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Cardiff Economics
Working Papers

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E2011/12

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ISSN 1749-6101
April 2011

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Abstract

This paper examines the convergence properties of cost efficiency for Indonesian banks for the period 1992-2007. It employs the Simar and Wilson's (2007) two stage semi-parametric double bootstrap DEA procedure to estimate cost efficiency. Using panel data estimation, the paper examines β-convergence and σ-convergence, to test the speed at which Indonesian banks are converging, towards the best practice and country average. We find evidence that in general the post-crisis structural reform process improved the average level of efficiency and improved the distribution of efficiency across banks significantly. The Asian financial crisis and the structural reform had the effect of slowing the adjustment speed of bank efficiency.

Key words

Banks, Efficiency, Indonesia, Convergence.

JEL Codes: G21, G28

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1. Introduction

Studies of bank efficiency in the far Eastern emerging economies have become a growth industry in recent years. The reasons for these are threefold. First, since capital and debt markets remain undeveloped and immature, the principal process of financial intermediation remains the banking system. The role of the banking system in propagating shocks to the rest of the economy is evident in the part it played in Indonesia during the Asian financial crisis[1]. Second, the banking sector of the developing economies face stronger competition even with tighter post crisis regulatory changes. This creates the imperative to evaluate the position of the domestic banks in term of their performance and efficiency. Thirdly, the pass-through of central bank policy will depend on the competitive structure and efficiency of the banking system. The efficiency and competitiveness of the banking system also affects the allocation of loanable funds to investment opportunities and ultimately the growth of the economy.

A number of studies of the efficiency of the Indonesian banking system have emerged in recent years, but hitherto none have posed the questions that are the purpose of this paper. This paper examines the evolution of efficiency in the banking system in Indonesia using non-parametric Data Envelopment Analysis (DEA) supplemented with a bootstrap technology to produce bias-corrected estimates that have inferential capability. Specifically it poses three questions. First, how sensitive are estimates of bank efficiency to semi-parametric methods of estimation? This question is answered by estimating efficiency using the two-stage semi-parametric bootstrap method of Simar and Wilson (2007). Second, has bank efficiency improved over the decade and a half to 2007? This question is answered by evaluating the level of bank efficiency around some benchmark cluster. Third,

[1] It is claimed that a stronger banking system in 2008 cushioned the economy from the global crisis. See Basri and Rhardjaa (2010)

have the 1997-1999 financial crises and the banking reform process hampered or promoted the speed at which banks have improved and caught up with the benchmark bank?

This paper is organized along the following lines. The next section describes the development of Indonesian banking, highlighting the deregulatory trend of the 1990s and the impact of the financial crisis of 1997-98. Section 3 reviews the literature of bank efficiency estimation and details the methodology of two stage semi-parametric double bootstrap DEA estimation. Section 4 outlines the methodology of the growth convergence literature and its application to the convergence of banking efficiency. Section 5 describes the model strategies and data. Section 6 details the empirical results. Section 7 concludes.

2. Indonesian banking system

Indonesian banks were heavily regulated up until June 1983, and thereafter followed a process of deregulation in two stages. The first stage, which began in 1983, was the removal of quantitative credit controls and interest rate ceilings. The second stage, which began in 1988, liberalised the process of liquidity creation and opened the way for joint venture banks. The deregulatory policies encouraged the opening of many new banks and intensified competition.

In common with many emerging economies, liberalization was followed by strong growth in bank credit and with it the growth in non-performing loans and fragility typically associated with banking crises (Halim, 2000, Goldstein and Turner, 1996). Reregulation was undertaken in 1991 and 1995 aimed at increasing capital adequacy. According to Halim (2000) policy enforcement was ineffective with the financial crisis of 1997 revealing some of the inherent weaknesses in the banking system. A programme of restructuring was initiated so that by the end of 1999, 66 out of 239 banks were closed (Suta and Musa, 2003).

As shown in Table 1, at the end of June 2007 there were 130 banks[2] operating in Indonesia with a combined balance sheet of over IDR 1,770 trillion (US$ 190 billion). This total compares with a figure of 222 banks in existence at end-December 1997. The shrinkage was largely due to post-crisis liquidation, suspension and merger, engineered by the Indonesian Bank Restructuring Agency (IBRA) under agreement with the IMF (Hadad et al., 2008a).

Table 1. The Structure of the Indonesian Banking Industry at end-June 2007.

Type of Bank	*Number of Banks*	*Total Assets (IDR tn.)*
State-owned banks	5	641.1
Foreign exchange private national banks	35	691.2
Non-foreign exchange private national banks	36	32.5
Regional government-owned banks	26	165
Joint venture banks	17	78
Foreign banks (branching)	11	163
Total	130	1770.8

* Data source: Bank Indonesia.

During 2000-2007 the government conducted a re-privatisation program of the formerly nationalised banks, by which government shares were sold to both domestic and foreign investors. The increased foreign presence changed the structure of the banking system with the share of foreign subsidiary banks rising from 4.5% in 2000 to 32.8% in 2007 (Besar and Milne, 2009), resulting in a stronger and better capitalized banking system (McCawley, 2009).

3. Bank efficiency literature review and methodology

In their survey of 130 studies that have employed frontier analysis in 21 countries, Berger and Humphrey (1997) note that studies on US financial institutions were the most common, accounting for 66 out of 116 single country studies, and only 8 were of developing and Asian countries (including 2 in Japan). Latterly, both single country and cross country efficiencies studies have been conducted for European countries, (e.g. Lozano

[2] This comprised 5 state-owned banks, 35 foreign exchange private national banks, 36 non-foreign exchange private national banks, 26 regional government-owned banks, 17 joint venture banks and 11 foreign banks.

