Environmental Factors Affecting Hong Kong Banking: A Post-Asian Financial Crisis Efficiency Analysis.

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ABSTRACT

Within the banking efficiency analysis literature there is a dearth of studies which have considered how banks have 'survived' the Asian financial crisis of the late 1990s. Considering the profound changes that have occurred in the region's financial systems since then, such an analysis is both timely and warranted. This paper examines the evolution of Hong Kong's banking industry's efficiency and its macroeconomic determinants through the prism of two alternative approaches to banking production based on the intermediation and services-producing goals of bank management over the post-crisis period. Within this research strategy we employ Tone's (2001) Slacks-Based Model (SBM) combining it with recent bootstrapping techniques, namely the non-parametric truncated regression analysis suggested by Simar and Wilson (2007) and Simar and Zelenyuk's (2007) group-wise heterogeneous sub-sampling approach. We find that there was a significant negative effect on Hong Kong bank efficiency in 2001, which we ascribe to the fallout from the terrorist attacks in America in 9/11 and to the completion of deposit rate deregulation that year. However, post 2001 most banks have reported a steady increase in efficiency leading to a better 'intermediation' and 'production' of activities than in the base year of 2000, with the SARS epidemic having surprisingly little effect in 2003. It was also interesting to find that the smaller banks were more efficient than the larger banks, but the latter were also able to enjoy economies of scale. This size factor was linked to the exportability of financial

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services. Other environmental factors found to be significantly impacting on bank efficiency were private consumption and housing rent.

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1. Introduction

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 ensuing years, has been well documented (see, for example, Goldstein (1998) Hunter, Kaufman and Krueger (1999), and 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 and strong capitalisation. Supervisory reform in the wake of the AFC was thus largely unnecessary in Hong Kong, although the process of financial liberalisation continued.

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 (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, and banks which followed the universal-style banking system experienced increasing returns to scale in the off balance sheet markets. In 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 scale efficiency by 5.1% over the period 2000-2001, post AFC. Finally, Drake et al. (2006) showed that x-efficiency scores utilising the non-parametric Slacks-Based Measure decreased by over half for some asset-sized groups of

Hong Kong banks after the 1997 AFC (for example, for banks with assets between US$1000m and US$4999m, mean x-efficiencies decreased from 62% (1997) to 39% (1998)). However, unlike the previous studies, Drake et al. (2006) differed in their analysis by arguing that when considering bank systems that experience a downturn in efficiency due to market conditions, external factors affecting the banking system should be taken into account empirically. This is especially important when a banking system that is to be modelled has numerous different sectors of the banking industry included for comparison. That is, certain environmental/macroeconomic factors could cause x-efficiencies to fall by more for a certain bank group than for a bank group not dependent upon that former bank group's primary market; for example, banks involved in the mortgage market and commercial investment markets. Given these difficulties, when modelling banking systems not only should inter-group bank differences be taken into account but also any changes in environmental/macroeconomic factors that could distort efficiency results, thus possibly biasing financial policy within the country considered.

With respect to the latter problem in modelling bank systems, it has long been recognised that external environmental factors can have a significant impact on relative efficiency scores. That is, Fried et al. (1999) argue that production efficiencies can be decomposed into three factors: management efficiencies or X-efficiencies; environmental factors; and 'the impact of good or bad luck'. The first is endogenous, whereas the latter two factors are exogenous to the bank management; the idea is therefore to disentangle the latter two effects in an analysis of Hong Kong banks. Hence, in this paper, using Monte Carlo methods, we remove the bias associated with the 'good/bad luck' as a random error using a new technique proposed by Simar and Zelenyuk (2007). This also allows us to further determine confidence intervals for the banks using a group-wise heterogeneous sub-sampling approach. Having taken into account the 'random error' problem, as discussed in Fried et al (1999), the paper then considers the effects of macroeconomic and environmental factors on the efficiency scores, rather than directly incorporating them into the DEA program (as done, for example, by Drake et al. (2006) and Lozano-Vivas et al. (2002)).

