Australasian Accounting, Business and Finance Journal

Volume 5
Issue 3 *Australasian Accounting Business and Finance Journal*

Article 4

2011

Analysing Productivity Changes Using the Bootstrapped Malmquist Approach: The Case of the Iranian Banking Industry

Amir Arjomandi
University of Wollongong, amira@uow.edu.au

Abbas Valadkhani
University of Wollongong, abbas@uow.edu.au

Charles Harvie
University of Wollongong

Analysing Productivity Changes Using the Bootstrapped Malmquist Approach: The Case of the Iranian Banking Industry

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 further decompose technical changes 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 banking efficiency studies, it has not previously been applied to any developing country's banking system. The results 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

Analysing Productivity Changes Using the Bootstrapped Malmquist Approach: The Case of the Iranian Banking Industry*

Amir Arjomandi[1], Abbas Valadkhani[1] and Charles Harvie[1]

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 further decompose technical changes 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 banking efficiency studies, it has not previously been applied to any developing country's banking system. The results 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

Acknowledgements: We wish to thank two anonymous referees and the editor, Dr Ciorstan Smark, for their constructive comments on an earlier version of this article. The views expressed in this paper do not necessarily reflect the views of the referees and the editor.

[1] School of Economics, University of Wollongong. Corresponding author: Abbas Valadkhani, Email: abbas@uow.edu.au

1. Introduction

Over the last decade the Iranian banking industry has undergone many substantial changes, such as liberalisation, 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 specialised banks) and private banks. The former have been the most successful in acquiring market share; in contrast, most private banks only joined the market after 2001 and have not yet caught up in market share with the government-owned banks. However, it seems that government-owned banks were affected more noticeably after government regulation initiatives launched in 2005 that 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) from 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 stated that the highest share of NPLs belongs to the manufacturing and mining (20.1%) and construction (19.5%) sectors. Thus, it is important to investigate the effect of government policies on the productivity of the Iranian banking industry.

Fethi and Pasiouras (2010), in a comprehensive survey covering 196 studies using operational research and artificial intelligence techniques to assess bank performance, revealed that almost all studies that obtained estimates of total factor productivity growth employed a DEA[2]-type Malmquist index. In other words, the Malmquist index is in widespread use for 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 demonstrated that the resulting total factor productivity (TFP) indices could be decomposed into efficiency-change and technical-change components. Färe, Grosskopf, Norris and Zhang(FGNZ) (1994b) further decomposed efficiency change into pure technical efficiency change and changes in scale efficiency, a development that has made the Malmquist index widely popular as an empirical index of productivity change.

However, Simar and Wilson (1998a) stated that the FGNZ model does not provide a useful measure of technical change. 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" (p.4). Moreover, they concluded that "Without a statistical interpretation, it is not meaningful

[2] Data Envelopment Analysis (DEA) is one of the most popular non-parametric approaches to frontier efficiency and productivity methods in the literature. The major advantage of the DEA approach is that one does not need to adopt a functional form and its associated coefficients for the production function. According to Boussofiane, Martin and Parker (1997) and Guan et al. (2006), firms' efficiency can be measured by the DEA approach without any need to know the weights for the different inputs and outputs in the production process.

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 proposed an alternative decomposition of the Malmquist index: they estimated changes in technology by changes in the variable returns to scale (VRS) estimate, and further decomposed 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 Coelli et al.(2005), Lovell (2000) 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, which in turn affects measurement of distances to all other units. Undoubtedly, uncertainty is carried through to parameters, such as the Malmquist indices of TFP changes, that are estimated from DEA distance functions.