(1997) on Spanish saving banks; Resti (1997) on Italian banks; Lozano-Vivas, Pastor and Hasan (2001) on a sample of banks from 10 EU countries; Vennet (2002) on cost and profit efficiency of banks from 17 European countries). More recently the studies have been expanded to Asian and other regions. A representative sample include Hong Kong (Drake et al., 2006), Greece (Pasiouras, 2008), Singapore (Sufian, 2007), Ukraine (Kyj and Isik, 2008) and studies focusing on countries in transition, like India (Ataullah and Le, 2006, Bhattacharyya et al. 1997), and Malaysia (Sufian, 2009).

Studies of Indonesian banks have been few, but significant. Using the stochastic frontier approach (SFA), estimates of cost efficiency, scale economies, technological progress and productivity growth of Indonesian banks over the period 1993-2000 have been produced by (Margono et al. 2010). They found that the average cost efficiency of all banks was 70% during the whole period, with 80% and 53% for pre-Asian crisis and post-Asian crisis respectively. Other papers (Hadad et al., 2008a, b, c) used non-parametric, slacks-based DEA with a Simar and Wilson's (2007) bootstrapping methodology to monthly/quarterly supervisory data within a relatively short period 2006-2007. They found that the average efficiency during the sample period was around 70%. Bank efficiencies are positively related to the JCI index of the Indonesian Stock Exchange, and state-owned banks are the most efficient. Using the Malmquist productivity index, technological progress was identified as the main driver of productivity growth. Besar and Milne (2009) examined the effects of ownership change during the re-privatisation program after the Asian financial crisis using a SFA model over 2000-2007. They found that the re-privatisation program had a positive impact on Indonesian bank's efficiency and competition.

While bank efficiency has been measured by either parametric or non-parametric methods, there remains no consensus on the preferred method for determining the best-practice frontier against which relative efficiencies are measured. The parametric approach, such as the stochastic frontier approach (SFA), specifies a functional form and allows for random errors which follow a symmetric normal distribution while the inefficiencies are measured by a truncated distribution.

However, the parametric approach suffers from the problem of misspecification of the functional form, and possibly inefficiency and multi-collinearity. Usually a local approximation such as the trans-log is specified, which has been argued to provide poor approximations for banking data (see McAllister and McManus, 1993; Mitchell and Onvural, 1996). In theory, parametric estimators offer faster convergence and produce consistent estimates, but this would be true only if there is no misspecification of the functional form. In contrast, the nonparametric model, such as the conventional Data Envelopment Analysis (DEA), does not require the explicit specification of the form of the underlying production relationship, but at the cost of slower convergence rates and hence larger data requirements. The nonparametric approach also has been criticized for not considering errors due to chance, measurement errors, or environmental differences; hence all deviations are attributed to the measured inefficiency. The conflict between the nonparametric and parametric approaches is important because the two types of methods tend to have different degrees of dispersion and do not always produce a common ranking of the same financial institutions (Berger and Humphrey, 1997).

The conventional DEA approach suffers from the drawback of finite sample bias, inconsistency due to slow convergence rate, (particularly in the case of multiple inputs and outputs, which increases the dimensionality of the problem). As stated by Kneip, Park and Simar (1998), large bias, large variance and very wide confidence intervals may be produced when the number of inputs and outputs is large, unless a very large quantity of data are available. Also, the efficiency measure is sensitive to outliers and is upward biased by construction. The bootstrap provides an attractive alternative to the conventional DEA[3].

The essence of the bootstrap idea (Efron, 1979, 1982; Efron and Tibshirani, 1993) is to approximate the sampling distributions of interest by simulating, or mimicking, the data generating process (DGP). The bias in the DEA estimator then can be estimated and confidence intervals can be built by using this approximated distribution.

Simar and Wilson (2007) propose a two-stage semi-parametric bootstrap model, which is capable of incorporating the effects of environmental variables in estimating efficiencies. Environmental factors are a set of factors that probably affect the production process, but are not under the control of firm's managers. These factors might reflect differences in ownership, size, market share, regulatory constraints, business environment, competition, *etc.* among the firms under analysis. Simar and Wilson (2007) cite 47 published papers that employed a two-stage approach wherein nonparametric, DEA efficiency estimates are regressed on a set of environmental variables in a parametric, second-stage analysis. The typical two-stage approaches do not provided a coherent description of a DGP, and the method of inference is flawed since the DEA efficiency estimates are biased estimates and are serially correlated, in a complicated, and unknown way.

In order to deal with the problem described above, Simar and Wilson (2007) define a DGP that provides a rational basis for regressing non-parametric, DEA efficiency estimates on a set of environmental variables in a second-stage analysis. In addition, they suggest bootstrap procedures to provide valid inference in the second-stage regression, as well as to increase the efficiency of estimation and correct the estimation bias[4].

[3] The first application of the bootstrap method to frontier models dates to Simar (1992). Its use in non-parametric envelopment estimators was developed by Simar and Wilson (1998, 2000)

[4] We adopt the algorithm 2 of the two-stage semi-parametric double bootstrapping method set out by Simar and Wilson (2007).

Following Färe, Grosskopf and Lovell (1985) the efficiency of a firm can be defined and measured as the radial distance of its actual performance from a frontier. In the first stage, we employ the Tone (2002) new cost efficiency model, which allows for heterogeneity in unit prices of input. As a general rule, efficiency levels measured relative to one frontier cannot be directly compared with efficiency levels measured relative to another frontier. In order to make the later cross-time convergence analysis more sensible, we use a meta-frontier framework, wherein, efficiencies of all observations are measured relative to a common frontier. We chose to use input oriented efficiency measure and constant return to scale (CRS) is assumed as an optimal scale in the long run.

