	1.0004*	0.8405**
Saman Bank	1.1387*	1.1847*	1.4870*	0.5171*	0.8969*
Parsian Bank	0.8804*	0.9007*	0.9943*	1.0232*	1.0139*
Bank Eghtesad Novin (EN Bank)	0.8332*	1.1086*	0.8291*	1.2109*	0.9565*
Mean	0.8939	1.0746	1.1067	1.2810	0.9045

Note: Numbers greater than unity indicate improvements and less than unity indicate declines.
Single asterisk (*) denote significant differences from unity at 90%; double asterisk (**) denote significant differences from unity at 95%.
Source: Authors' calculations.

Table 5
Estimates of change in pure efficiency

Bank	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008
- Government-owned Banks:					
Commercial Banks:					
National Bank	1.00*	1.00*	1.00*	1.00*	1.00*
Bank Sepah	0.9910*	0.9994*	1.0000	1.00*	0.9046*
Export Bank	1.0477*	1.00*	0.9568*	1.0140*	0.7610*
Trade Bank	1.2196*	1.00*	1.00*	1.00*	0.9615*
Bank Mellat	1.00*	1.00*	1.00*	1.00*	1.00*
Bank Refah	1.4970*	1.00*	1.00*	1.00*	1.00*
Specialized Banks:					
Agricultural Bank	1.00*	1.00*	1.00*	0.9883*	1.0118*
Housing Bank	0.7051*	1.1618*	1.1770*	0.9850*	1.0528*
Export development Bank (ED Bank)	1.00*	1.00*	1.00*	1.00*	1.00*
Bank of Industry and Mines (BIM)	1.00*	1.00*	1.00*	1.00*	1.00*
- Private Banks:					
Karafarin Bank	1.5435*	1.3415*	1.00*	1.00*	1.00**
Saman Bank	1.4351*	1.00*	1.00*	0.5883*	0.8879*
Parsian Bank	1.00*	1.00*	1.00*	1.00*	1.00*
Bank Eghtesad Novin (EN Bank)	1.00*	1.00*	0.9588*	1.0429*	1.00*
Mean	1.1028	1.0359	1.0066	0.9728	0.9677

Note: Numbers greater than unity indicate improvements and less than unity indicate declines.
Single asterisk (*) denote significant differences from unity at 90%; double asterisk (**) denote significant differences from unity at 95%.
Source: Authors' calculations.

Table 6
Estimates of change in scale efficiency

Bank	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008
- Government-owned Banks:					
Commercial Banks:					
National Bank	1.0940*	1.00*	0.9916*	0.5217*	1.7376*
Bank Sepah	0.9437*	0.9856*	0.9111*	0.7321*	1.0454*
Export Bank	1.2852*	0.9868*	0.8594*	0.4986*	1.8684*
Trade Bank	0.9586*	1.0120*	0.9962*	0.6048*	1.6495*
Bank Mellat	0.9552*	1.0401*	1.0065*	0.6837*	1.4624*
Bank Refah	1.0029*	1.00**	1.0000	1.00***	1.00***
Specialized Banks:					
Agricultural Bank	0.8808*	0.9940*	1.0521*	0.5659*	1.2925*
Housing Bank	0.7966*	0.9547*	0.9785*	0.9392*	0.9916*
Export development Bank (ED Bank)	1.00*	0.9041*	0.7461*	1.1078*	1.3207*
Bank of Industry and Mines (BIM)	1.0000	1.0000	1.0000	1.0000	1.0000
- Private Banks:					
Karafarin Bank	0.9078*	0.8151*	1.1262*	0.9555*	0.8010*
Saman Bank	0.8895*	1.1712*	1.00*	0.9458*	0.9559*
Parsian Bank	1.00***	1.0000	1.0000	1.00*	1.00*
Bank Eghtesad Novin (EN Bank)	1.00*	1.00*	0.9849*	1.0152*	0.9373*
Mean	0.9796	0.9903	0.9752	0.8265	1.2187

Note: Numbers greater than unity indicate improvements and less than unity indicate declines.
Single asterisk (*) denote significant differences from unity at 90%; triple asterisk (***) denote significant differences from unity at 99%.
Source: Authors' calculations.

Estimated changes in pure efficiency have been reported in Table 5. In sum, for consecutive years, out of the 70 estimates of changes in pure efficiency, only 24 estimates were different from unity while all of them were statistically significant. A number of banks showed no changes in pure efficiency for all reported years (e.g. National Bank, Bank Mellat, Agricultural Bank, ED Bank, BIM, and Parsian Bank). During 2006-2007 and 2007-2008 (i.e. in the post regulation era) when interest rates and the allocation of direct lending facilities were regulated, the number of banks with losses in pure efficiency increased to four and five banks, respectively. Hence, the industry, on average, showed negative changes in technical efficiency as a result of inappropriate policies.

