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Accounting for environmental factors, bias and negative numbers in efficiency estimation: A bootstrapping application to the Hong Kong banking sector.

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Abstract

This paper examines the evolution of Hong Kong's banking industry's technical efficiency, and its macroeconomic determinants, during the period 2000-2006 through the prism of two alternative approaches to efficiency estimation, namely the intermediation and production approaches. Using a modified (Sharp, Meng and Liu, 2006) slacks-based model (Tone, 2001), and purging the efficiency estimates for random errors (Simar and Zelenyuk, 2007) , we firstly analyse the trends in bank efficiency. We then identify the 'environmental' factors that significantly affect the efficiency scores using an adaptation (Kenjegalieva et al. 2009) of the truncated regression approach suggested by Simar and Wilson. 2007).

The first part of the analysis reveals that the Hong Kong banking industry suffered a severe downturn in estimated technical efficiency during 2001. It subsequently recovered, posting average efficiency scores of 92 per cent and 85 percent under the intermediation and production approaches respectively by the end of 2006. As for the sub-group analysis, commercial banks are, on average, shown to be the most efficient operators, while the investment bank group are shown to be the least efficient. Finally, with respect to the truncated regression analysis, the results suggest that smaller banks are more efficient than their larger counterparts, although larger banks are still able to enjoy gains from scale economies and benefit from the export of financial services. Moreover, private housing rent and the net export of goods and services are found to be negatively correlated with bank efficiency, while private consumption is shown to be positively correlated.

Keywords: Hong Kong Banks; DEA; Slacks; Environmental factors, Negative numbers; Bias.

JEL Classification: C23 · C52 · G21

1 Introduction

As outlined in Fethi and Pasiouras (2010), modern day researchers have to address a number of important issues when designing their research strategies for empirical efficiency/productivity analysis. This involves, *inter-alia*, answering the following questions. Should parametric or non-parametric modelling be undertaken? What input/output specification should be used? Is there a need to account for the possible input and output slacks in non-parametric models? How should negative numbers be dealt with if they feature in the input and output data sets? And how can 'bias' in the estimation process and environmental factors be accounted for to allow for a meaningful comparison of the success, or otherwise, of firms' management in optimising performance.

In common with most researchers these days we adopt the non-parametric Data Envelopment Analysis (DEA) approach, associated with Charnes et al. (1978), Banker et al. (1984) and Färe et al. (1985), rather than the stochastic frontier analysis (SFA) associated with the likes of Aigner et al. (1977), largely because it does not require any assumptions to be made about the distribution of inefficiencies or require a particular functional form in the construction of the frontier. Moreover, without any clear *a priori* guidance as to the most appropriate input/output specifications to be applied and in recognition of the model-dependency of X-efficiency scores (see, for example, Drake et al. 2009), we adopt both an intermediation approach (Sealey and Lindley 1997) and a production-based approach (Lozano-Vivas et al. 2002) to cater for possible material divergence in the estimation of the technical efficiency scores. An adapted (Simar and Zelenyuk. 2006) Li (1996) test is used to formally test for the equality of the X-efficiency distributions; and Kernel density analysis (Tortosa-Ausina. 2002) is deployed to illustrate the differences in the associated probability density functions. In addition, with no certainty that banks in Hong Kong operate without input and/or output slacks we also adopt Tone's (2001) slacks-based model (SBM). As for the other outstanding issues - how to handle negative numbers and account for bias and environmental factors – recent theoretical advances have called into question much of the previous empirical literature in much the same way as rapid advances in econometrics in the 1970s/1980s led to a reassessment of previous empirical studies on the demand for money relationship (see Lewis and Mizen 2000, Chapter 11). Our study thus represents one of the first to embrace what we regard as current 'state of the art' research design, embracing the latest theoretical advances.[1] Accordingly, and for the reasons set out in Section 3 below, we adopt the modified SBM (MSBM) of Sharp et al. (2006) to account both for input/output slacks and the negative numbers in both input and output data. We remove the 'bias' in the (stage one) estimated efficiency scores using Simar and Zelenyuk's (2007) sub-sampling bootstrap approach. And we then, in the second stage of the analysis, use an adaptation (see Kenjegalieva et al. 2009) of Simar and Wilson's (2007) double bootstrapping procedure and truncated regression analysis to formally assess the impact of 'environmental' (that is, macroeconomic and regulatory) factors on the estimated efficiency scores, duly accounting for potential bias in the parameter estimates.

Apart from embracing these latest methodologies in a combined fashion, we add to the existing literature on bank efficiency in South East Asia – a region growing in importance owing to the continuous drift of economic and financial power from West to East – by providing one of the first studies to analyse bank efficiency in the region post-Asian financial crisis (AFC).

The paper is organised as follows. In the next Section we discuss the changing nature of Hong Kong banking and its regulatory environment since the AFC. In Section 3 we present our non-parametric methodology and boot strapping approaches used to examine Hong Kong banking efficiency and its macroeconomic determinants, and also the data utilised in both the 'intermediation' and 'production' modelling methodologies. Our results are presented in Section 4 and we conclude in Section 5.

2 Hong Kong banking, the Asian financial crisis and more recent developments

The Asian Financial Crisis (AFC), which erupted in Thailand during the Summer of 1997 and went on to cause such economic and financial devastation in the region in the ensuing years, has been well documented (see, for example, Goldstein 1998, Hunter et al. 1999, and

[1] Avkiran and Rowlands' (2008) claim to "state-of-the-art" multi-stage methodology (as advanced by Avkiran and Thoraneenitiyan. 2009) is undermined by their use of SFA regression analysis at the second stage-see Section 3.2 below. Moreover, they have nothing to say about how to handle negative input and output data nor about the model-dependency of X-efficiency scores.

Jao 2001). Hong Kong was one of just a few countries in the region to escape relatively unscathed, successfully avoiding a banking crisis although, of course, some damage was inflicted on the banks. The damage wrought by the AFC on the banks' balance sheets was limited, however, by sound regulation introduced in the aftermath of the 1983-86 crisis (Hall 1985) and strong capitalisation. Supervisory reform in the wake of the AFC was thus largely unnecessary in Hong Kong, and the process of financial liberalisation continued.

Following the earlier "structural" reforms, which culminated in the creation of a three-tier banking system in 1990 (whereby "licensed banks" are distinguished from "restricted license banks" and "deposit-taking companies" – see Jao 2003, for further details) interest rate controls were gradually lifted and restrictions on foreign banks relaxed. The former involved the removal of the interest rate cap on retail deposits of more than one month on 1 October 1994, followed by the removal of interest rate caps on retail deposits of more than seven days and exactly seven days on 3 January 1995 and 1 November 1995 respectively. The cap on time deposits of less than seven days duly disappeared on 3 July 2000, followed by the complete deregulation of savings and current account deposit rates on 3 July 2001. As for the restrictions imposed on foreign banks, the "one-building" restriction was relaxed to a "three-building" restriction on 17 September 1999 and then, in November 2001, this latter restriction was abolished. Market entry criteria for foreign banks were also relaxed in May 2002. Such, then, was the nature of the more liberal regulatory environment within which Hong Kong's banks operated post-1999, the time-frame of this paper's analysis. Moreover, the banks have been able to engage in renminbi- dominated *retail* banking operations since January 2004.