The cost efficiency $\hat{\rho}$ for the j-th bank is defined as;

$$\hat{\rho}_j = e\bar{x}_j^* / e\bar{x}_j \qquad (1)$$

where $e \in R^m$ is a row vector with all elements being equal to unity, and $\bar{x}_j^*$ is the optimal solution of the LP given below;

$$[\text{Cost}] \qquad e\bar{x}_j^* = \min_{\bar{x},\, \lambda} e\bar{x}_j$$

$$\begin{aligned} s.t. \quad & \bar{x}_j \geq \bar{X}\lambda \\ & y_j \leq Y\lambda \\ & \lambda \geq 0 \end{aligned} \qquad (2)$$

where $\bar{X} = (\bar{x}_1, \ldots, \bar{x}_n)$, with $\bar{x}_j = (p_{1j}x_{1j}, \ldots, p_{mj}x_{mj})^T$, is the matrix of individual factor costs, and $Y = (y_1, \ldots, y_n) \in R^{s \times n}$ is a matrix of outputs.

The cost efficiency measure $\hat{\rho}_j \leq 1$ is the scalar efficiency score for the j-th bank. If $\hat{\rho}_j = 1$ the *i*-th bank is cost efficient as it lies on the frontier, whereas if $\hat{\rho}_j < 1$ the bank is inefficient and need a (1- $\hat{\rho}_j$) reduction in the total cost.

In the second stage, the efficiency estimates $\hat{\rho}_j$ are regressed on a set of environmental variables z_j by using a maximum likelihood method. In practice, Shephard's (1970) definition of efficiency is used to avoid two boundaries points. Shephard's efficiency measure is merely the reciprocal of the conventional Farrell efficiency score ($\hat{\gamma}_j = 1/\hat{\rho}_j$), and can be treated as a measure of inefficiency. If z_j is a vector of environmental variables for the j^{th} bank and β is a vector of parameters associated with each factor to be estimated, then equation (3) below describes the model to be estimated

$$\hat{\gamma}_j = z_j\beta + \varepsilon_j \geq 1 \qquad (3)$$

under (left normal) truncated regression (use only $\hat{\gamma}_j > 1$ in this step) and ε_j is a truncated random error $N(0, \hat{\sigma}_\varepsilon^2)$, truncated at $(1 - z_j\hat{\beta})$. The algorithm steps are;

Step 1: bootstrap, for each $j = 1,...,n$, we draw ε_j^* from the distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with left-truncation at $(1 - z_j\hat{\beta})$ and compute $\gamma_j^* = z_j\hat{\beta} + \varepsilon_j^*$.

Step 2: construct a pseudo sample by setting $x_j^* = x_j\hat{\gamma}_j / \gamma_j^*$ for all banks and keep the output measure unchanged, $y_j^* = y_j$.

Step 3: re-estimate DEA cost efficiency $\hat{\gamma}_j^*$ by replacing (x_j, y_j) by (x_j^*, y_j^*).

Step 4: loop over this procedure 100 times ($L_1 = 100$), take the mean, $\bar{\hat{\gamma}}_j^*$, of 100 $\hat{\gamma}_j^*$ estimates, then compute the bias-corrected estimator $\hat{\hat{\gamma}}_j$ for each bank, such that $\hat{\hat{\gamma}}_j = 2\hat{\gamma}_j - \bar{\hat{\gamma}}_j^*$. The bias-corrected Farrell efficiency score can be easily obtained by taking the reciprocal of $\hat{\hat{\gamma}}_j$, that is $\hat{\hat{\rho}}_j = 1/\hat{\hat{\gamma}}_j$.

Step 5: re-estimate the marginal effects of environmental variables, z_j, using the bias-corrected efficiency estimate, $\hat{\hat{\gamma}}_j$, to obtained coefficients estimates $\hat{\hat{\beta}}$, by left-truncated regression with $L_2 = 1000$ bootstrap replications. Once the set of L_2 bootstrap parameter estimates for β and σ_{ε}^{2} have been obtained, the percentile bootstrap confidence intervals can then be constructed.

4. Convergence of Bank Efficiency

While the majority of studies of bank efficiency have examined efficiency gains and losses and their determinants, recent studies have focussed on the convergence properties of bank efficiency. The growth literature[5] distinguishes between unconditional *β-convergence* and *conditional β-convergence*, where the former relates to convergence to a common point or steady-state and the latter relates to different points or steady-states. An alternative concept is *σ-convergence*, which relates to dispersion of measures across groups of economies. The two concepts of convergence are related but conceptually different: *σ-convergence* studies of growth show how the distribution of income evolves over time whereas *β-convergence* studies the mobility of income within the same distribution. Beta-convergence is a necessary, but not sufficient condition for *σ-convergence* (Sala-i-Martin,1996).

Testing for *β-convergence* and *σ-convergence* of cost efficiency of banks for 10 EU countries between 1994 and 2005 using SFA to estimate efficiency, Weill (2008) supports the view of a convergence in the cost efficiency of banks across European countries, with the single banking market having had a positive impact on banking efficiency. However, the evidence of financial integration from Casu and Girardone (2008) is ambiguous. The same concepts of convergence are applied to non-parametric DEA cost efficiency of banks from 15 EU countries in the period 1997-2003, and the results provide supporting evidence of convergence of efficiency levels towards an EU average rather than the best-practice. The potential gains brought about by increased integration are offset by a decrease in the overall efficiency level. Another convergence study on EU bank efficiency is Mamatzakis

[5] See Barro and Salai-Martin (1991,1992,1995) and Quah (1996)

et al. (2008), which tests the convergence of cost and profit efficiency of banks from 10 new EU members over 1998-2003. The results indicate weak convergence in cost efficiency, but no convergence in profit efficiency.