The paper is organised as follows. In the next Section we discuss the changing nature of Hong Kong banking since the AFC. Following a brief review of the AFC and its impact on Hong Kong's financial system, the impact of the post-AFC liberalisation programme on

Hong Kong's banking industry is assessed. In Section 3 we present our non-parametric methodology and boot-strapping approach to examine Hong Kong Banking, and also the data utilised in both the 'intermediation' and 'production' approach modelling methodologies. Section 4 presents our results and we conclude in Section 5.

2. **Hong Kong, The Asian Financial Crisis and More Recent Developments**

Although there was some prior evidence – the over-valuation of real exchange rates, widening balance of payments deficits, a rapid build-up of external debt and a dramatic expansion in bank lending – of incipient problems in certain countries, the sudden appearance of the AFC, its rapid subsequent spread throughout South East Asia and its persistence came as a nasty surprise to most commentators. Indeed, only a few years earlier the region's economic performance had been hailed as a "miracle" by none other than the World Bank (World Bank, 1993), given the relatively low inflation rates, budget surpluses, low unemployment, strong economic growth and declining official foreign debt (as a share of GDP) figures posted by most countries in the region.

The AFC erupted in Thailand during the Summer of 1997. The trigger was the floating of the Thai baht on 2 July of that year following a failed attempt by the authorities to hold the previous peg against the US dollar in the face of a sustained speculative attack against the currency which began in May of that year. Flushed with success and their ill-gotten gains, the speculators immediately looked for other targets in the region, forcing the Philippines' central bank to abandon its currency peg on 11 July 1997. Similar action followed almost immediately in Malaysia, which stopped supporting its currency on 14 July 1997, with the Indonesians falling into line on 14 August 1997 with the free float of the rupiah. Taiwan (on 17 October 1997) and South Korea (on 6 December 1997) also subsequently abandoned the defence of their currency pegs and switched to a free float.

Whilst the initial phase of the AFC thus manifested itself in currency crises, these were typically followed by banking/financial crises as a result of the impact of the extreme movements in interest and exchange rates on debtors and asset markets. Wide-scale corporate failure, currency trading losses, and plunging asset values soon led to a dramatic deterioration in banks' earnings rendering many insolvent. Depositor panic then ensured the spread of contagion further afield. And finally, the real effects of the financial crisis were crystallised in the form of rising unemployment, falling standards of living and a return to poverty for many. In some countries, this economic malaise duly led to political crises often followed by social disruption. The three worst-affected countries – Indonesia, Thailand and South Korea – which each experienced a mixture of currency, banking and debt crises, were required under the terms of IMF assistance to undertake financial sector restructuring, including the closure of financial institutions.

Like Japan, *Hong Kong* acted as a creditor in the IMF-sponsored aid packages generated for those worst affected by the AFC and, as with the Peoples' Republic of China (PRC), it held its exchange rate throughout the 1997-99 period. The latter policy, however, came at a severe cost to the financial sector and the real economy (Jao, 2001, Part II). The successful defence of the exchange rate peg of HK$ 7.8 to US$ 1, first introduced in the aftermath of the 1982-83 currency crisis engendered by the "crisis of confidence" resulting from stalemate in the Sino-British negotiations over the future of Hong Kong, resulted in dramatic increases in nominal interest rates during the two-year period from mid-October 1997, precipitating heavy stock and property price falls. Whilst the damage to stock prices was ameliorated by concerted governmental action, in the form of substantial direct purchases and the imposition of restrictions on short-selling, the combination of damaging effects on the real economy could not be avoided. Accordingly, real GDP growth slipped into negative territory in the first quarter of 1998, with a contraction of 5.1 per cent being recorded for the whole of 1998 (compared with a pre-AFC, 1990s average of +5.1 per cent). Unemployment, in turn, rose (from a pre-AFC 1990s average of 2.2 per cent) to over 5.0 per cent in 1998, standing at 6.1 per cent by the end of 1999. And, as a further sign of economic depression, positive inflation rates of around 7.0 per cent in the early 1990s gave way to deflation in November 1998 (it was to last for five years) of – 0.7 per cent (as measured by the Composite Consumer Price Index). By the end of 1999 deflation had accelerated to – 4.0 per cent. Success in beating the speculators had thus come at the cost of a severe recession which lasted for five quarters, ending end-March 1999. By way of contrast, the economy grew by 6.9 per cent in 2006, government finances were back in the black and unemployment was down to 4.8 per cent.