Table 6 reveals the estimated changes in scale efficiency where all changes from unity are statistically significant. Results for BIM are not significant in any of the reported periods. The results for 2003-2004, 2004-2005 and 2005-2006 are mixed. Over these three periods most of the banks experienced negative changes in scale efficiency (i.e. the estimates are less than unity) or very low levels of positive changes. Over the period 2006-2007, the results deteriorated and only two banks show some improvements in scale efficiency (i.e. ED Bank and EN Bank). Other banks either experienced negative changes or their scale efficiency remains more or less unchanged (e.g. Bank Refah, BIM and Parsian Bank). Hence, these results, in conjunction with those for changes in pure efficiency, indicate that the considerable changes in bank productivity for 2006-2007 cannot be attributable to efficiency change components (pure efficiency change or scale efficiency change); they can be explained only by technological changes. The results for 2007-2008 were enhanced as nearly all of the government-owned banks showed considerable positive changes in scale efficiency. However, the situation for private banks deteriorated as demonstrated by larger declines. As can be seen by the last row of Table 6, only the final period shows positive changes in scale efficiency, suggesting that scale inefficiency was a major source of inefficiency among the Iranian banks.

Tables 7 and 8 show the estimated changes in pure technology in production possibilities and scale of technology, respectively. The estimated changes are significantly different from unity in all cases at different significance levels. In a number of cases these changes for specialized banks and private banks could not be computed due to the constraints imposed in the linear programming to estimate cross-period distance functions. We have indicated these cases by INF in Tables 7 and 8, indicating that they were infeasible to compute. [6] The results from Table 7 reveal that in 2003-2004 technology among the government-owned banks shifted inwards for all but Export Bank. However, in 2004-2005, 2005-2006, and 2006-2007, the estimated changes in pure technology were greater than unity for nearly all firms with the only exception being Export Bank in 2004-2005, suggesting an overall technological progress in the industry. This is most probably due to the technological advances in the banking industry which commenced in 2004 such as increased numbers of automated teller machines (ATM), credit cards, debit cards and online-branches. Almost all banks also showed large decreases in technology for the period 2007-2008. For the private banks all these changes, except for EN Bank in the last period, were significantly greater than unity in the sample period.

[6] This difficulty is also experienced by Gilbert and Wilson (1998).

Table 7

Estimates of change in pure technology

Bank	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008
- Government-owned Banks:					
Commercial Banks:					
National Bank	0.9636*	1.1555*	1.1698*	1.1883*	0.9340*
Bank Sepah	0.8489*	1.0850*	1.1528*	1.1672**	0.9145*
Export Bank	1.0988*	0.7439*	1.2648*	1.2298***	0.9431*
Trade Bank	0.8309*	1.1080*	1.0750*	1.0640*	0.8204*
Bank Mellat	0.9138*	1.0802*	1.1977*	1.1675*	0.9043*
Bank Refah	0.6698*	1.0794*	1.2865*	1.1072***	0.7392*
Specialized Banks:					
Agricultural Bank	0.7891*	1.0766*	1.0232*	1.0932**	0.9049*
Housing Bank	0.9454*	1.2338*	1.1366*	1.2158**	1.1001*
Export development Bank (ED Bank)	INF	INF	INF	1.3235***	INF
Bank of Industry and Mines (BIM)	INF	INF	INF	INF	INF
- Private Banks:					
Karafarin Bank	INF	INF	INF	INF	INF
Saman Bank	INF	1.1151***	1.6001***	INF	1.0815*
Parsian Bank	INF	1.1631*	1.0889*	1.1016*	1.0615*
Bank Eghtesad Novin (EN Bank)	INF	INF	INF	1.1260**	0.9374*
Mean	0.8825	1.0841	1.1996	1.1622	0.9401

Note: Estimates greater than unity indicate an increase in pure technology and estimates less than unity indicate a decrease in pure technology. INF=Infeasible to compute.
Single asterisk (*) denote significant differences from unity at 90%; double asterisk (**) denote significant differences from unity at 95%; triple asterisk (***) denote significant differences from unity at 99%.
Source: Authors' calculations.