To our knowledge, Fung (2006) is the only paper that has examined convergence of bank efficiency for a single country, with an investigation on the convergence in pure technical efficiency and scale efficiency for the US bank holding companies (BHCs). The convergence speed is a measure of how quickly the less productive banks catch-up with the more productive ones. The findings do not support the hypothesis of "absolute convergence", but show strong evidence in favour of "conditional convergence", which means the steady-state productivity to which a BHC is converging is conditional on the BHCs own level of technical efficiency. In our study, bank specific characteristics have already been incorporated into efficiency estimation as environmental variables in the second stage estimation; therefore, unconditional *β-convergence* and *σ-convergence* are sufficient for our interests.

To estimate unconditional β-convergence we employ the following equation:

$$\ln \hat{\hat{\rho}}_{j,t} - \ln \hat{\hat{\rho}}_{j,t-1} = \phi + \theta \ln \hat{\hat{\rho}}_{j,t-1} + v_{j,t} \qquad (4)$$

where

$\hat{\hat{\rho}}_{j,t}$ = the bias-corrected cost efficiency of bank j at time t

$\hat{\hat{\rho}}_{j,t-1}$ = the bias-corrected cost efficiency of bank j at time $t-1$

ϕ and θ are the parameters to be estimated and

$v_{j,t}$ is error term

A negative value for the parameter θ implies unconditional *β-convergence*. The higher the coefficient in absolute terms the greater the speed of convergence. The intercept ϕ indicates the equilibrium average efficiency level.

To estimate cross sectional dispersion or *σ-convergence*, which is testing the convergence towards the industry average level of efficiency, we adopt the following autoregressive distributed lag model specification[6].

$$E_{j,t} - E_{j,t-1} = \alpha + \eta E_{j,t-1} + \omega_{j,t} \qquad (5)$$

where

$E_{j,t} = \ln(\hat{\hat{\rho}}_{j,t}) - \ln(\overline{\hat{\hat{\rho}}}_{t})$

$E_{j,t-1} = \ln(\hat{\hat{\rho}}_{j,t-1}) - \ln(\overline{\hat{\hat{\rho}}}_{t-1})$

$\overline{\hat{\hat{\rho}}}_{t}$ is the mean efficiency of banking sector at time *t*,

$\overline{\hat{\hat{\rho}}}_{t-1}$ is the mean efficiency of banking sector at time *t-1,*

α and η are parameters to be estimated,

and $\omega_{j,t}$ is the error term.

A negative value for the parameter η implies unconditional σ *-convergence*. The intercept α indicates the average dispersion from the mean.

5. Model strategy and Data

Our data set is drawn primarily from the balance sheet and income statements of banks from the Bureau van Dijk Bankscope database. Data for missing periods were obtained from the annual reports of individual bank and central bank statistics. We focus on commercial banks in this study as it comprises the largest segment of depository institution in Indonesia (98.6% of banking industry assets[7]). Where possible, the unconsolidated financial reports are used, to avoid double-counting.

Due to the major structural change of the banking system following the financial crisis and to smooth out the distortion effect, we take the years of the financial crisis (1997-1999) out of the sample as a separate period, and leave the pre-crisis (1992-1996) and post crisis

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[6] Similar specifications have been estimated, among others, by Fung (2006), Weill (2008) and Casu and Girardone (2008).

7 Figures are calculated from reported values in 2007 Banking Statistics, Bank of Indonesia.

period (2000-2007) as two distict periods[8]. The sample sizes of different time periods are summarized in Table 2.

Table 2: Sample sizes

	Number of Bank-year observations
1992-1996	171
1997-1999	98
2000-2007	312

Debates also rage about the appropriate choices of the input/output specification. There are two main approaches to the choice of input/output variables. One is the traditional "intermediation approach" (Sealey and Lindley, 1977), in which the input of funds and their interest cost is included in the analysis, since funds are the main "raw material" which is transformed in the intermediation process (e.g. Berger and Humphrey, 1991). The other is the "production" approach, in which only physical inputs such as labour and physical capital are included (e.g. Kuussaari and Vesala, 1995). We choose three classic input variables under the intermediation approach, which are the *Number of Employees* (LAB), *Fixed Assets* (FA) and *Total Deposits* (TD=customer and interbank deposits + other deposits and short-term borrowings). On the output side, bank asset creation and income generation are not always highly correlated because of the creation of non-performing loans. Therefore we use three different combinations of outputs to test for robustness. Model 1 concerns asset creation, and uses pure stock variables, *Loans* (total customer loans + total other lending) and *Other Earning Assets* (OEA= interbank assets + securities), as outputs. Model 2 takes the income flows of a bank as the output. We include the traditional measure of bank income, *Total Interest Income* (TIY=interest income on loans + other interest income) and *Other Operating Income* (OOY=net gain on trading and derivatives + net fees and commissions +other non-interest income) to proxy the growing non-traditional business

8 We also divide the sample into two periods, 1992-1999 (the pre-crisis period), and 1998-2007 (the post-crisis period). The data overlap 1998-1999 is maintained to assess the extent of the difference in level of the sub-periods' efficiency frontiers.

activities of Indonesian banks. Model 2 measures revenue efficiency and would be expected to have a closer correspondence to the accounting concepts of performance. Model 3 is a mixture of the previous two models and uses both stock and flow variables as outputs: *Loans, OEA* and *OOY*. Except for LAB, all variables are measured in real terms (2005 = 100).