Whilst the indirect damage done to the real economy by the AFC was thus similar to that experienced in other South East Asian countries, a banking crisis was, however, avoided. Indeed, no bank failed during the AFC and only one local bank actually slipped into the red. This was in stark contrast to the experience of 1983-86 when a major banking crisis did occur because of a collapse in asset prices (largely due to the uncertainty surrounding Hong Kong's transition from a British Crown Colony to a Special Administration Region (SAR) of the PRC, mismanagement (e.g. over-exposure to the property sector) and fraud). This is not to deny, however, that the banks were damaged by the AFC; they were. For example, most experienced steady deterioration in asset quality from the fourth quarter of 1997, a situation which didn't stabilise until the fourth quarter of 1999. [The ratio of "problem" to total loans for all authorised institutions quadrupled from 1.1. per cent to 4.1 per cent during 1998 and, for locally-incorporated banks, rose from 1.8 per cent to 5.1 per cent during the same period.] Moreover, most also experienced a sharp drop in profitability, with both average pre-tax and post-tax operating profits for locally-incorporated banks falling by around 34 per cent during 1998. Whilst sound regulation introduced in the aftermath of the 1983-86 crisis and strong capitalisation thus served to limit the damage wrought by the AFC on bank balance sheets, the subsequent credit contraction served only to fuel the recession.

Given the remarkable degree of resilience to the AFC shown by Hong Kong's banking sector, it is not surprising that clarion calls for *supervisory reform* were notable for their absence. This would suggest that the reforms implemented in 1986 embracing, *inter alia* (*see* Hall, 1985, for further details), a tightening up of licensing procedures (e.g. involving tougher vetting of all prospective owners, directors and managers), the imposition of stricter limits on loan exposures to group companies and directors, and the introduction of a 5 per cent minimum capital adequacy ratio (which could be raised to 8 per cent for banks and 10 per cent for deposit-taking companies) – replaced in 1990 with a Basel I compliant risk-based minimum ratio of 8 per cent – had done their job in restoring stability to the sector.

Financial liberalisation, however, continued apace – see Table 1. 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 have been 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 timeframe of this paper’s analysis. And, as noted in Table 1, the banks have been able to engage in renminbi- dominated *retail* banking operations since January 2004.

INSERT TABLE 1

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; whilst 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 has 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.

3. Modelling Theory and Data

3.1. Estimation of efficiency

Data Envelopment Analysis (DEA) originated from Farrell's (1957) seminal work and was later elaborated on by Charnes et al. (1978), Banker et al. (1984) and Fare et al. (1985). The objective of DEA is to construct a relative efficiency frontier through the envelopment of the Decision Making Units (DMUs) where the 'best practice' DMUs form the frontier. In this study, we utilize a DEA model which takes into account input and output slacks, the so-called Slacks-Based Model (SBM), which was introduced by Tone (2001) and ensures that, in non-parametric modelling, the slacks are taken into account in the efficiency scores. Or, as Fried et al. (1999) argued, in the 'standard' DEA models based on the Banker et al. (1984) specification "the solution to the DEA problem yields the Farrell radial measure of technical efficiency plus additional non-radial input savings (slacks) and output expansions (surpluses). In typical DEA studies, slacks and surpluses are neglected at worst and relegated to the background at best" (page 250). Indeed, in the analysis of non-public sector Decision Making Units (DMUs), for which DEA was originally proposed by Farrell, the idea of slacks was not a problem unlike it is when DEA is employed to measure cost efficiencies in a 'competitive market' setting. That is, in a 'competitive market' setting output and input slacks are essentially associated with the violation of 'neo classical' assumptions. For example, in an input-oriented approach, the input slacks would be associated with the assumption of strong or free disposability of inputs which permits zero marginal productivity of inputs and hence extensions of the relevant isoquants to form horizontal or vertical facets. In such cases, units which are deemed to be radial or Farrell efficient (in the sense that no further proportional reductions in inputs is possible without sacrificing output), may nevertheless be able to implement further additional reductions in some inputs. Such additional potential input reductions are typically referred to as non-radial input slacks, in contrast to the radial slacks associated with DEA or Farrell inefficiency i.e., radial deviations from the efficient frontier.