To solve this problem, Simar and Wilson (1998b; 2000) defined 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 a later study, Simar and Wilson (1999) demonstrated 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, we also employ the bootstrap simulation method (Simar & Wilson 1998b; 2000) in the context of a developing country 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 using the bootstrapped Malmquist. Only a small number of studies have applied the statistical properties of the Malmquist estimates; see Balcombe, Davidova and Latruffe (2008), Galdeano-Gómez (2008), Hoff (2006) and Latruffe Davidova and Balcombe (2008)[3]. The exception is Tortosa-Ausina et al. (2008), who used both the FGNZ model and the bootstrap technique to investigate the productivity of the Spanish banking system over the

[3] 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.

post-deregulation period 1992-1998. They found that the productivity growth that occurred 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. Gilbert and Wilson (1998) and Wheelock and Wilson (1999) analysed the banking systems of developed countries with a focus on the US, and Korea, respectively. Wheelock and Wilson (1999), using the alternative decomposition of the Malmquist productivity index, showed 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) studied the effect of deregulation on the productivity of Korean banks between 1980 and 1994. The index of changes in pure technology indicated 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 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 (*Frontier Efficiency Analysis with R*) software package, 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 that 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 *of input and output* are x_{t_2} and y_{t_2}, respectively. The production-possibilities set at time *t* is:

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

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:

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

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, it is 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:

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

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

However, Simar and Wilson (1999) argued that the production possibility set S_t is never observed and, consequently, that 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, $\hat{y}(x)$. Burgess and Wilson (1995) wrote the estimated production set as:

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

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

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

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

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

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

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

where $\widehat{D^{oc}_{it_1|t_2}}$ features the assumption of constant returns to scale and $\widehat{D^{ov}_{it_1|t_2}}$ 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 Equation 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 >, < or = unity depending on whether the considered 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 is improving, stagnating, or deteriorating, permitting a comparison to the evaluated firm. It can be >, < or = unity depending on whether the technical change is positive, zero or negative.

Färe et al. (1994a) demonstrated 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 Equation 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) stated 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), the $\triangle Tech$ presented in Equation 12 will 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:

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

$$\underbrace{\sqrt{\left(\frac{\widehat{D^{ov}_{it_1|t_2}}}{\widehat{D^{ov}_{it_2|t_2}}} \times \frac{\widehat{D^{ov}_{it_1|t_1}}}{\widehat{D^{ov}_{it_2|t_1}}}\right)}}_{\triangle PureTech} \times \underbrace{\sqrt{\left(\frac{\widehat{D^{oc}_{it_1|t_2}} / \widehat{D^{ov}_{it_1|t_2}}}{\widehat{D^{oc}_{it_2|t_2}} / \widehat{D^{ov}_{it_2|t_2}}} \times \frac{\widehat{D^{oc}_{it_1|t_1}} / \widehat{D^{ov}_{it_1|t_1}}}{\widehat{D^{oc}_{it_2|t_1}} / \widehat{D^{ov}_{it_2|t_1}}}\right)}}_{\triangle ScaleTech} \qquad (13)$$

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 that measure the shift in the VRS frontier estimate relative to the bank's position at times 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 suggests that the technology is moving toward constant returns to scale; and when equal to unity suggests no changes in the shape of the technology.

A similar decomposition of the Malmquist index was also proposed by Ray and Desli (1997). They combined changes in the scale of efficiency and the scale of technology into a single term (SCH). However, Simar and Wilson (1999) stated that Ray and Desli's SCH confuses changes in the shape of the technology and in scale efficiency experienced by the production unit. Färe, Grosskopf and Norris (1997) agreed 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 were described by Fried, Lovell and Schmidt (2008), who concluded that the choice of appropriate decompositions depends 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) pioneered 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 builds a good approximation of the true distribution. Simar and Wilson (1998b) showed that the statistically consistent estimation of such confidence intervals very much depends on the consistent replication of a data-generating process. In other words, the most important problem of bootstrapping in frontier models relates to the consistent mimicking of the data-generating process.[4] They argued that this problem refers to the bounded nature of the distance functions. Since the distance estimation values are close to unity, resampling directly from the set of original data

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

(the so-called naive bootstrap) to construct pseudo-samples will provide an inconsistent bootstrap estimation of the confidence intervals.