Input prices are crucial for estimating cost efficiency. The price of labour (p_1) is calculated as the ratio of personnel expenses divided by the number of employees[9]. The price for total deposits (p_2), is calculated by the ratio of interest expenses to total deposits. The price of fixed assets (p_3), is measured by the ratio of operating expenses less personnel expenses to fixed assets. Here we are interpreting this operating expense as capital maintenance (see also Shen et al., 2009). Table 3 provides a snapshot of the data.

Table 3: Statistical data description

	1992-1996				**1997-1999**				**2000-2007**			
	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Total Cost (C)	2078.98	3439.20	48.84	14860.56	4448.49	9530.58	61.98	62651.13	2755.39	5629.01	18.88	44537.37
Inputs												
Fixed Assets (x1)	362.09	553.06	1.06	2439.96	393.96	681.39	1.54	3000.49	509.58	991.63	0.72	6159.35
Deposit (x2)	13377.73	21803.61	320.16	102235.56	17391.53	33203.09	302.46	140959.85	23904.56	46362.94	133.65	275132.10
Labour (x3)	1386.11	2485.99	16.89	14059.28	2257.01	4161.83	10.51	21606.76	4370.28	7887.67	9.34	39915.00
Input Prices												
price of fixed assets (p1)	1.18	1.75	0.14	11.67	2.40	3.77	0.09	26.38	1.89	2.08	0.15	15.68
price of deposit (p2)	0.12	0.03	0.03	0.23	0.22	0.11	0.06	0.74	0.08	0.05	0.02	0.76
price of labour (p3)	0.20	0.15	0.01	1.00	0.15	0.20	0.01	1.29	0.14	0.21	0.02	2.11
Output												
Total Loan	13473.86	22356.62	293.02	85334.65	10987.25	23407.24	62.31	126756.95	10742.43	18079.98	10.64	94903.96
Other Earning Assets	4754.50	8736.26	51.55	41248.63	6913.40	17695.51	43.85	130098.07	15381.06	36326.28	49.32	299111.87
Other Operating Income	206.74	385.57	0.39	2171.20	339.38	1366.92	-6688.57	9825.54	404.07	903.51	-38.02	8726.17
Total Interest income	2193.48	3561.37	53.10	16235.89	3286.08	5918.48	72.50	31388.26	3063.77	6223.17	17.81	44379.79

*Except for No. of employee, other variables are measured in bil.IDR. 2005=100

[9] Where data on either personnel expenses or employees are not reported, the calculation of the price of labour is conducted according to what is standard in the literature and assume that the growth rate of the number of employees is the same as the growth rate of total assets for a given bank and the ratio of personnel expenses to operational expenses is the same as the closest available year (see for example Altunbas, et al, 2001 and Vander Vannet, 2002).

What is noteworthy is the evolution of the loan-to-deposit ratio which can be taken as a measure of leverage. In the pre-crisis period the ratio was greater than unity but in the final period this has dropped to an average of 0.45. This adjustment to a lower level of leverage is also seen in the liquidity ratio taken as the ratio of other earning assets to loans, which has risen from 35% in the pre-crisis period to 143% in the post-crisis period. A further noteworthy observation is that despite the growth in average earning assets between the pre and post crisis periods, the real price of labour has remained remarkably stable.

The environmental variables, z_j used in the second stage truncated regression, contains the bank-specific characteristics which may be related to the efficiency level of bank *i*. Following the literature on the determinants of bank efficiency (e.g. Sufian, 2009), we include the following seven variables, which have been found to be typical determinants of bank efficiency, for the bank-specific characteristics vector z_j [10], which are summarised in Table 4[11].

Table 4: Environmental variables used in truncated regression

Variables	*Description*	*Hypothesized relationship with inefficiency*[12]	
Ownership Dummy (OWN)	1 denotes >50% foreign ownership, 0 otherwise	-	A negative relationship with cost inefficiency is expected
HHI	Sum of the squares of the market shares of all banks in each year	+/-	A proxy of market concentration. No priori expected sign.
Size	Natural logarithm of total assets	+/-	A proxy of bank size. No priori expected sign.
Diversification (DIV)	Non-interest income/total assets	-	A proxy of diversification in traditional banking business. A negative relationship with cost inefficiency is expected
Cost to Income ratio (CtoI)	Overheads / (net interest revenue + other operating income)	+	Accounting measurement of cost inefficiency. Positive relationship with economic (DEA) cost inefficiency measurement.

10. Other variables were included, such as measure of banks risk; measure of bank profitability, but were statistically insignificant.

[11] Appendix A provides some descriptive statistics of those variables.

[12] The dependent variable used in truncated regression is Shephard's (1970) definition of efficiency, which indicates higher inefficiency by higher value.

ΔGDP	Growth rate of GDP	+/-	Included as Macroeconomic condition. No priori expected sign.
SOB	1 denotes SOB's, 0 otherwise	+/-	No priori expected sign

Over the two periods before and after the financial crisis, the average size of Indonesian banks increased by 3.5%. More significant increases have been the measure of foreign ownership (26%), market concentration (18%), business diversification (32%) and cost to income ratio (11%). Average GDP growth rate was lower after the financial crisis and fewer state-owned banks existed in the post-crisis period following the structural reform process.