As far as the likely impact of these regulatory developments on bank fortunes is concerned, the main focus of attention should probably be on the interest rate liberalisation programme and relaxed market entry criteria. Assuming that, in the past, the profitability of banks operating in Hong Kong was boosted, via monopsonistic rents, by the application of such controls – especially the caps imposed on deposit rates and the restrictions imposed on new bank entry and branching – it is to be expected that reforms adopted in these areas will have served to dampen the banks' profits. Indeed, the Hong Kong Monetary Authority noted as early as 2002 (HKMA 2002) that the increased competition had resulted in a reduction in bank lending spreads, particularly in the mortgage loan market, and downward pressure on net interest margins, particularly for small banks. Some banks, however, and especially the larger ones, managed to offset such adverse effects on profitability by boosting non-interest (i.e. fee and commission-based) income and reducing operating costs by, for example, encouraging customers with low and volatile balances to use less-costly delivery channels, such as the Internet. Account charges are now also the norm. As far as the smaller banks are concerned, the introduction of deposit insurance in 2006 should have acted to increase the relative attraction of small licensed banks by reducing the competitive advantage enjoyed by "Too-Big-Too-Fail" banks; while many also view deposit deregulation as an opportunity allowing them to compete more effectively for deposits with large listed banks. Finally, the opening-up of some renminbi-denominated business to Hong Kong's licensed banks in January 2004 served to provide these banks with some additional revenue, despite the PRC's stringent capital controls. Moreover, the Chinese government's subsequent decision to relax exchange controls by allowing Mainland banks to issue renminbi-denominated credit cards which can be used at ATMs in Hong Kong should further boost fee income for the latter region's banks.

Previous studies that have investigated those countries that were involved in the AFC have primarily considered how banking systems operated throughout the turbulent period. For example, Shen (2005) employed a smooth transition parametric model to analyse the changes to banks' balance sheets (from traditional loans to off-balance-sheet items) during the AFC of Taiwanese banks during 1996-2001. It was found that, during this period, the traditional banks experienced decreasing returns to scale in loan markets, but banks which followed the universal-style mode of operation experienced increasing returns to scale in their off-balance-sheet markets. For Malaysia, Krishnasamy et al. (2003) showed that the banking system consolidated from 86 banks in 1997 to 45 in 2002 as the AFC hit profits. They found, utilising non-parametric Malmquist indices, that the top ten banks in Malaysia faced a reduction in technical efficiency of 4.2% and in scale efficiency of 5.1% over the period 2000-2001. As far as Hong Kong is concerned, Kwan (2006), using the stochastic frontier approach, found that the average level of X-inefficiency for all banks over the sample period 1992 to 1999 was equal to 32%, with the level of inefficiency falling to 29% by the end of 1999. In contrast, Drake et al. (2006), utilising the non-parametric Slacks-Based Model (SBM) and adopting a profit-based approach, showed that (unadjusted) X-efficiency scores decreased by over a third for some asset-sized groups of Hong Kong banks after the AFC (for example, for banks with assets between US$1000m and US$4999m, mean X-efficiencies decreased from 62% (1997) to 39% (1998) – see their Table 1). Moreover, by end-1999, this group of banks' average X-efficiency scores had only recovered to 42%. Indeed, no asset-sized group or sub-group achieved an average level of X-efficiency of over 64% - the figure posted by the largest bank grouping – by this date, the majority posting figures of less than 50%. (The intermediation-based figures, however, were somewhat higher – see their Table 1).

3 Modelling theory and data

3.1 Estimation of efficiency

In this study, we utilize the non-parametric Data Envelopment Analysis (DEA) model of Tone (2001) which takes into account input and output slacks, the so-called Slacks-Based Model (SBM). This reflects acceptance of Fried et al's. (1999) critique of the 'standard' DEA models based on the Banker et al. (1984) specification in a situation where there can be no certainty that input and output slacks do not exist.

In addition, most DEA models do not deal directly with, or allow for, negative data in the program variable set. For example, if input variable(s) are found to be negative, then a large arbitrary number is usually added to make that variable(s) positive so that the standard output-oriented Banker et al. (1984) program can then be utilised. The same problem occurs with negative output variable(s), and in this case the input-oriented Banker et al. (1984) model has to be used. Both of these situations occur due to the restricted translation invariance of the Banker et al. (1984) model (see Pastor 1996). However, a problem arises if both input and output variables include negative values, because in this case, the Banker et al. (1984) - based programs cannot be utilised; see Silva-Portela et al. (2004).[2] Accordingly to

[2] Indeed, it is not uncommon for many financial intermediaries to experience negative inputs and outputs in the normal process of production modelling. For example, many banks have entered the lucrative off-balance-sheet market (an output) but in some years trading losses have exceeded gains and hence given rise to a negative output. Unlike in other DEA models, this could not be modelled as a 'bad' output as it may only involve a

overcome this problem, as well as to allow for possible input and output slacks, we adopt the Modified Slacks-Based Model (MSBM) suggested by Sharp, Meng and Liu (2006), who combined the ideas of Tone (2001) and Silva Portela et al. (2004), in one of the first applications of the methodology that we are aware of. An exposition of the (input-orientated) MSBM approach follows.

In modelling, we assume there are n DMUs operating in the banking industry which convert inputs X ($m \times n$) into outputs Y ($s \times n$) using common technology T which can be characterised by the technology set $\hat{T}$ estimated using DEA:

$$\hat{T} = \{(x, y) \in \mid y_o \leq Y\lambda, x_o \geq X\lambda, \sum \lambda = 1, \lambda \geq 0\} \tag{1}$$

where x_o and y_o represent observed inputs and outputs of a particular DMU and λ is the intensity variable. $\hat{T}$ is a consistent estimator of the unobserved true technology set under variable returns to scale.

Given these conditions, the individual input-oriented efficiency for each DMU is computed relative to the estimated frontier by solving the following MSBM linear programming problem:

$$\begin{aligned} \text{min} \quad & \hat{\rho}(x, y | T(x)) = 1 - \frac{1}{m} \sum_{k=1}^{m} s_k^- / P_{ko}^- \\ \text{subject to} \quad & x_o = X\lambda + s^-, \\ & y_o = Y\lambda - s^+, \\ & \sum \lambda = 1, \\ \text{and} \quad & \lambda \geq 0, \quad s^- \geq 0, \quad s^+ \geq 0, \end{aligned} \tag{2}$$

small section of the sample banks. In relation to negative inputs, again in banking this is common, and in this study we examine the use of 'Total Provisions' as an input instead of a 'bad' output.

where s^- is output shortfall, s^+ is input excess, and an optimal solution of program (2) is given by $(\hat{\tau}, \hat{\lambda}, \hat{s}^-, \hat{s}^+)$. P_{ko}^- is a range of possible improvements for inputs of unit o and is given by $P_{ko}^- = x_{ko} - \min_i(x_{ki})$.

However, the efficiencies calculated utilizing program (2) are biased downwards in relation to the true slacks-based technical efficiencies, $\rho_i(x, y|T)$. The bias arises due to the piecewise linear frontier used as a benchmark (the *true* frontier is smooth) and to differences in the environment (or in other exogenous factors) in which banks operate. In addition, it can potentially capture leads and/or lags in the variables used in the panel data analysis, as well as some reporting errors. Mathematically, it is expressed as $BIAS(\hat{\rho}_i(x, y|T)) \equiv E(\hat{\rho}_i(x, y|T)) - \rho_i(x, y|T)$ and decreases asymptotically with an increase in the number of observations in the sample and in the number of bootstrapped iterations and as a result of a reduction in the number of input/output variables considered.

To overcome this problem, as well as to examine the performance of various sub-groups of banks, we therefore utilize the group-wise, heterogeneous sub-sampling bootstrap approach suggested by Simar and Zelenyuk (2007). First, we compute the X-efficiency score $\hat{\rho}_i(x, y|T)$ for each bank in the sample using program (2). Then, we aggregate the estimates of individual efficiencies into the L-subgroup aggregates using the price-independent aggregation method suggested by Färe and Zelenyuk (2003) shown below:

$$\bar{\hat{\rho}}^l = \sum_{i=1}^{n\,l} \hat{\rho}^{l,i} \cdot S^{l,i}, \quad \text{in which } S^{l,i} = \frac{1}{D}\sum_{d=1}^{D} \frac{x_d^{l,i}}{\sum_{i=1}^{n\,l} x_d^{l,i} \cdot S^l},\ i = 1, \ldots, n_l;$$

and

$$\bar{\hat{\rho}} = \sum_{l=1}^{L} \bar{\hat{\rho}}^l \cdot S^l, \quad \text{in which } S^l = \frac{1}{D}\sum_{d=1}^{D} \frac{\sum_{i=1}^{n\,l} x_d^{l,i}}{\sum_{l=1}^{L}\sum_{i=1}^{n\,l} x_d^{l,i}},\ i = 1, \ldots, n_l,\ l = 1, \ldots, L. \tag{3}$$

In this exposition, $\bar{\hat{\rho}}^{l}$ is the aggregate X-efficiency of sub-group *l*, $S^{l,i}$ is a price-independent weight of firm *i* which belongs to sub-group *l*, $\bar{\hat{\rho}}$ is the aggregate X-efficiency of the industry, and S^{l} is a price-independent weight of sub-group *l*.