To overcome this problem, they proposed a smoothed bootstrap procedure. They used a univariate kernel estimator of the density of the original distance function estimates (for efficiency scores in that case), and constructed the pseudo-data from this estimated density. However, to estimate the Malmquist indices, this study uses panel data instead of a single cross-section of data with the possibility of temporal correlation. Simar and Wilson (1999), in adapting the bootstrapping procedure for Malmquist indices, proposed 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; Simar and Wilson noted (1999) that a bivariate kernel estimator value under this condition is biased and asymptotically inconsistent. To account for this issue, Simar and Wilson (1998b, 1999) adapted a univariate reflection method proposed by Silverman (1986).[5] Therefore, to achieve consistent replication of the data-generating procedure that takes all these features into account, one must use the smoothed bootstrap. Repeatedly resampling from the Malmquist indices via the smoothed bootstrap mimics 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 summarised as follows:

1. Calcuating 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 in Equations 8 and 9 and their reversals.
2. Constructing 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. Calculating 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 and 3 for a large number of B times (in this study B=2000) to facilitate B sets of estimates for each firm.
5. Constructing 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:

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

[5] 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 Equation 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 with the application of a simple procedure outlined by Simar and Wilson (1999):

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 and 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 $\left\{{}^*\widehat{M_i^o}(t_1,t_2)(b)\right\}_{b=1,\dots,B}$ is less than one-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 efficiency scores. Only the time-dependence structure of the data 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* in the FEAR program.

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 employed the intermediation approach. In this approach banks are viewed as financial intermediaries with outputs measured in local currency, and with labour, capital and various funding sources as inputs. This approach has several variants: *asset*, *value-added* and *user-*

cost views. Sealey and Lindley (1977) focused on the role of banks as financial intermediaries between depositors and final users of bank *assets*; they also classified 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) classified loans and all types of deposits as "important" outputs, since these balance-sheet categories contribute to bank's *value added*, and classified labour, capital and purchased funds as inputs. Alternatively, Aly et al. (1990) and Hancock (1991) implemented a *user-cost* framework to determine whether a financial product is an input or an output depending on its net contribution to bank revenue. In this approach a bank asset can be categorised as an output if the financial return on the asset exceeds the opportunity cost of the investment, and a liability can be categorised 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), Burgess and Wilson (1995) and Wheelock and Wilson (1999), 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). Since the private banks joined the market effectively from 2003, and significant technological changes and economic reforms took place in 2004 and 2005, the sample period 2003-2008 was deemed appropriate. Due to the unavailability of the data, the sample expansion was not feasible. All data were obtained from Iran's Central Bank archives (CBI 2005; 2008). We considered all banks operating in the Iranian banking industry except three banks that are not homogenous in input and output mixes. The study uses balanced panel data for 14 banks and six 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. 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 summarises annual mean efficiency for the banking industry over the period 2003-2008. Column 2 lists the mean efficiency estimates, and columns 3 through 6 list the bias-corrected estimates, the 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 reflects the theory behind the construction of the confidence intervals presented by Simar and Wilson (1998b).

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 the statistical location of the true efficiency, were quite 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 – commercial, specialised and private banks – in Tables 2 and 3. For the sake of brevity, these tables present only the bootstrap of efficiency scores for the years 2003 and 2008, respectively[6].

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.

A comparison of Table 2 and Table 3 shows that the specialised banks were 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 was quite inefficient in 2003, became efficient in 2008. On the other hand, the situation of Export Bank worsened in 2008, and its efficiency deteriorated from 0.95 in 2003 to 0.74 in 2008. Private banks also show similar disparities: Parsian Bank and EN Bank appear to be quite efficient in both periods. Karafarin Bank improved its efficiency significantly in 2008 to an efficiency score of 1.0, but Saman Bank performed exactly the opposite. According to Tables 2 and 3, in 2003 and 2008 specialised banks and private banks were the most efficient, respectively, and commercial banks (i.e., Bank Sepah, Export Bank and Trade Bank) were the most inefficient banks in the market. However, these results only provide a general guide to identify the most and the least technically efficient banks in the market. A comprehensive investigation of why some banks are more efficient than others will requires a further in-depth analysis of changes in government or banks’ policies within a historical perspective.