6. Empirical Results

Table 5 shows the yearly average cost efficiency scores for each model split by the individual estimation periods[13]. The non-bootstrap DEA cost efficiency estimate is given by $\hat{\rho}$, and as shown in the table, they are upward biased comparing with $\hat{\hat{\rho}}$, the bootstrapped bias-corrected cost efficiency estimate. The biases are significant according to the bootstrapped 95% confidence interval for $\hat{\hat{\rho}}$'s. These estimates are significantly lower than the estimates available in the extant literature. The reason is that as we use a constant return to scale meta-frontier framework, efficiencies of *all* observations in each sample period are estimated relative to a common frontier, which explains the relatively low cost efficiency scores in this study. This meta-frontier is like an envelopment of individual year frontiers, so some of the observations may be found further away from the frontier than it could be if using a single year frontier. Despite the absolute level of efficiency scores, the indicative information delivered by them should still hold.

Table 5: Bootstrapped cost efficiency results

	Model 1	***Model 2***	***Model 3***

[13] The model is estimated by using FEAR: A software package for frontier efficiency analysis with R

		$\hat{\rho}$	$\hat{\hat{\rho}}$	$\hat{\rho}$	$\hat{\hat{\rho}}$	$\hat{\rho}$	$\hat{\hat{\rho}}$
Pre-crisis	1992	0.2981*	0.1795	0.5084*	0.3884	0.4127*	0.2767
	1993	0.2851*	0.1704	0.4587*	0.3286	0.3830*	0.2506
	1994	0.2859*	0.1707	0.4127*	0.2800	0.3239*	0.2003
	1995	0.2861*	0.1705	0.4678*	0.3381	0.3288*	0.2037
	1996	0.2793*	0.1656	0.4616*	0.3311	0.3390*	0.2119
Financial crisis	1997	0.3407*	0.2120	0.3450*	0.2170	0.3454*	0.2160
	1998	0.2817*	0.1679	0.5078*	0.3839	0.3419*	0.2154
	1999	0.3339*	0.2069	0.3036*	0.1849	0.3704*	0.2378
Post-crisis	2000	0.4517*	0.3169	0.4146*	0.2781	0.4645*	0.3338
	2001	0.4503*	0.3139	0.4833*	0.3453	0.4620*	0.3282
	2002	0.4415*	0.3043	0.4612*	0.3225	0.4504*	0.3150
	2003	0.4424*	0.3054	0.3918*	0.2561	0.4517*	0.3170
	2004	0.3937*	0.2595	0.3002*	0.1813	0.3978*	0.2643
	2005	0.4066*	0.2715	0.3421*	0.2134	0.4075*	0.2733
	2006	0.4248*	0.2886	0.4217*	0.2827	0.4267*	0.2919
	2007	0.4195*	0.2838	0.3553*	0.2242	0.4200*	0.2853

* denotes basic DEA efficiency is outside the bootstrapped 95% confidence interval, i.e. it is significantly different from the bias-corrected efficiency score.

Interestingly, Model 1 and Model 2 exhibit different patterns in the results for the pre-crisis and post-crisis periods. Average efficiency rose in the post-crisis period measured by Model 1 but fell as measured by Model 2, highlighting the sensitiveness of the results to the choice of outputs. It also demonstrates that different output measures may need broader contextual background to understand the development of efficiency. The loan write-offs during the crisis period would have been unevenly distributed between the efficient and inefficient banks but the inefficient banks would have had to reduce costs faster than the efficient banks resulting in an overall increase in average efficiency. However, the inefficient banks may have carried more non-performing loans in the crisis period resulting in lower interest earnings and lower average revenue efficiency measured by Model 2, in the post-crisis period.

The efficiency scores also clearly reflect the impact of the re-regulation period 1993-1995, which leads to a short-period decline in bank efficiency after 1993 in all three cases. Average cost efficiency level was low during the 1997-1999 Asia crises but improves post crisis, reaching a peak in 2000-2001 and declines due to two major events. One is the re-privatisation process which occurred around 2003 and the global financial crisis beginning in 2007. This is seen in the drop in average efficiency post 2003. While in general the consensus of the literature is that privatisation and increased foreign ownership has increased the efficiency of formerly state-owned enterprises (for example Megginson, 2005 and Megginson and Netter, 2001) it is probable that in the case of Indonesian banks, the change was gradual until the new culture and system was properly assimilated (Besar and Milne, 2009). The short period increase in cost might be explained by the increased of bank's investment in the newly acquired subsidiaries.

Did the crisis period act as a catalyst to change average performance of banks as measured by efficiency? In other words is there a significant difference between the average efficiency performance of banks in the pre-crisis period and post-crisis period? Table 6 reports the results of a Mann-Whitney two-sample non-parametric test for differences in overall efficiency between the two periods for the three models, which shows a clear statistically significant difference between the two periods.

Table 6: Tests for two-period differences

Mean efficiency	Model 1	Model 2	Model 3
Pre-Crisis period	0.1709	0.3272	0.2218
Post-Crisis period	0.2920	0.2531	0.2997
Z value	-10.95***	5.43***	-5.06***

*** significant at the 1% level

Table 7 reports the truncated regression results using the conventional DEA cost efficiency estimates ($\hat{\beta}$) and the bias-corrected DEA cost efficiency estimates ($\hat{\hat{\beta}}$) as the dependent variable. The differences are notable and confirm the expectation that using biased DEA estimates in the second stage parametric regression on environmental variables produces inaccurate estimates. Most of the estimates on the environmental variables exhibit the expected sign and is consistent in all periods when significant at the 5%, however, inconsistency does exist for few cases.