Next, the bootstrap sequence $\Xi^{*}_{s\,l,b} = \left\{\left(x_b^{*i}, y_b^{*i}\right): i = 1,....,s_l\right\}$ is obtained by sub-sampling and replacing the data independently for each sub-group *l* of the original sample $\Xi^{*}_{n\,l} = \left\{\left(x^{i}, y^{i}\right): i = 1,....,n_l\right\}$ for each bootstrap iteration *b*=1,…,*B* (where $s_l \equiv (n_l)^k$, and where *k*<1 and *l*=1, …, *L*). The Monte-Carlo evidence presented in Simar and Zelenyuk (2007) indicates that values of k in the range 0.5 and 0.7 will offer the most precise results in the simulated examples so, consistent with this, k = 0.65 is utilised in this paper for each sub-group.

Step 4 involves computing the bootstrap estimates of slacks-based efficiency $\hat{\rho}_b^{*l,i}$ for banks $i = 1,....,s_l < n_l$ for all groups *l*=1, …, *L* using (2) but with respect to the bootstrapped sample $\Xi^{*}_{n,b}$ obtained in Step 3, i.e.,

$$\text{min:} \qquad \hat{\rho}_b^{*l,i}(x, y|T(x)) = 1 - \frac{1}{m}\sum_{k=1}^{m} s_{b\,k}^{*-} / x_{ko}$$

$$\text{subject to} \qquad x_o = X_b^{*}\lambda + s_b^{*-},$$

$$y_o = Y_b^{*}\lambda - s_b^{*+},$$

$$\sum \lambda = 1 \text{ and}$$

$$\lambda \geq 0, \quad s_b^{*-} \geq 0, \quad s_b^{*+} \geq 0.$$

Finally, in Step 5, the bootstrapped estimates of the aggregated X-efficiencies are computed using the following equations:

$$\bar{\hat{\rho}}_b^{*l} = \sum\nolimits_{i=1}^{n\,l} \hat{\rho}_b^{*l,i} \cdot S_b^{*l,i}, \text{ where } S_b^{*l,i} = \frac{1}{D}\sum\nolimits_{d=1}^{D} \frac{x_{b,d}^{*l,i}}{\sum\nolimits_{i=1}^{s\,l} x_{b,d}^{*l,i} \cdot S_b^{*l}}, \ i = 1, \ldots, s_l < n_l;$$

and

$$\hat{\bar{\rho}}_b^* = \sum_{l=1}^{L} \hat{\bar{\rho}}_b^{*l} \cdot S_b^{*l}, \quad \text{where } S_b^{*l} = \frac{1}{D}\sum_{d=1}^{D} \frac{\sum_{i=1}^{n\,l} x_{b,d}^{*l,i}}{\sum_{l=1}^{L}\sum_{i=1}^{s\,l} x_{b,d}^{*l,i}},\ i = 1, \ldots, s_l < n_l,\ l = 1, \ldots, L. \tag{4}$$

Repeating Steps 3 – 5 B times provides us with B bootstrap estimates of aggregate X-efficiencies for each sub-group. These estimates allow us to obtain confidence intervals, bias-corrected estimates and standard errors for the aggregate efficiencies.

3.2 Analysis of the determinants of banking efficiency

It has long been recognised in efficiency analysis that environmental factors – in principle, anything outside the control of management and not reflected in the traditional inputs – can have a significant impact on relative scores, possibly in a differential way on different bank groupings and asset-sized groups (see Drake et al. 2006). Fried et al (1999), for example, having critiqued earlier approaches adopted by researchers, in order to adjust the efficiency estimates for the external environment duly recommended, within a traditional Banker et al. (1984) DEA input-orientated modelling specification, a multi-stage approach.[3] Firstly, the Farrell radial technical efficiency scores are obtained in the usual way, as well as non-radial input slacks. Dependent variables, comprising the sum of radial and non-radial input slacks, are then separately regressed (using Tobit regression) on a set of environmental factors thought to be likely to influence the efficiency of banks. The primary inputs are then adjusted to account for the slacks-based regression results. Finally, the original DEA program is re-estimated using the adjusted inputs and the original outputs to generate new radial measures of inefficiency, incorporating the impact of environmental factors. The resulting efficiency scores, which measure the inefficiency attributable to management, can then be compared with the stage one, unadjusted scores to assess the impact of environmental factors on bank efficiency. An adjusted score in excess of an unadjusted score indicates that the external environment is having a significant negative impact on bank efficiency.

[3] Other studies that utilise this multi-stage approach include Drake et al. (2006) and Avkiran (2009).

As recognised by Casu and Molyneux (2003), however, there are problems with the second-stage Tobit regression, although their single (naïve) bootstrap solution has, in turn, been criticized by Simar and Wilson (2007). Moreover, in their follow-up paper, Fried et al. (2002) themselves argued for a three-stage approach, involving the use of SFA to regress first-stage performance measures against a set of environmental variables at the second stage, in acceptance of the problems associated with the use of second-stage Tobit regression and in a desire to also account for statistical noise arising from 'measurement errors' (see page. 161).[4] Accordingly, in our own study of the determinants of banking efficiency, we use the double bootstrap procedure advanced by Simar and Wilson (2007)[5] to examine the impact of interest rate reforms and the macroeconomic environment on Hong Kong bank X-efficiency.[6] This means, however, that rather than providing an assessment of the aggregate impact of environmental factors on bank efficiency through the incorporation of the adjusted inputs in the DEA program (as in Fried et al. 1999) or isolating managerial efficiency from environmental effects and statistical noise (as in Fried et al. 2002), we simply regress the estimated efficiency scores on the potentially-significant environmental factors to assess the significance of the latter as determinants of X-efficiency. The novelty of our approach, however, lies in the first stage where the efficiency scores are first purged of 'bias' using the Monte Carlo methods of Simar and Zelenyuk (2007) described above. In this way, the 'good or bad luck, omitted variables and related phenomena' (treated as a random error) component of efficiency identified by Fried et al. (2002) – at page. 158 - is accounted for using bootstrapping techniques rather than their second-stage SFA regression analysis, which suffers from the drawback of being a parametric approach producing serial correlation among

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4 Thoraneenitiyan and Avkiran (2009) also adopt this approach in their analysis of post-crisis East Asian bank efficiency although they do not acknowledge their theoretical antecedents.

5 It should be noted, however, that Simar and Wilson's (2007) approach has, itself, subsequently been criticised by McDonald (2009) for being too restrictive (although Simar and Zelenyuk. 2007 defend the use of statistical bootstrap in efficiency analysis-see page. 1378) [The full assumptions underlying Simar and Wilson's. 2007 Data Generating process (DGP) are outlined at pages 34-37 of their article]. He favours the use of ordinary least squares in the second stage as it is a consistent estimator, 'familiar' and an 'easy to compute' method 'understood by a broad community of people' (see page. 6). He claims however, that the 'gold standard' is provided by the QMLE procedure advocated by Papke and Wooldridge (1996). Like Simar and Wilson (2007), however, he argues against the use of Tobit regression at the second stage on the grounds that second-stage DEA efficiency scores should be treated as descriptive measures, not generated by a censoring DGP (i.e., they are fractional data). In this situation, Tobit is generally believed to be an inconsistent estimator.