In addition, most DEA models do not deal directly with or allow 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).[1] Further, as argued above, there are also limitations in the Banker et al. (1984) program due to slacks, which also need to be taken into account in the efficiency estimation of profit-orientated firms. Hence, we believe that it is important that both these potential problems are overcome. In this paper, this is done by utilising a Modified Slacks-Based Measure (MSBM) model suggested by Sharp et al. (2006), who combined the ideas of Tone (2001) and Silva Portela et al. (2004). An exposition of the 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:

[1] Indeed, it is not uncommon for many types of industry 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 other DEA models this could not be modelled as a ‘bad’ output as it may only involve a small section of the sample banks. In relation to negative inputs, in banking this is common, and in this study we examine the use of Loan Loss Provisions as an input instead of a ‘bad’ output.

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

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. This means that, given our aim of analyzing the impact of environmental factors on the SBM efficiency scores, the assumptions outlined in Simar and Wilson (2007) hold, hence allowing for the provision of consistent estimators of the parameters in a fully specified, semi-parametric Data Generating Process (DGP).

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:

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

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, $\rho_i(x, y | P(x))$. To overcome this problem as well as to examine the groups of banks by type and time period, we utilize the group-wise heterogeneous sub-sampling approach suggested by Simar and Zelenyuk (2007)[2]. First, we compute the efficiency score $\hat{\rho}_i(x, y|P(x))$ for each bank in the sample using program (2). Then, we aggregate the estimates of individual efficiencies into the L-subgroup estimated aggregates by type of bank and also by time period. In our analysis, for aggregation we use the price independent aggregation method suggested by Färe and Zelenyuk (2003) shown below:

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

and

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

where, $\bar{\hat{\rho}}^{l}$ is the aggregate 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 efficiency of the industry, and S^l is a price independent weight of sub-group *l*.

Next, in Step 3, we obtain the bootstrap sequence $\Xi^*_{s\,l,b} = \{(x_b^{*i}, y_b^{*i}) : i = 1, \ldots, s_l\}$ by sub-sampling and replacing data independently for each sub-group *l* of the original sample $\Xi^*_{n\,l} = \{(x^i, y^i) : i = 1, \ldots, n_l\}$ for each bootstrap iteration *b*=1,…,*B*, where $s_l \equiv (n_l)^k$, and where *k*<1, *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. Hence, in our analysis, we use *k*=0.65 for each sub-group.

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

[2] Matlab codes for the group-wise heterogeneous sub-sampling procedure for the traditional DEA models coded by Simar and Zelenyuk (2007) were obtained from the Journal of Applied Econometrics web-site.

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

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

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

$\sum \lambda = 1$,

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

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

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

and

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

Repeating the Steps 3 – 5 B times provides us with B bootstrap-estimates of estimated aggregate efficiencies for each sub-group by type of bank and time period. 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

In the second stage, the inverse of the efficiency measures ($\hat{\delta}_i = 1/\hat{\rho}_i$) estimated using program (2) are regressed on environmental factors[3]. That is, z_i is the vector of environmental variables of the *i*-th DMU and β is a vector of parameters to be estimated associated with each environmental variable, as shown in equation (5)

$$\hat{\delta}_i = z_i\beta + \varepsilon_i \geq 1 \tag{5}$$

However, the dependent variable $\hat{\delta}_i$ in (5) is an estimate of the unobserved true efficiency δ_i, i.e., $\delta_i = \hat{\delta}_i = \left(\hat{\rho}\left(x_i, y_i \middle| \hat{T}\right)\right)^{-1}$. Thus, all $\hat{\delta}_i$'s are serially correlated in a complicated, unknown way; moreover, ε_i is also correlated with z_i. To overcome this problem we utilize the single bootstrap procedure (Algorithm 1) proposed by Simar and Wilson (2007) where, in the bootstrap analysis, the *true* efficiency scores are regressed on the environmental factors, as in the following equation:

$$\delta_i = \psi(z_i, \beta) + \varepsilon_i \geq 1 \tag{6}$$

In equation (6), δ_i is the inverse of the efficiency measure ρ_i of the *i*-th DMU ($\hat{\rho}_i$), calculated using program (2), and is considered as an estimate for (ρ_i); 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 $1-\psi(z_i,\beta)$.