Table 8

Estimates of change in scale of technology

Bank	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008
- Government-owned Banks:					
Commercial Banks:					
National Bank	0.7785*	0.9294*	1.0168*	1.8428*	0.5596*
Bank Sepah	0.8715*	1.0108*	1.1041*	1.2343*	0.8799*
Export Bank	0.7642*	1.0396*	1.0493*	1.9619*	0.5370*
Trade Bank	0.8736*	0.9784*	0.9985*	1.8736*	0.6908*
Bank Mellat	0.7458*	1.0338*	1.0548*	1.5739*	0.6820*
Bank Refah	1.0121*	1.0022*	1.0012*	0.9928*	1.0400*
Specialized Banks:					
Agricultural Bank	0.8412*	1.0466*	1.0432*	1.6936*	0.7918*
Housing Bank	0.8534*	0.9454*	1.0008*	1.0640*	1.0064*
Export development Bank (ED Bank)	INF	INF	INF	1.5681*	INF
Bank of Industry and Mines (BIM)	INF	INF	INF	INF	INF
- Private Banks:					
Karafarin Bank	INF	INF	INF	INF	INF
Saman Bank	INF	INF	0.9070*	0.9288*	0.9769*
Parsian Bank	INF	0.7744*	0.9130*	0.9288*	0.9551*
Bank Eghtesad Novin (EN Bank)	INF	INF	INF	INF	1.0885*
Mean	0.8425	0.9668	1.0111	1.4734	0.8371

Note: Estimates greater than unity show that the technology is moving farther from constant return to scale, and estimates less than unity indicate that the technology is moving toward constant returns to scale.
INF=Infeasible to compute.
Single asterisk (*) denote significant differences from unity at 90%.
Source: Authors' calculations.

Finally, as to the shape of technology, the estimated changes in the scale of technology are presented in Table 8. The estimated changes in the private banks are significantly less than unity in almost every case, indicating that the technological region of these banks in the input-output space was moving toward constant returns to scale between 2004 and 2008. Among the government-owned banks the results are the opposite in three periods; 2004-2005, 2005-2006, and 2006-2007, meaning that returns to scale of technology were becoming increasingly convex and more variable. Given that the private banks are much smaller than the government-owned banks, these results seem to imply that the most efficient scale size is falling over these periods. However, the technology faced by government-owned banks in the last period moved toward constant returns to scale; since the estimated changes showed values less than unity for most of them. In brief, the results in Tables 6 and 8 emphasize that the portion of the technology confronting government-owned banks seems to have moved substantially further from constant returns to scale, and the banks have performed under decreasing returns to scale for a long period.

In general, the results in Tables 4 to 8 indicate that while government ownership resulted in large advances in the technology of commercial and specialized banks over time, it also caused scale inefficiencies and kept the most efficient scale size smaller than it otherwise would have prevailed. Government-owned banks show no positive changes in pure technical efficiency during the sample period. Also, after the regulation, three of the largest commercial banks have become considerably inefficient. This may be attributed to the significant growth of NPLs since 2006. However, the technology advances of government-owned banks offset the increase in scale and pure technical inefficiencies over 2004-2005, 2005-2006, and 2006-2007, and hence, productivity increases in almost all government-owned banks. But, over the period 2007-2008 large increases in the scale efficiency of these banks do not offset the rise in pure technical inefficiency and the reduction in pure technology (in production possibilities). Hence, on average, their productivity deteriorates considerably through time.

7. Conclusions

This paper has employed bootstrapped Malmquist indices and efficiency scores developed by Simar and Wilson (1998b, 1999) to investigate the effects of Iranian government regulation launched in 2005 on the technical efficiency and productivity changes of the banking industry over the period 2003-2008. We also applied an alternative decomposition of the Malmquist index, introduced by Simar and Wilson (1998a), to provide a more comprehensive analysis of productivity and technical changes in the banking industry. Hence, four different components of productivity changes were estimated; i.e. changes in pure technical efficiency, changes in scale efficiency, pure changes in technology and changes in scale of technology. The bootstrap approach emphasises that the majority of our estimates are statistically significant.

Based on our results, it appears that the industry efficiency level (output-oriented technical efficiency) has improved over the period 2003-2006, and deteriorated considerably soon after the regulatory changes were introduced. Also, our findings show that the highly efficient banks are among either private or government-owned banks but not the specialised banks. Productivity changes show the same fluctuations as technical efficiency and the extent of productivity changes declines significantly after 2006. In general, it can be concluded that although the regulatory changes had different effects on different banks, the efficiency and productivity of the industry has declined after introducing the regulation. There is a significant room for improvement in government-owned banks in terms of technical and scale efficiency. It seems that government control of these banks tends to limit incentives and the ability of managers to operate efficiently. As a result, government-owned banks move farther from constant returns to scale, and the banks perform under decreasing returns to scale for a long period.

It can therefore be suggested that the privatization of banking industry should be expedited and the government should reduce its political interference to boost the efficiency and productivity of banks in Iran. We found that the productivity of private banks has fallen considerably after regulations have been imposed since 2005-2006. One may argue that the lacklustre performance of banks was mainly due to a considerable rise in deposits and scale inefficiency attributable to the lack of institutional growth.

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