6 Early studies embracing this methodology have been undertaken by Brissimis et al. (2008) and Delis and Papanikolaou (2009) in examinations of European banking markets.

the estimated efficiencies.[7] As Simar and Zelenyuk (2007) put it: "tests on sample means of estimated DEA efficiencies may lead to quite a different conclusion from tests based on aggregate efficiencies, whose weights account for the economic importance of each firm in the sample" (page. 1385).

Consistent with the above, in the second stage of our analysis, the X-efficiency estimates ($\hat{\rho}_i$) derived using program (2) are regressed on environmental factors[8]. If we let z_i be the vector of environmental variables affecting the i-th DMU and β a vector of parameters to be estimated, then a regression of equation (5) below can be estimated:

$$0 \le \rho_i = z_i \beta + \varepsilon_i \le 1 . \qquad (5)$$

However, when utilising non-parametric efficiency estimates, the dependent variable $\hat{\rho}_i$ in equation (5) is an estimate of the unobserved true efficiency ρ_i, i.e., $\rho_i = \hat{\rho}_i = \hat{\rho}\left(x_i, y_i \middle| \hat{T}\right)$. Thus, all the $\hat{\rho}_i$'s are serially correlated in a complicated, unknown way, and, moreover, ε_i is also correlated with z_i. To overcome this problem, and to secure a better coverage of estimated confidence intervals, we therefore utilize the double bootstrap procedure (Algorithm 2)[9] proposed by Simar and Wilson (2007), with 2 truncation points, as suggested by Kenjegalieva et al. (2009), where, in the bootstrap analysis, the X-efficiency scores are regressed on the environmental factors, as shown in equation (6) below:

$$0 \le \rho_i = \psi(z_i, \beta) + \varepsilon_i \le 1 \qquad (6)$$

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7 Avkiran and Thoraneenitiyan's (2010) analysis of UAE bank efficiency, based upon Avkiran and Rowlands (2008), suffers from the same drawback.

8 Note that, in this stage, the estimates from program (2) are utilised as we are interested in the individual banks' scores and not the aggregate, bias-corrected, bank sub-group scores which result from the program (4) estimates.

9 Unlike Algorithm 1 of Simar and Wilson (2007), this also takes into account the (negative) bias of the X-efficiency scores, a concern raised over the 'two-stage' approach by Fried et al. (1999) (page 251). It may, however, add to statistical noise unless the bias being corrected is large. Following Simar and Wilson (2007), we used 100 replications to compute the bias-corrected efficiency estimates and 2000 replications to estimate the confidence intervals.

where, ρ_i is the X-efficiency estimate and approximated by $\hat{\rho}_i$ of the *i*-th DMU, ψ is a smooth continuous function, β is a vector of parameters, and ε_i is a truncated random variable $N(0, \sigma_i^2)$ truncated at $(-\psi(z_i, \beta))$ and $(1-\psi(z_i, \beta))$ and independent of z_i.

In the bootstrap procedure, the X-efficiency estimates $\hat{\beta}_i$ are used in the truncated regressions to obtain the bootstrap of the coefficients of the environmental variables affecting the performance of the banks and the variance of the regression. Thus, the bootstrap provides a set of bootstrapped parameters of the material environmental factors which allows us to estimate their probabilities and confidence intervals (for further details see Kenjegalieva et al. 2009).

The second-stage truncated regression of Simar and Wilson (2007) outlined above helps us to empirically determine the impact of interest rate reforms and the macroeconomic environment on Hong Kong bank X-efficiency. This allows us to identify the macroeconomic factors which stimulate the efficient financial intermediation of funds and provision of banking services. We account for the potential effects of macroeconomic developments by considering a large set of macroeconomic factors which have the potential to influence the performance of banks, including individual components of GDP, such as private consumption expenditure (expected to have a positive effect on efficiency), government expenditure (positive), gross fixed capital formation (positive), and the net export of goods and services (positive). In addition, we consider the inclusion of other variables such as unemployment (negative), expenditure on housing (positive), the current account balance (positive) and the discount rate (negative). Finally, to capture the effect of the scale efficiency of banks, in the regression specification we include a proxy for the size of the banks. In other words, we test the interaction of macroeconomic factors with size.

3.3 Data description

In this study we present comparative results from the two main methodologies utilised in the literature to model bank efficiency, the intermediation and the production approaches. In modelling the intermediation approach we specify 4 outputs and 4 inputs (consistent with Sealey and Lindley 1977). The first output is 'total loans' (total customer loans + total other lending), the second output is 'other earning assets', the third output is 'net commission, fee and trading income', and the final output is 'other operating income'. The third and fourth outputs are included in the analysis to reflect the fact that banks around the world have been diversifying, at the margin, away from traditional financial intermediation (margin) business and into 'off-balance-sheet' and fee income business. Hence, it would be inappropriate to focus exclusively on earning assets as this would fail to capture all the business operations of modern banks. The inclusion of 'other operating income' is therefore intended to proxy the residual non-traditional business activities of Hong Kong banks.

The inputs estimated in the intermediation approach are: 'total deposits' (total deposits + total money market funding + total other funding); 'total operating expenses' (personnel expenses + other administrative expenses + other operating expenses); 'total fixed assets'; and 'total provisions' (loan loss provisions + other provisions). Ideally, the labour input would be proxied either by the number of employees or by personnel expenses. However, details on employment numbers are not available for all banks in the sample, while operating expenses data is not available on a disaggregated basis. Hence a 'total operating expenses' variable was utilised. The summary statistics and distribution of banks covered in the sample are given in Table 1.[10]

INSERT TABLE 1

With respect to the last-mentioned input variable (i.e., provisions), it has long been argued (Altunbas et al. 2000) in the literature that the incorporation of risk/loan quality is vitally important in studies of banking efficiency. Akhigbe and McNulty (2003), for example, utilising a profit function approach, include equity capital "to control, in a very rough fashion, for the potential increased cost of funds due to financial risk" (page. 312). In contrast to Akhigbe and McNulty (2003), however, Laevan and Majnoni (2003) argue that risk should be incorporated into efficiency studies via the inclusion of loan loss provisions. In agreement with this view, because we believe that credit risk was the main risk facing Hong Kong banks during the sample period, we also incorporate 'total provisions' as an

[10] The input and output data were obtained from the Bank-scope resource package by Bureau Van Dijik (BVD).

input/cost in the DEA relative efficiency analysis, as is also done by Drake and Hall (2003) in their analysis of Japanese bank efficiency.

Finally, in the case of the production approach, where deposits are treated as an output rather than as an input (see, for example, Lozano-Vivas et al. 2002), we have five outputs and three inputs. The outputs are: 'total loans' (total customer loans + total other lending); 'net commission, fee and trading income'; 'total deposits'; 'other earning assets'; and 'other operating income'. The three inputs are: 'total operating expenses'; 'total fixed assets'; and 'total provisions'. In the next Section we present our results.

4 Estimation results

4.1 First stage: SBM efficiency estimates

Tables 2 and 3 provide a summary of the aggregate input–oriented, modified slacks-based, bias-corrected, X-efficiency scores obtained under the intermediation and production approaches to describing the banking production process. Although both approaches report similar trends in X-efficiency - see Figures 1 and 2 - the intermediation approach generally produces higher results than the production methodology. This is consistent with the findings of Drake et al. (2009), in their analysis of the Japanese banking industry.

INSERT FIGURES 1 AND 2

INSERT TABLES 2 AND 3

In the year 2000, Hong Kong banks (taken as a group) exhibited relatively high levels of intermediation and production X-efficiency (88% and 67% respectively). However, in 2001, according to both approaches, the banks experienced a sharp decline in their X-efficiency levels (to 56% and 45% respectively).[11] Although the overall X-efficiency level remained moderately low in 2002 (at 62% and 52% respectively) commercial banks did, however, begin to show an improvement in financial intermediation relative to the other sub-

[11] Using dummy variables, we formally tested for the possibility that the removal of interest rate controls (see Section 2) in 2001 was the cause of the decline but the results proved insignificant.

groups. This improvement was particularly marked under the production approach where efficiency increased from 42% to 66%. After 2002, most banks recorded a steady improvement in X-efficiency, despite the SARS epidemic of 2003 (consistent with the industry's profit performance for 2003 reported in HKMA 2004), although the investment bank grouping's efficiency dipped quite markedly in 2006 (especially under the intermediation approach). This meant that, by the end of the sample period, average bank X-efficiency stood at 92% according to the intermediation approach and 85% according to the production approach, well above the levels (88% and 67% respectively) recorded at the beginning of the sample period.