In the bootstrap procedure, the efficiency measures $\hat{\delta}_i$ 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 influencing factors which allows us to estimate their

[3] In the second stage, we use the inverse of the efficiency scores as this will give us efficiency measures which are bounded only at 1 and it is the only boundary to take into account in the truncated regression and, therefore, in the subsequent bootstrapping procedure, unlike the original input-oriented measures where, in the truncated regression, we need to consider 2 boundaries (at 0 and 1), which considerably complicates the likelihood function.

probabilities and confidence intervals. The following steps are performed in the second bootstrap procedure of Algorithm 1:

1. Estimate the truncated regression of $\hat{\delta}_i$ on z_i in (6) for m=n observations using the method of maximum likelihood estimation to obtain estimates for $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$.

2. Compute a set of L bootstrap estimates (we set L to equal 1000 replications) for β and σ_ε, $A = \{(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)_b\}_{b=1}^{L}$, in the following way: for each i =1,..., m, draw ε_i from the normal distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with the left truncation of the distribution at $(1 - z_i\hat{\beta})$ and estimate $\delta_i^* = z_i\hat{\beta} + \varepsilon_i$; then estimate the truncated regression of δ_i^* on z_i using maximum likelihood methods to obtain the parameter estimates $(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)$. . Once the set of L bootstrap parameter estimates for β and σ_ε have been obtained, the percentile bootstrap confidence intervals can then be constructed. In addition, it becomes possible to test hypotheses, for example, to determine whether the p-value for a particular estimate where $\hat{\beta} < 0$ is the relative frequency of the non-negative $\hat{\beta}^*$ bootstrap estimates.

This statistical procedure allows us to test the impact of environmental variables on banking inefficiency. Hence, in our regression stage of the modelling, we begin with a large set of macroeconomic factors which has the potential to influence the performance of banks, including individual components of GDP, such as private consumption expenditure, government expenditure, gross fixed capital formation, and net export of goods and services. In addition, we consider the inclusion of variables such as unemployment, expenditure on housing, the current account balance and the discount rate. 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. We utilise Matlab software in all estimations, except in step 1 of Algorithm 1 where Stata 9 is utilised to obtain initial estimates of $\hat{\beta}$ and $\hat{\sigma}$ by use of a general-to-specific methodology ensuring a consistent step-down procedure to obtain the model specification with the best fit.

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 (see 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 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 income' is therefore intended to proxy the 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 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 expense' variable was utilised. The summary statistics are given in Table 2.[4]

INSERT TABLE 2

With respect to the last-mentioned input variable (i.e. provisions), it has long been argued 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). Altunbas et al. (2000) and Drake and Hall (2003) also find that the failure to adequately account for risk can have a

[4] The input and output data were obtained from the Bank-scope resource package by Bureau Van Dijik (BVD). The panel data sample consists of 319 operations over the period 2000-2006. The number of banks in the sample each year is: 2000, 56; 2001, 52; 2002, 49; 2003, 46; 2004, 45; 2005, 40; and 2006, 31.

significant impact on relative efficiency scores. 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. That is, "following the general consensus among risk agent analysts and practitioners, economic capital should be tailored to cope with unexpected losses, and loan loss reserves should instead buffer the expected component of the loss distribution. Consistent with this interpretation, loan loss provisions required to build up loan loss reserves should be considered and treated as a cost; a cost that will be faced with certainty over time but that is uncertain as to when it will materialise" (page 181). Hence, we also incorporate provisions as an input/cost in the DEA relative efficiency analysis of Hong Kong banks.

Finally, in the case of the Production approach, we have five outputs and three inputs. The outputs are: 'total customer loans' (customer loans + other lending); 'net commission, fee and trading income'; 'total deposits'; 'other earning assets'; and 'other operating income'. Ideally, a more appropriate measure of deposits to be used in the Production approach would be the number of deposit accounts. However, the required data for this specification was not available across the bank sample. The three inputs are: 'total other non-interest expenses' (personnel expenses + other administrative expenses); 'other operating expenses'; and 'total provisions' (loan loss provisions and other provisions). In the next Section we present our results.