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

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 is the finding that Housing Bank was efficient in both periods (as its estimated efficiency was 1.0 for both), 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 efficiency may have improved in 2008. In this case bias-corrected efficiency scores can be very helpful in distinguishing between decision units. For instance, the bias-corrected efficiency of Housing Bank increased 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 1.0) in both years. There are also substantial dissimilarities between banks' confidence intervals: Tables 2 and 3 both 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
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.

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.

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. 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 technology.

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 – based on all 14 estimates of productivity changes only five banks showed productivity gains. In this period, two of the specialised 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) showed moderate gains, and all specialised banks showed productivity expansions. In the period 2005-2006 the results indicate significant gains for ten banks, and significant decreases in productivity for four banks (two specialised banks and two private banks). All commercial banks showed 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 specialised banks – ED Bank and BIM – demonstrated massive productivity advances of 2.29 and 2.67, respectively. The results for 2007-2008, however, were quite 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 and 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 those less than unity indicate declines. Single asterisk (*) denotes significant differences from unity at 90%; double asterisk (**) denotes 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 those less than unity indicate declines. Single asterisk (*) denotes significant differences from unity at 90%; double asterisk (**) denotes 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 those less than unity indicate declines. Single asterisk (*) denotes significant differences from unity at 90%; triple asterisk (***) denotes significant differences from unity at 99%.
Source: Authors' calculations.

Table 5 reports estimated changes in pure efficiency. For consecutive years, out of the 70 estimates of changes in pure efficiency, only 24 estimates differed from unity, and all were statistically significant. A number of banks showed no changes in pure efficiency for all reported years (National Bank, Bank Mellat, 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 and as can be seen 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, with only two banks showing some improvements in scale efficiency (ED Bank and EN Bank). Other banks either experienced negative changes or kept their scale efficiency more or less unchanged (for example, Bank Refah, BIM and Parsian Bank). 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. In 2007-2008 nearly all of the government-owned banks showed considerable positive changes in scale efficiency. However, the situation for private banks deteriorated. 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 for 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 changes for specialised 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.[7] 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; these results suggest an overall technological progress in the industry. This is most probably due to the technological advances in the banking industry starting in 2004, such as increased numbers of automated teller machines (ATM), credit cards, debit cards and online branches. However, almost all banks showed large decreases in technology for the period 2007-2008.

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 (*) denotes significant differences from unity at 90%; double asterisk (**) denotes significant differences from unity at 95%; triple asterisk (***) denote significant differences from unity at 99%.
Source: Authors' calculations.

[7] This difficulty was also experienced by Gilbert and Wilson (1998).

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 (*) denotes significant differences from unity at 90%.
Source: Authors' calculations.

Finally, Table 8 presents the estimated changes in the scale of technology. The estimated changes in the private banks are significantly less than unity in almost every case, indicating that between 2004 and 2008 the technological region of these banks in the input-output space was moving toward constant returns to scale. Among the government-owned banks the results are the opposite in 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 decreased over these periods. However, the technology faced by government-owned banks in the last period moved toward constant returns to scale, as the estimated changes showed values less than unity for most of them. In brief, the results in Tables 6 and 8 emphasise 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 specialised banks over time, it also caused scale inefficiencies and kept the most efficient scale size smaller than it otherwise would have been. Government-owned banks showed no positive changes in pure technical efficiency during the sample period. Also, after regulation, three of the largest commercial banks became 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 large increases in the scale efficiency of these banks over the period 2007-2008 did not offset the rise in pure technical inefficiency and the reduction in pure technology (in production possibilities). Hence, on average, their productivity deteriorated considerably over 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 have 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. Four different components of productivity changes were estimated: changes in pure technical efficiency, changes in scale efficiency, pure changes in technology and changes in scale of technology. The bootstrap approach shows that the majority of our estimates are statistically significant.