Comparing these results with earlier studies of Hong Kong bank X-efficiency, it is interesting to recall that Kwan (2006) found that the mean level of X-inefficiency for all banks over the sample was around 0.32, and that X-inefficiency levels generally declined over his sample period (from 0.41 in 1992:Q1 to 0.29 in 1999:Q4). He attributed this trend to the impact of technological innovation. However, in Drake et al. (2006), the Hong Kong (overall) banking sector's mean (unadjusted) X-efficiency scores declined continuously between 1995 (0.60) and 1998 (0.41), increased in 1999 (to 0.46) and 2000 (to 0.54) and then subsequently declined in 2001 (to 0.49) (see their Table 1). While the latter pattern matches that established in our present study for the overlapping years (i.e., 2000/2001), it should be noted that their results derived from the application of the profit approach, the corresponding X-efficiency scores under the intermediation approach (see their Table 3) showing an *increase* in 2001 (to 0.79) as well as in 1999 (0.61) and 2000 (0.74).[12]

In addition to the above results, commercial banks were typically found in our study to be more X-efficient than other types of banking firms under both approaches over most of the considered time period. Bank Holdings and Holding Companies were found to be somewhat less efficient than commercial banks, with Investment Banks being the least efficient, with aggregate X-efficiency scores varying between a low of 36% in 2002 and a high of 68% in 2000 under the intermediation approach, and between 24% in 2002 and 62% in 2000 under the production approach.

[12] Note, however, that the results of Drake et al. (2006) were based on Tone's (2001) original SBM specification and not on the Sharp et al. (2006) program used in this study.

Returning to a comparison of the results obtained under the two methodologies, Table 4 reports the results of the tests for the equality of the X-efficiency distributions estimated under the alternative methodologies using an adapted version of Li (1996), the tests being modified to a DEA context in accordance with Simar and Zelenyuk (2006). As can be seen, the X-efficiency scores estimated under the production and intermediation approaches are from different populations (i.e., have statistically different distributions), for all three groups of banks and the overall banking industry studied. This shows that the SBM efficiency scores and the efficiency scores obtained utilising the traditional DEA technique (Tortosa-Ausina, 2002) are alike in that they are both sensitive to the choice of inputs and outputs adopted.

INSERT TABLE 4

INSERT FIGURE 3

To further aid discussion of the differences between the results of the two methodologies, the estimated densities for all groups of banks using univariate kernels are depicted in Figure 3. The kernel density distributional analysis of efficiency scores facilitates a wider view on sector efficiency since it allows us to visualise the efficiency estimates and their probability densities. As can be seen, and consistent with Table 4, the distribution of the production-based MSBM X-efficiency scores (the dashed line) has a higher probability density at the mode than that of the intermediation-based MSBM X-efficiency scores (the solid line) in all but one case, thereby indicating that more banks are concentrated around the mode under the production methodology. A possible explanation for this result is that the pursuit of service-oriented objectives rather than financial intermediation-based objectives may be the motivational force behind most banks' activities. However, the mode of the intermediation X-efficiency scores' distribution is more to the right than that of the production X-efficiencies in all cases, implying that banks are more efficient in their role as financial intermediaries than as service providers.

INSERT FIGURE 4

Finally, the bivariate kernel analysis, which visualises the transition of efficiency scores (changes in their position relative to the industry average), presented in Figure 4 further suggests that, although the absolute value of the efficiency level is sensitive to the choice of the input and output specification adopted, in general, Hong Kong banks tend not to change their efficiency positions relative to that of the industry's average. This is due to the fact that the probability mass of the normalized efficiency scores relative to the geometric mean efficiency weighted by the size of the banks (proxied by the volume of deposits) is somewhat concentrated along the positive diagonal line.

4.2 Analysis of the determinants of bank efficiency

Tables 5 and 6 present results of the truncated regression analysis for the intermediation and production approaches respectively. The following macroeconomic variables were used in the specification of the truncated regression as they gave the model with the best fit following the adoption of the usual 'general to specific' econometric methodological approach: LPRIVCONS - log of private consumption; LEXPORT - log of net exports (sum of the net export of services and the net export of goods); and LRENT - log of the rent for private flats on Hong Kong Island (as a proxy for housing expenditure). To capture the effects of time and bank-specific characteristics, we further included a time trend (TIME) variable along with group dummies. Additionally, to capture the effects of scale we included the SIZE variable (log of total deposits) and the square of SIZE (SIZE^2). Finally, we included an interaction variable of LEXPORT and SIZE (LEXPORT_SIZE) to capture the effect of the exportability of financial services by Hong Kong banks, which is likely to depend on the size of banking firm. For, according to the Information Services Department of the Hong Kong Special Administrative Region's Government, in 2006, the share of exports of services accounted for by the financial services industry was 12%. Therefore, it is particularly appealing to examine the influence of this variable on the efficiency of Hong Kong banking firms.

INSERT TABLES 5 AND 6

In looking at the results, the first point to note is that, although the statistical significance of the regression variables is different under the production and intermediation methodologies, the signs of the explanatory variables are the same. In both models, the indicators of size are found to be significant at the 1% level of significance, with a negative coefficient for SIZE and a positive one for SIZE^2. This implies that, in the Hong Kong banking industry, smaller banks are more efficient than their larger counterparts, although larger banks are also able to enjoy gains from scale economies. This is thus empirical evidence challenging the idea of U-shaped scale economies implied by the theoretical literature and supporting the findings of Simar and Wilson (2007) in their empirical investigation of US commercial banks.

With respect to the macroeconomic determinants of banking X-efficiency, the results suggest that the level of private consumption has a positive impact on banking X-efficiency, as expected. This implies that an increase in private consumption stimulates banking activity. Both LRENT and LEXPORT are, unexpectedly, found to be negatively correlated with efficiency and significant at the 1% level in the production and at the 1% and 10% levels respectively under the intermediation methodologies.[13] However, the coefficient for the interaction variable LEXPORT_SIZE is positive and significant in the production methodology, at the 1% level, although insignificant in the intermediation approach. This suggests that larger banks have a greater potential to export financial services, thereby boosting their X-efficiencies. However, this does not significantly affect banks' financial intermediation activities.

The analysis of the performance of different types of banks is undertaken with respect to the "Bank Holdings and Holding Companies" group (BHHC), which serves as the control group. Intriguingly, the bias-corrected results show that the coefficient for the commercial banks' dummy is positive and significant (at the 10% level) only in the intermediation methodology, whereas the coefficient for the investment banks is positive and significant (at the 1% level) in both approaches. This implies that investment banks are successful under

[13] As a proxy for housing expenditure, a priori, one would expect an increase in LRENT to increase bank X-efficiency to the extent that it is financed by bank loans. Similarly, an increase in net exports of services, implied by a rise in LEXPORT, would be expected to raise bank earnings, ceteris paribus, thereby boosting X-efficiency again.

both intermediation and service-producing objectives, whereas commercial banks are only successful under the former.