4. Results

4.1. First stage: SBM efficiency estimates

Tables 3 and 4 provide a summary of the aggregate input–oriented, modified, slacks-based, bias-corrected efficiency scores obtained under the Intermediation and Production approaches to describing the banking production process. Although both approaches report similar trends in efficiency evolution, see Figures 1 and 2, the Intermediation approach generally produces higher results than the Production methodology. This is in line with the findings of Drake et al. (2008) who, in their case study of the Japanese banking industry, found Intermediation scores of 0.714 and 0.334 and Production scores of 0.334 and 0.286 in 2002 and 2001 respectively.

INSERT FIGURES 1 AND 2

Interestingly, in 2000, Hong Kong banks (taken as a group) exhibit high levels of Intermediation and Production efficiency (88% and 67% respectively). However, in 2001, according to both approaches, the banks experienced a sharp decline in their efficiency levels (to 56% and 45% respectively). This may be attributed to two possible causes: firstly, the removal of interest rate controls in 2001 (see Table 1 and the discussion in Section 2), and secondly, the possible impact of the fallout from the 9/11 terrorist attacks in the US on the banking industry of Hong Kong. Although the overall efficiency level remained moderately low in 2002 (at 62% and 52% respectively) commercial banks did, however, begin to show an improvement in their efficiencies. This improvement was particularly marked under the Intermediation approach indicating a potentially enhanced ability among Hong Kong Commercial Banks to efficiently shuttle funds from their deposit bases into credit channels. Thus, while the banks improved on their ability to build a strong deposit base, as is evident from the improvement in the efficiency scores under the Production approach, their ability to then convert this deposit base into revenue-generating credit assets was stronger, as is evidenced by the greater improvement in efficiency scores under the Intermediation approach. After 2002, most banks recorded a steady improvement in efficiency, despite the SARS epidemic of 2003 (this is consistent with the industry's profits performance for 2003 reported in HKMA (2004)), although the investment bank grouping's efficiency dipped quite markedly in 2006.

Further, it is illuminating to note that, with respect to Hong Kong banks, Kwan (2002) found that the mean level of X-inefficiency for all banks over the sample was around 0.32, and that inefficiency levels generally declined over the sample period (from 0.41 in 1992:Q1 to 0.29 in 1999:Q4). Kwan (2002) attributes the latter to the impact of technological innovation. However, in Drake et al. (2006), who utilised the SBM approach, the Hong Kong (overall) banking sectors' mean efficiency scores declined from 1995 (0.604) to 1999 (0.458), increased in 2000 (0.543) and then subsequently declined in 2001 (0.488). The latter pattern matches that established in our present study for the overlapping years (i.e. 2000/2001).[5]

INSERT TABLES 3 AND 4

Another, interesting finding is that commercial banks were also found to be more efficient than other types of banking firms under both approaches over the considered time period. Bank Holdings and Holding Companies (BHHC) are somewhat less efficient than commercial banks. Regarding the performance of Investment Banks, the results suggest that this group of banking firms is the most inefficient with aggregate efficiency varying between a low of 36% in 2002 and a high of 68% in 2000 under the Intermediation approach, and 24% in 2002 and 62% in 2000, respectively, under the Production approach.

Table 5 reports the results of the tests for equality of efficiency distributions estimated under the alternative approaches 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 efficiency scores estimated by the Production and Intermediation approaches are from different populations for all three groups of banks and the overall banking industry studied. This suggests that the SBM efficiency scores, and the efficiency scores obtained utilising the traditional DEA technique (Tortosa-Ausina, 2002) are alike in that they are sensitive to the choice of outputs adopted.

INSERT TABLE 5

INSERT FIGURE 3

The visualisation of the estimated density for all groups of banks using univariate kernels further supports this finding (Figure 3). The distribution of Production SBM efficiency scores (the dashed line) in all four diagrams is less steep than that of the Intermediation SBM efficiency scores (the solid line) in all but one case thereby indicating that more banks are concentrated around the mode of the Production approach. The pursuit

[5] Note that, although in Drake et al. (2006) the results were based on Tone's (2001) original SBM specification and not on the Sharp et al. (2006) program used in this study, a general picture concerning trends can still be interpreted.

of service-oriented objectives rather than financial intermediation activities may be the driving force behind this finding. However, the mode of the Intermediation efficiency scores' distribution is more to the left than of the Production efficiencies, implying that banks are more efficient in their role as financial intermediaries.