Based on our results, it appears that the industry efficiency level (output-oriented technical efficiency) improved over the period 2003-2006, and deteriorated considerably soon after the regulatory changes were introduced. Furthermore, our findings show that the estimates of productivity changes exhibit almost the same fluctuations as changes in pure technology. Hence, we observe some improvements in productivity during the period 2004-2007, followed by significant productivity fall in 2007-2008 (i.e., a decline from 1.28 in 2006-2007 to 0.90 in 2007-2008). Changes in the production-possibilities set (i.e., pure technology) can be attributable to changes in factors such as technological changes and/or government regulations. Hence, the overall technological progress in the industry during 2004-2007 was most probably due to technological advances in the banking industry, starting in 2004. These advances include, among others, the rising use and number of automated teller machines (ATM), credit cards, debit cards and online branches, as well as increased pressure on commercial banks to expand credit in 2006. This can be regarded as a technological advance because the provision of more intermediary services can shift the production frontier upward. The large decrease in the banks' absolute efficiency (regress of the production-possibilities set) in 2007-2008 can be largely attributable to the substantial rise in the banks' NPLs.

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 since the introduction of the regulation. There is significant room for improvement in government-owned banks' technical and scale efficiency. It seems that government control of these banks tends to limit incentives and managers' ability to operate efficiently. As a result, government-owned banks move farther from constant returns to scale, and the banks tend to perform under decreasing returns to scale.

Therefore, one may argue that the decline in government intervention and its political interference should be helpful in boosting the efficiency and productivity of the public banks. We found that the productivity of private banks has fallen considerably since the introduction of the regulations. One may argue that the lacklustre performance of banks has been mainly due to a considerable rise in deposits and scale inefficiency attributable to the lack of institutional growth.

References

Aly, H Y, Grabowski, R, Pasurka, C & Rangan, N 1990, 'Technical, scale, and allocative efficiencies in U.S. banking: An empirical investigation', *The Review of Economics and Statistics*, vol.72, pp211-218.

Balcombe, K, Davidova, S & Latruffe, L 2008, 'The use of bootstrapped Malmquist indices to reassess productivity change findings: an application to a sample of Polish farms', *Applied Economics*, vol.40, no.16, pp2055-2061.

Berger, A N, Hanweck, G A & Humphrey, D B. 1987, 'Competitive viability in banking: Scale, scope, and product mixeconomies', *Journal of Monetary Economics*, vol.20, pp501-520.

Boussofiane, A, Martin, S & Parker, D 1997, 'The impact on technical efficiency of the UK privatization programme', Applied Economics, vol.29, no.3, pp297-310.

Burgess, J F & Wilson, P W 1995, 'Decomposing hospital productivity changes, 1985-1988: A nonparametric Malmquist approach', *The Journal of Productivity Analysis*, vol.6, pp343-363.

Caves, D W, Christensen, L R & Diewert, W E 1982, 'The economic theory of index numbers and the measurement of input, output, and productivity', *Econometrica*, vol.50, no.6, pp1393-1414.

CBI 2005, *Iranian Banks Performance Report 2005*, Central Bank of Iran, Tehran.

CBI 2006, *Annual Report 2006*, Central Bank of Iran, Tehran.

CBI 2008, *Iranian Banks Performance Report 2008*, Central Bank of Iran, Tehran.

Coelli, T J, Rao, D S P, O'Donnell, C J & Battese, G E 2005, *An Introduction to Efficiency and Productivity Analysis*, Springer Science and Business Media, New York.

Färe, R, Grosskopf, S, Lindgren, B & Roos, P 1992 'Productivity Changes in Swedish Pharmacies 1980-1989: A Nonparametric Malmquist Approach', *Journal of Productivity Analysis*, vol.3, no.3, pp85-101.

Färe, R, Grosskopf, S, Lindgren, B & Roos, P 1994a 'Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach'. in Charnes, A, Cooper, W W, Lewin A Y.& Seiford L M (eds.) *Data Envelopment Analysis: Theory, Methodology and Applications*, Boston: Kluwer.

Färe, R, Grosskopf, S & Norris, M 1997 'Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Reply', *American Economic Review*, vol.87, no.6, pp1040-1043.