5 Conclusions

Using the MSBM of Sharp et al. (2006) to account for possible input/output slacks and the negative numbers in the data we have demonstrated that, under both the intermediation and production approaches to efficiency estimation – which are formally shown to produce materially different X-efficiency distributions - the Hong Kong banking industry as well as all of its sub-groups suffered a substantial decline in technical efficiency during 2001.[14] Purging the MSBM efficiency scores for random errors using the sub-sampling bootstrap approach of Simar and Zelenyuk (2007) confirmed this result. Utilising the latter (bias-corrected) scores, the industry as a whole, with little damage done by the SARS epidemic of 2003, is shown to subsequently recover, posting end-2006 average efficiency scores of 92 per cent and 85 per cent under the intermediation and production approaches respectively, well above the levels obtaining at end-2000. As for the sub-groups, the commercial banks are, on average, shown to be the most efficient operators, posting end-2006 efficiency scores of 97 per cent and 94 per cent under the two approaches, while the investment banks are shown to be furthest from the efficiency frontier (posting end-2006 scores of just 46 per cent and 37 per cent respectively), although the truncated regression analysis reveals that, unlike commercial banks, they are successful under both intermediation and service-producing objectives.

With respect to the rest of the results of the truncated regression analysis, our results suggest that the smaller banks are more efficient than their larger counterparts (confirming the findings of Simar and Wilson 2007 in their study of US banks), although the latter are also able to enjoy economies of scale and benefit more from the export of financial services. Moreover, private consumption is shown to be positively correlated with bank efficiency,

[14] Although, for the sack of brevity, the biased, unadjusted scores are not reported in the text, they are available, on request, from the authors.

while private housing rent and the net exports of goods and services are shown to be negatively correlated with bank efficiency.

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Table 1 Hong Kong banks: Summary statistics and distribution of analyzed banks across the banking groups

	mean	min	max	st. dev
Total operating expenses	1541876	1800	45167256	4659830
Total fixed assets	2769599	100	49216374	7331098
Total deposits	122029945	1761	3249308598	358086443
Total loans	61695841	338	1229425206	162984058
Other earning assets	67505775	0	1993631331	205726006
Total provisions	318161	-3104460	8593000	1092042
Net commission, fee and trading income + other operating income	1174795	-1865023	38054181	4019743
	BHHC	CB	IB	Total
2000	4	23	29	*56*
2001	5	22	25	*52*
2002	6	23	20	*49*
2003	6	22	18	*46*
2004	6	21	18	*45*
2005	4	20	16	*40*
2006	5	18	8	*31*

Notes. Figures for variables are expressed in HK$ millions and deflated using the Hong Kong GDP deflator. ‘BHHC’ denotes Bank Holdings & Holding Companies, ‘CB’ - Commercial Banks, ‘IB’ – Investment Banks/Securities Houses.

Table 2 Group-wise heterogeneous sub-sampling bootstrap aggregate efficiencies under the intermediation approach

		2000	2001	2002	2003	2004	2005	2006
BHHC – Bank Holdings and Holding Companies								
Original SBM score		0.827	0.659	0.714	0.747	0.874	0.743	0.905
Bootstrap estimates	Bias-corr MSBM eff.	**0.821**	**0.585**	**0.517**	**0.641**	**0.866**	**0.661**	**0.868**
	Stn.dev.	0.092	0.115	0.094	0.069	0.103	0.049	0.109
	CI 5% Up	0.669	0.360	0.428	0.521	0.748	0.560	0.811
	CI 5% Lo	0.976	0.793	0.767	0.773	1.115	0.749	1.204
CB – Commercial Banks								
Original SBM score		0.893	0.712	0.756	0.873	0.922	0.931	0.935
Bootstrap estimates	Bias-corr MSBM eff.	**0.937**	**0.560**	**0.699**	**0.862**	**0.926**	**0.967**	**0.972**
	Stn.dev.	0.068	0.065	0.116	0.073	0.087	0.061	0.074
	CI 5% Up	0.822	0.455	0.538	0.768	0.880	0.884	0.889
	CI 5% Lo	1.096	0.705	0.944	1.041	1.219	1.107	1.131
IB – Investment Banks								
Original SBM score		0.745	0.681	0.623	0.662	0.792	0.687	0.669
Bootstrap estimates	Bias-corr MSBM eff.	**0.684**	**0.499**	**0.362**	**0.515**	**0.668**	**0.551**	**0.458**
	Stn.dev.	0.075	0.042	0.055	0.047	0.036	0.048	0.062
	CI 5% Up	0.573	0.426	0.285	0.426	0.612	0.469	0.346
	CI 5% Lo	0.863	0.588	0.484	0.613	0.749	0.660	0.588
All Banks								
Original SBM score		0.860	0.699	0.733	0.827	0.898	0.891	0.911
Bootstrap estimates	Bias-corr MSBM eff.	**0.881**	**0.560**	**0.618**	**0.788**	**0.938**	**0.905**	**0.919**
	Stn.dev.	0.059	0.066	0.088	0.058	0.071	0.050	0.068
	CI 5% Up	0.776	0.453	0.499	0.704	0.833	0.829	0.843
	CI 5% Lo	1.003	0.707	0.828	0.917	1.105	1.019	1.091

Notes: We use 1000 group-wise heterogeneous bootstrap replications, Gaussian density, and the Silverman (1986) reflection method; and the bandwidth is obtained using the Sheather and Jones (1991) solve-the-equation plug-in-approach. CI 5% Up and CI 5% Lo indicate 5% Confidence Intervals at the Upper and Lower levels respectively and represent a range within which the 95 percentile of bootstrapped efficiency scores lies..

Table 3 Group-wise heterogeneous sub-sampling bootstrap aggregate efficiencies under the production approach

		2000	2001	2002	2003	2004	2005	2006
BHHC – Bank Holdings and Holding Companies								
Original SBM score		0.867	0.584	0.605	0.654	0.827	0.637	0.868
Bootstrap estimates	Bias-corr MSBM eff.	**0.962**	**0.545**	**0.359**	**0.600**	**0.836**	**0.530**	**0.756**
	Stn.dev.	0.113	0.067	0.125	0.066	0.107	0.073	0.056
	CI 5% Up	0.764	0.390	0.210	0.453	0.686	0.375	0.735
	CI 5% Lo	1.160	0.658	0.673	0.692	1.065	0.620	0.893
CB – Commercial Banks								
Original SBM score		0.691	0.617	0.652	0.739	0.879	0.887	0.902
Bootstrap estimates	Bias-corr MSBM eff.	**0.632**	**0.424**	**0.656**	**0.612**	**0.985**	**0.916**	**0.938**
	Stn.dev.	0.081	0.079	0.122	0.082	0.091	0.073	0.072
	CI 5% Up	0.466	0.282	0.410	0.507	0.820	0.809	0.827
	CI 5% Lo	0.795	0.569	0.863	0.810	1.172	1.080	1.098
IB – Investment Banks								
Original SBM score		0.671	0.603	0.493	0.556	0.573	0.586	0.591
Bootstrap estimates	Bias-corr MSBM eff.	**0.615**	**0.432**	**0.238**	**0.365**	**0.254**	**0.377**	**0.369**
	Stn.dev.	0.074	0.051	0.054	0.053	0.048	0.057	0.090
	CI 5% Up	0.488	0.327	0.118	0.258	0.168	0.285	0.193
	CI 5% Lo	0.780	0.531	0.341	0.474	0.356	0.494	0.526
All Banks								
Original SBM score		0.708	0.609	0.619	0.697	0.820	0.825	0.866
Bootstrap estimates	Bias-corr MSBM eff.	**0.666**	**0.452**	**0.521**	**0.586**	**0.837**	**0.815**	**0.851**
	Stn.dev.	0.069	0.066	0.100	0.068	0.072	0.060	0.062
	CI 5% Up	0.536	0.322	0.353	0.472	0.707	0.717	0.755
	CI 5% Lo	0.793	0.570	0.715	0.718	0.983	0.944	0.990

Notes: We use 1000 group-wise heterogeneous bootstrap replications, Gaussian density, and the Silverman (1986) reflection method; and the bandwidth is obtained using the Sheather and Jones (1991) solve-the-equation plug-in-approach. CI 5% Up and CI 5% Lo indicate 5% Confidence Intervals at the Upper and Lower levels respectively and represent a range within which the 95 percentile of bootstrapped efficiency scores lies.