The dependent variable in Table 7 is Shephard's (1970) definition of efficiency, which indicates higher inefficiency by higher value. Thus positive/negative marginal effects in the truncated regression indicate negative/positive marginal effects on cost efficiency. Unsurprisingly, foreign ownership always has a positive impact on bank cost efficiency, like the case in most developing countries. Given the foreign banks are relatively more efficient, SOB's also consistently exhibit higher efficiency. Cost efficiency is also negatively correlated with bank size and cost to income ratio, when significant.

Table 7: Truncated regression results

		1992-1996		***1997-1999***		***2000-2007***	
		$\hat{\beta}$	$\hat{\hat{\beta}}$	$\hat{\beta}$	$\hat{\hat{\beta}}$	$\hat{\beta}$	$\hat{\hat{\beta}}$
Model 1	Const.	4.2725	7.1945	2.2213	2.5056	2.6309	3.4399
	OWN	-0.1824	-0.0331	-1.4342	-2.5669*	-0.6384	-1.0887*
	HHI	-19.4372	-32.0615	-11.4329	-14.536	-8.074	-15.187
	Size	0.0384	0.0021	0.3019	0.5992*	0.1508	0.2822*
	DIV	0.4237	0.6696*	0.0658	0.018	-0.0429	-0.0716
	CtoI	0.0257	0.0449*	0.0194	0.0379*	0.0259	0.0238
	ΔGDP	-0.0872	-0.0823	-0.057	-0.1294*	-0.038	0.0743
	SOB	-1.6964	-3.08948	-0.208	-0.3845	-0.6144	-1.2567*
	Sigma	0.8766	1.6399	1.4202	2.8115	0.6802	1.2809
Model 2	Const.	6.2136	12.0604*	-2.5046	-6.5457*	1.982	2.3741
	OWN	-0.0868	-0.1087	-0.576	-1.2949*	-0.1126	-0.2994
	HHI	-26.3348	-58.7551*	22.9392	46.9658*	-9.7569	-19.2493
	Size	0.1499	0.2773*	0.3347	0.6953*	0.0909	0.1763*
	DIV	-0.4779	-0.9039*	-0.0436	-0.0855	-0.0613	-0.0063
	CtoI	0.0098	0.0163*	-0.0016	-0.0026	0.0232	0.0469
	ΔGDP	-0.3493	-0.6863*	0.0979	0.2026*	0.2116	0.4741
	SOB	-0.8814	-1.7521*	-0.0961	-0.2466	-0.618	-1.4030*
	Sigma	0.459	0.9267	0.8858	1.896	0.8858	1.8961
Model 3	Const.	6.3595	10.5728	4.1113	6.6790*	2.7641	3.3137
	OWN	-0.1579	-0.0162	-1.2295	-1.7238*	-0.6289	-1.1239*
	HHI	-29.9489	-49.5821	-15.9499	-19.8219	-8.6528	-13.7195
	Size	-0.0035	-0.1073	0.1797	0.2544	0.1358	0.2316*
	DIV	-1.2422	-2.6463*	-0.2162	-0.4724*	-0.1077	-0.0509
	CtoI	0.0249	0.0417*	0.015	0.0288*	0.0235	0.0195
	ΔGDP	-0.075	0.0407	-0.0438	-0.1010*	-0.0169	0.1445
	SOB	-1.5114	-2.7600*	-0.1633	-0.1174	-0.5587	-1.1659*
	Sigma	0.8805	1.6347	1.0857	1.8211	0.6597	1.2254

*denotes coefficient is significant at 5% significance level.

Market concentration measured by HHI is positively significant in Model 2 in the pre-crisis period but negatively related to cost efficiency in the crisis period. This suggests that market power may have been prevalent in loan pricing in the pre-crisis period driving up revenues relative to costs but is reversed in the crisis period. The macroeconomic environment measured by GDP growth shows no clear pattern of influence on cost efficiency over the individual models or over separate periods.

Using the results of Table 7, we conduct unconditional β-convergence, and σ-convergence in banking cost efficiency by unbalanced panel estimation. The convergence models are estimated using fixed effects[14]. Table 8 details the results for convergence analysis. We find strong evidence for both types of convergence in banking efficiency for all models and in all periods. The convergence tendency towards best practice, (β-convergence), and the reduction in dispersion, (σ-convergence), signal the dynamic improvement in cost efficiency of Indonesian banks. However, the speed of convergence alters over each sub-period. The speed of convergence was significantly slower in the crisis period. The post-crisis period also indicates a significant slowing in the speed of convergence, indicating a more conservative strategy to risk-taking and asset growth as a means by which inefficient banks catch-up with best practice banks.

Overall, the convergence prosperities have shown evidence of improvement in cost efficiency over time; however, the 1997-1999 financial crisis and structural reform following it have seen a slowing down the speed of adjustment towards best practice.

Table 8: Convergence results

		1992-1996		*1997-1999*		*2000-2007*	
		Coefficient	*P>|z|*	*Coefficient*	*P>|z|*	*Coefficient*	*P>|z|*
MODEL1	**Unconditional β-convergence**						
	Intercept	-1.6019***	0.0000	-1.4694***	0.0000	-0.9142***	0.0000
	wald test			0.5200	0.4723	98.6700***	0.0000

[14] Results of model selection tests are reported in Appendix B.