Färe, R, Grosskopf, S, Norris, M & Zhang, Z 1994b 'Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries', *The American Economic Review*, vol.84, no.1, pp66-83.

Farrell, M J 1957 'The Measurement of Productive Efficiency', *Journal of the Royal Statistical Society*, vol. series A (general) l20, no.3, pp229-253.

Fethi, M D & Pasiouras, F 2010 'Assessing Bank Performance with Operational Research and Artificial Intelligence Techniques: A Survey', *European Journal of Operational Research*, vol.204, pp189-198.

Fried, H O, Lovell, C A K & Schmidt, S S (eds.) 2008 *The Measurement of Productive Efficiency and Productivity Growth*, New York, Oxford University Press.

Galdeano-Gómez, E 2008 'Productivity effects of environmental performance: evidence from TFP analysis on marketing cooperatives', *Applied Economics*, vol.40, no.14, pp1873-1888.

Gilbert, R A & Wilson, P W 1998 'Effect of Deregulation in the Productivity of Korean Banks', *Journal of Economics and Business*, vol.50, no2, pp133-155.

Guan, J C, R Yam, C K Mok & N Ma 2006 'A study of the relationship between competitiveness and technological innovation capability based on DEA models', European Journal of Operational Research, vol.170, no.3, pp971-986.

Hancock, D 1991 *A Theory of Production for the Financial Firm*, Kluwer Academic Publishers, Boston.

Hoff, A 2006 'Bootstrapping Malmquist Indices for Danish Seiners in the North Sea and Skagerrak', *Journal of Applied Statistics*, vol.33, no.9, pp891-907.

Kneip, A, Park, B & Simar, L 1996 Note on the Convergence of Nonparametric DEA Efficiency Measures, *CORE Discussion Papers 1996039, Université catholique de Louvain*, Center for Operations Research and Econometrics (CORE).

Latruffe, L, Davidova, S & Balcombe, K 2008 'Productivity Change in Polish Agriculture: an Illustration of a Bootstrapping Procedure Applied to Malmquist Indices', *Post-Communist Economies*, vol.20, no.4, pp449-460.

Lovell, C A K 2000 'Editor’s introduction', *Journal of Productivity Analysis*, vol.13, pp5-6.

Ray, S C & Desli, E 1997 'Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Comment', *The American Economic Review*, vol.87[50], pp1033-1039.

Sealey, C W & Lindley, J 1977 'Inputs, Outputs and a Theory of Production and Cost at Depository Financial Institutions', *Journal of Finance*, vol.32, pp1252-1266.

Shephard, R W 1970 *Theory of Cost and Production Functions*, Princeton: Princeton University Press.

Silverman, B W 1986 *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, London.

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*, vol.3, pp167-203.

Simar, L & Wilson, P W 1998a Productivity Growth in Industrialized Countries, *CORE Discussion Papers 1998036, Université catholique de Louvain*, Center for Operations Research and Econometrics (CORE).

Simar, L & Wilson, P W 1998b 'Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models', *Management Science*, vol.44, no.1, pp49–61.

Simar, L & Wilson, P W 1999 'Estimating and Bootstrapping Malmquist Indices', *European Journal of Operational Research*, vol.115, pp459-471.

Simar, L & Wilson, P W 2000 'Statistical Inference in Nonparametric Frontier Models: The state of the art', *Journal of Productivity Analysis*, vol.13, no.1, pp49-78.

Tortosa-Ausina, E, Grifell-Tatje, E, Armero, C & Conesa, D 2008 'Sensitivity Analysis of Efficiency and Malmquist Productivity Indices: An Application to Spanish Savings Banks', *European Journal of Operational Research*, vol.184, pp1062–1084.

Wheelock, D C & Wilson, P W 1999 'Technical Progress, Inefficiency and Productivity Change in U.S Banking 1984-1993', *Journal of Money, Credit and Banking*, vol.31, no.2, pp212-234.

Wilson, P W 2006 FEAR 1.0 User’s Guide, Department of Economics, Clemson University, Clemson, USA.