Table 4 Simar-Zelenyuk-adapted Li test for equality of efficiency distributions

Null hypothesis	Test statistics	Bootstrap p-value
$f(\text{Eff}_{\text{Prod}}) = f(\text{Eff}_{\text{Interm}})$	15.681	0.000**
$f(\text{Eff}_{\text{Prod}BHHC}) = f(\text{Eff}_{\text{Interm}BHHC})$	1.6015	0.0396*
$f(\text{Eff}_{\text{Prod}CB}) = f(\text{Eff}_{\text{Interm}CB})$	5.4755	0.000**
$f(\text{Eff}_{\text{Prod}IB}) = f(\text{Eff}_{\text{Interm}IB})$	10.660	0.000**

Notes: (Interm) Intermediation Approach, (Prod) Production Approach. The number of bootstrap iterations is 5000. For these tests, we use the Gaussian density, and the bandwidth h used in the tests is the minimum of the two bandwidths for $\text{EFF}_{\text{Approach1}}$ and $\text{EFF}_{\text{Approach2}}$, which are calculated according to Silverman (1986). Statistical significance: * statistically significant at 5% level; ** statistically significant at 1% level.

Table 5 Results of truncated regression analysis using algorithm 2 with 2 truncations: Intermediation approach

	Est.Coeff. (p-value)	Bounds of the Bootstrap Est. confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
SIZE	-0.647***	-0.908	-0.408	-0.999	-0.352	-0.859	-0.442
SIZE^2	0.017***	0.012	0.022	0.011	0.024	0.013	0.021
LPRIVCONS	2.581**	0.603	4.591	-0.034	5.282	0.888	4.280
LEXPORT	-0.497*	-1.024	0.043	-1.194	0.207	-0.934	-0.045
LRENT	-1.520***	-2.664	-0.347	-3.000	-0.029	-2.465	-0.532
LEXPORT* SIZE	0.025	-0.005	0.055	-0.014	0.065	-0.001	0.050
TIME	-0.007	-0.068	0.053	-0.085	0.077	-0.058	0.043
CB	0.095*	-0.005	0.186	-0.036	0.213	0.012	0.171
IB	0.206***	0.090	0.320	0.058	0.361	0.107	0.300
Constant	-1.983	-11.566	7.145	-15.251	10.065	-10.194	5.680
$\hat{\sigma}_{\varepsilon}$	0.206***	0.176	0.232	0.168	0.243	0.180	0.226

Notes: *,**,*** denote significance at the 10%, 5% and 1% levels respectively according to the bootstrap confidence intervals. We perform 1000 bootstrap iterations to correct for bias and 5000 replications to estimate the bootstrapped coefficients. The α-% lower and upper bounds of confidence intervals represent a range within which the (100-α) percentile of bootstrapped coefficients lies.

Table 6 Results of truncated regression analysis using algorithm 2 with 2 truncations: production approach

	Est.Coeff. (p-value)	Bounds of the Bootstrap Est. confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
SIZE	-0.511***	-0.670	-0.363	-0.722	-0.314	-0.645	-0.383
SIZE^2	0.010***	0.008	0.013	0.007	0.014	0.008	0.013
LPRIVCONS	2.500***	1.014	3.942	0.483	4.427	1.261	3.723
LEXPORT	-0.635***	-0.995	-0.272	-1.099	-0.169	-0.936	-0.326
LRENT	-1.409***	-2.234	-0.568	-2.461	-0.303	-2.108	-0.694
LEXPORT* SIZE	0.033***	0.012	0.053	0.006	0.059	0.016	0.049
TIME	-0.013	-0.056	0.032	-0.071	0.045	-0.050	0.025
CB	0.044	-0.030	0.116	-0.052	0.138	-0.016	0.103
IB	0.120***	0.036	0.204	0.006	0.234	0.049	0.191
Constant	-2.491	-9.292	4.280	-11.493	6.432	-8.229	3.136
$\hat{\sigma}_{\varepsilon}$	0.176***	0.157	0.190	0.151	0.197	0.159	0.188

Notes: *,**,*** denote significance at the 10%, 5% and 1% levels respectively according to the bootstrap confidence intervals. We perform 1000 bootstrap iterations to correct for bias and 5000 replications to estimate the bootstrapped coefficients. The α-% lower and upper bounds of confidence intervals represent a range within which the (100-α) percentile of bootstrapped coefficients lies.

Figure 1 Dynamics of aggregate efficiency of banking groups (intermediation approach)

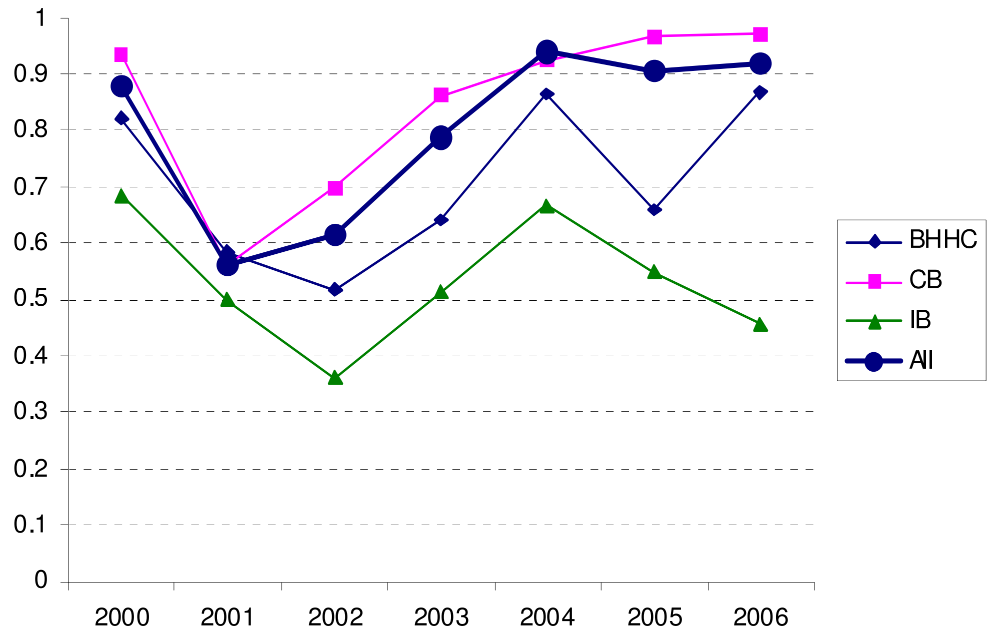


Figure 2 Dynamics of aggregate efficiency of banking groups (production approach)