INSERT FIGURE 4

The bivariate kernel analysis 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 realtive 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 mean efficiency is somewhat concentrated along the positive diagonal line.

4.2. Analysis of the determinants of bank efficiency

Tables 6 and 7 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 and gave the model with the best fit: 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 the interaction variable of the LEXPORT and SIZE (LEXPORT_SIZE) to capture the effect of the exportability of financial services of Hong Kong banks depending on the size of banking firm. According to the Information Services Department of the Hong Kong Special Administrative Region Government, in 2006, the share of exports of the financial services industry was 12% of the total value of the export of services. Therefore, it is particularly appealing to examine the influence of this variable on the efficiency of Hong Kong banking firms.

INSERT TABLES 6 AND 7

It is interesting to note that, although the significance of the variables is different for the inverse of the SBM efficiency scores under both Production and Intermediation approaches, 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 positive coefficient for SIZE and a negative one for SIZE^2. This implies that in the Hong Kong banking industry, smaller banks are more efficient than their larger counterparts. However, larger banks are more likely to enjoy gains from scale economies. This is thus empirical evidence for the U-shaped scale economies implied by the theoretical literature. Moreover, similar signs of coefficients were found by Simar and Wilson (2007) in their empirical investigation of US commercial banks.

With respect to the macroeconomic determinants of banking (in)efficiency, the results suggest that the level of private consumption has a negative impact on banking inefficiency as expected. This implies that an increase in private consumption stimulates banking. Both LRENT and LEXPORT are found to be positively correlated with inefficiency and significant at the 1% level in the Production approach model and at the 10% level under the Intermediation framework. Interestingly, the coefficient for the interaction variable LEXPORT_SIZE is negative and significant in the Intermediation approach at the 10% level and with respect to the Production methodology, at the 1% level. This suggests that larger banks show a greater exportability of financial services. It can also be interpreted as larger banks having more opportunities to engage in exporting activities, thereby enhancing their efficiency.

Intriguingly, the results also show that the coefficient for the commercial banks' dummy is negative and significant in both models, whereas the coefficient of IB is negative and significant only in the Intermediation model.[6] This implies that commercial banks are

[6] The dummy for bank holdings and holding companies was dropped from the model due to collinearity problems.

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

5. Conclusions

The analysis presented in this paper shows that, under both the Intermediation and Production approaches, Hong Kong banks suffered a substantial decline in efficiency in the year 2001. This was probably due to deposit rate deregulation and the adverse consequences of the 9/11 terrorist attacks in the US. Utilising a relatively-new technique (Sharp et al. (2006)) to purge the Slacks-Based Methodology scores of any random error, we also find that the efficiency of banks was most affected in 2001. Adoption of the latter model is necessary because exogenous events can lead to 'bad luck' and hence interfere with the managerial operations of banks. Indeed, in the analysis of subsequent years, it was found that the same exogenous events which happened economy-wide could have a negative or positive effect on the efficiency results dependent on the bank sector considered. For example, under the Intermediation approach, commercial banks experienced negative bias and investment banks positive bias during 2004-2006 (see Table 3). Finally, with respect to the bias-corrected efficiency scores, commercial banks were consistently closer to the best practice frontier than the other sectors of the industry (see Figures 1 and 2), starting at 0.937 (2000) and ending at 0.972 (2006) under the Intermediation approach.

Having obtained the bias-corrected efficiency scores, we proceeded to analyse the effects of macroeconomic factors on bank efficiency. Utilising a 'general-to-specific' step-down procedure we found that all but the time trend (the other variables being private consumption, net exports and rent (all in logarithmic form)), had a significant effect on bank efficiency scores over the sample period, under both the Intermediation and Production approaches. It was interesting to find that the smaller banks were more efficient than the larger banks, but the latter were also able to enjoy economies of scale. This size factor was linked to the exportability of financial services, whereby the larger banks enjoyed a positive effect on bank efficiency given their ability to export services.