	LnEFFt-1	-0.9838***	0.0000	-0.9871***	0.0000	-0.8459***	0.0000
	wald test			0.0000	0.9782	5.2600**	0.0227
	overall R^2	0.0582		0.2126		0.0924	
	σ-convergence						
	Intercept	0.1438***	0.0000	0.1190**	0.0130	0.1178***	0.0000
	wald test			0.2800	0.5960	1.6700	0.1970
	Ei,t-1	-0.9647***	0.0000	-0.8620***	0.0000	-0.7912***	0.0000
	wald test			0.7000	0.4068	7.7400***	0.0058
	overall R^2	0.0586		0.2032		0.0651	
MODEL 2	**Unconditional β-convergence**						
	Intercept	-1.0653***	0.0000	-2.1226***	0.0000	-1.0454***	0.0000
	wald test			78.2400***	0.0000	0.0700	0.7918
	LnEFFt-1	-1.0436***	0.0000	-1.8300***	0.0000	-0.8249***	0.0000
	wald test			54.6700***	0.0000	14.8200***	0.0002
	overall R^2	0.2650		0.4336		0.2880	
	σ-convergence						
	Intercept	0.1252***	0.0000	0.2075***	0.0000	0.0816***	0.0000
	wald test			3.1200*	0.0831	4.9300**	0.0273
	Ei,t-1	-1.0509***	0.0000	-1.5105***	0.0000	-0.8997***	0.0000
	wald test			15.5600***	0.0002	6.7500***	0.0099
	overall R^2	0.2287		0.3312		0.2695	
MODEL 3	**Unconditional β-convergence**						
	Intercept	-1.3135***	0.0000	-1.5126***	0.0000	-0.8891***	0.0000
	wald test			1.2100	0.2755	36.4300***	0.0000
	LnEFFt-1	-0.9869***	0.0000	-1.1662***	0.0000	-0.8528***	0.0000
	wald test			1.7000	0.1985	4.4300**	0.0364
	overall R^2	0.1565		0.1820		0.0998	
	σ-convergence						
	Intercept	0.2192***	0.0000	0.2462***	0.0000	0.1335***	0.0000
	wald test			0.2100	0.6509	13.8400***	0.0002
	Ei,t-1	-1.0419***	0.0000	-1.1814***	0.0000	-0.8154	0.0000
	wald test			0.9700	0.3296	12.0200	0.0006
	overall R^2	0.1329		0.1859		0.0818	

*** denotes coefficient significant at 1% significance level. ** denotes coefficient significant at 5% significance level. *denotes coefficient significant at 10%significance level.

7. Conclusion

We have estimated cost efficiency for a sample of Indonesian banks over the period 1992-2007 using the Simar and Wilson's (2007) two stage semi-parametric double bootstrap DEA procedure. The estimates of cost efficiency obtained by the conventional DEA method were shown to be significantly biased. Convergence towards benchmark clusters defined by second-stage truncated regression shows that in general, the post crisis period saw a temporary rise in cost efficiency. The estimates of cost efficiency produced by this method are starkly in variance with the findings of the extant literature. This is explained by the assumption of constant returns to scale along with the meta-frontier approach adopted in the estimation methodology. However, the absolute measures of efficiency are unlikely to influence its dynamic pattern.

We have shown that cost efficiency in Indonesian banks has improved in general over the last two decades. Our results were used to test the hypothesis concerning the effect of the Asian financial crisis and the structural reform program on bank efficiency. In general, the process of reform improved average efficiency in the immediate post crisis period. The speed of convergence slowed in the post-crisis period suggesting that the reforms created an environment of caution that resulted in a slower catch-up by the inefficient banks to the efficient frontier.

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Appendix A: Descriptive Statistics of Firm-specific Characteristic/Environmental Variables

		Mean	*S.D.*	*Min.*	*Max.*
1992-1996	Ownership Dummy	0.5088	0.5014	0.0000	1.0000
	HHI	0.1028	0.0093	0.0946	0.1170
	Size	8.6271	1.5775	5.9610	11.6821
	Diversification	0.8955	0.5287	0.0159	3.2629
	Cost to Income ratio	0.5881	0.2147	0.2128	2.1888
	Growth of GDP	7.4455	0.6334	6.4600	8.2200
	SOB	0.1404	0.3484	0.0000	1.0000
1997-1999	Ownership Dummy	0.5612	0.4988	0.0000	1.0000
	HHI	0.1249	0.0168	0.1014	0.1447
	Size	8.6673	1.5866	6.0620	12.0815
	Diversification	1.7966	2.0747	-5.0493	8.7001
	Cost to Income ratio	2.2194	22.4067	-36.3600	206.8813
	Growth of GDP	-3.1251	7.8182	-13.1270	4.7000
	SOB	0.0918	0.2903	0.0000	1.0000
2000-2007	Ownership Dummy	0.6410	0.4805	0.0000	1.0000
	HHI	0.1212	0.0146	0.1033	0.1430
	Size	8.9332	1.7029	5.7541	12.8809
	Diversification	1.1809	0.9375	-0.5078	8.3749
	Cost to Income ratio	0.6533	1.4156	-2.9322	24.4664
	Growth of GDP	5.0183	0.7616	3.6430	6.3450
	SOB	0.1026	0.3039	0.0000	1.0000

Appendix B: Panel data model selection test results:

			FE vs. OLS	*FE vs. RE*	*RE vs. OLS*
model 1	1992-1996	BETA	FE	FE	RE
		SIGA	FE	FE	RE
	1997-1999	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS
	2000-2007	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS
model2	1992-1996	BETA	FE	-	OLS
		SIGA	FE	FE	OLS
	1997-1999	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS
	2000-2007	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS
model3	1992-1996	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS
	1997-1999	BETA	FE	FE	RE
		SIGA	FE	FE	RE
	2000-2007	BETA	FE	FE	OLS
		SIGA	FE	FE	OLS