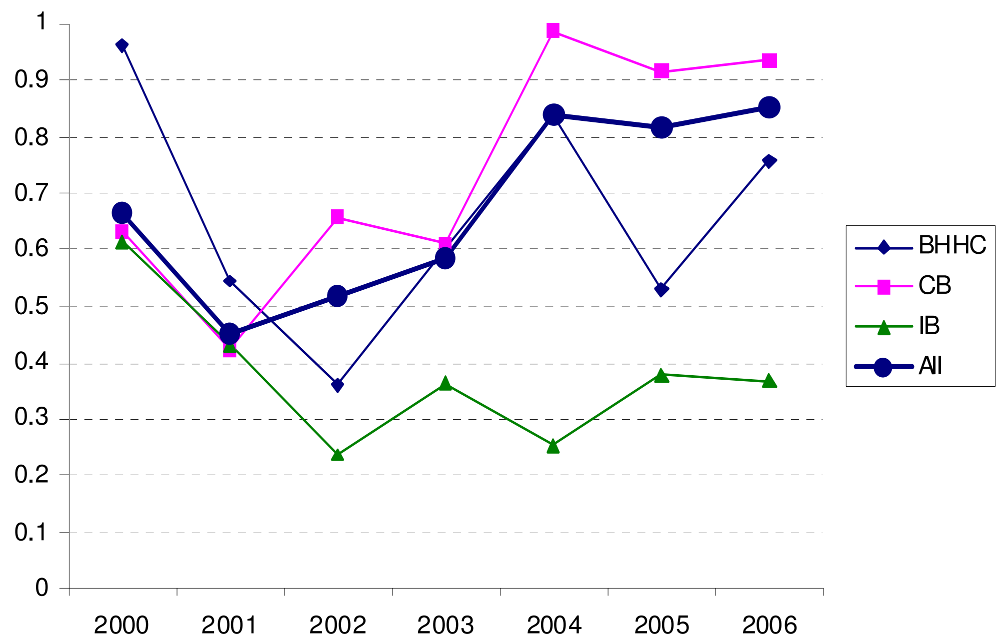
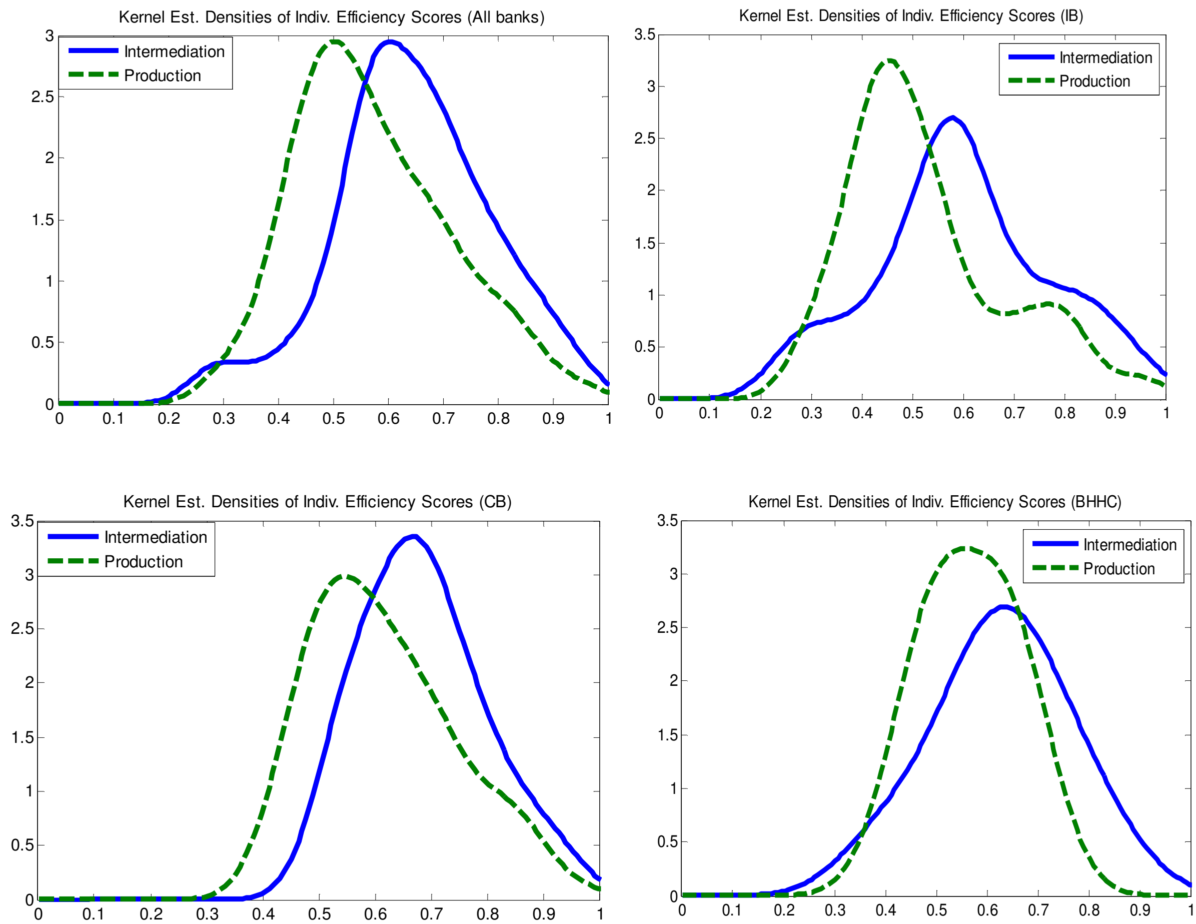
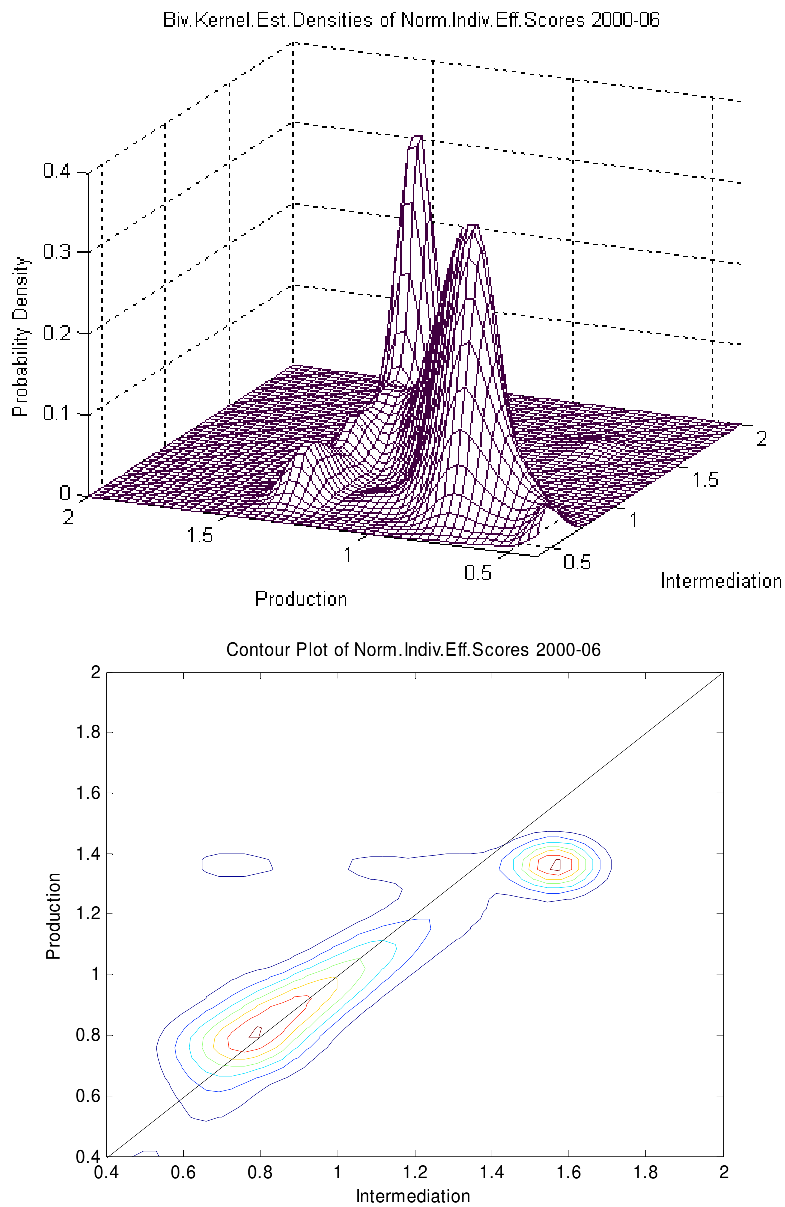


Figure 3 Distribution of MSBM efficiency scores by type of banking firm under the two alternative methodologies.



Note. Vertical axis refers to (estimated) probability density function of the distribution of efficiency scores and horizontal axis refers to efficiency scores (reflected). The univariate Gaussian kernel is used, and the bandwidth is obtained using the Sheather and Jones (1991) solve-the-equation plug-in approach.

Figure 4 Normalised modified slacks-based efficiency $\hat{\rho}_i$'s: transition across alternative output definitions



Note. The bivariate Gaussian kernel is used, and the bandwidths are calculated according to the solve-the-equation plug-in approach for the bivariate Gaussian kernel, based on Wand and Jones (1994).