Finally, it is worth re-iterating that we found that the commercial banks enjoyed relative efficiency improvements over the sample period due to their ability to combine both intermediary and service-producing business activities. A possible policy conclusion from these results is that the financial system within Hong Kong could be further deregulated for non-commercial banks, hence allowing a possible increase in stability of the financial markets if a future Asian Financial Crisis, or any other 'bad luck' scenario in the World economy, happened. Thus, deregulation could allow for further diversification for, as we have seen, the banks which are able to diversify their assets most, appear to be the most insulated against external shocks with respect to their efficiency.

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Table 1

Liberalisation and Reform of the Hong Kong Banking Industry Post 1999: A Chronology of Major Events

Event	**Date**
Interest rate cap on time deposits of less than 7 days was lifted, along with the prohibition on the provision of benefits to depositors (other than for Hong Kong dollar savings and current accounts)	3 July 2000
Deposit rate deregulation (of savings and current accounts) completed	3 July 2001
The "three-building" restriction imposed on foreign banks was removed	November 2001
Relaxation of market entry criteria for foreign banks	May 2002
Government announced that, with effect from 1 January 2004, banks licensed in the territory will be allowed to accept deposits, arrange remittances, make foreign exchange transactions and issue credit and debt cards in *renminbi*. [Renminbi-denominated corporate banking operations remain off limits, however, for the time being.] This announcement followed the People's Bank of China's decision to provide clearing arrangements for Hong Kong's licensed banks for personal renminbi business transacted in Hong Kong	November 2003
Deposit insurance introduced.	2006

Source: Jao, 2003.

Table 2.
Hong Kong Banks: Summary Statistics

	mean	min	max	st. dev
Total Operating Expenses	1541876	1800	45167256	4659830
Fixed Assets	2769599	100	49216374	7331098
Total Deposits and Funding	122029945	1761	3249308598	358086443
Total Loans	61695841	338	1229425206	162984058
Other Earning Assets	67505775	0	1993631331	205726006
Loan loss provisions	318161	-3104460	8593000	1092042
Net com Income + Other operating Income	1174795	-1865023	38054181	4019743

All figures in HK$ millions and deflated using the Hong Kong GDP deflator.

Table 3.
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 SBM 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 SBM 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 SBM 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 SBM 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.

Table 4.
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 SBM 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 SBM 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 SBM 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 SBM 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.

Table 5.
Simar-Zelenyuk-Adapted Li Test for Equality of Efficiency Distributions

Null Hypothesis	Test Statistics	Bootstrap p-value
$f(\mathrm{Eff}_{\mathrm{Prod}}) = f(\mathrm{Eff}_{\mathrm{Interm}})$	15.681	0.000**
$f(\mathrm{Eff}_{\mathrm{Prod}BHHC}) = f(\mathrm{Eff}_{\mathrm{Interm}BHHC})$	1.6015	0.0396*
$f(\mathrm{Eff}_{\mathrm{Prod}CB}) = f(\mathrm{Eff}_{\mathrm{Interm}CB})$	5.4755	0.000**
$f(\mathrm{Eff}_{\mathrm{Prod}IBSH}) = f(\mathrm{Eff}_{\mathrm{Interm}IBSH})$	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 h is the minimum of the two bandwidths for EFFM1 and EFFM2, which are calculated according to Silverman (1986). Statistical significance: * statistically significant at 5% level; ** statistically significant at 1% level.

Table 6.
Results of Truncated Regression Analysis Using Algorithm 1
(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	1.6990*** (0.000)	0.812	2.717	0.656	3.210	0.922	2.482
SIZE^2	-0.0403*** (0.000)	-0.064	-0.022	-0.077	-0.018	-0.059	-0.024
LPRIVCONS	-4.4699** (0.012)	-8.900	-0.396	-10.267	0.669	-8.036	-0.966
LEXPORT	1.3270* (0.073)	-0.300	3.102	-1.093	3.681	-0.128	2.822
LRENT	3.0003* (0.059)	-0.544	6.610	-1.780	8.141	-0.127	5.995
LEXPORT* SIZE	-0.0923* (0.052)	-0.205	0.017	-0.268	0.058	-0.182	0.001
TIME	0.0697 (0.220)	-0.115	0.255	-0.166	0.309	-0.082	0.220
CB	-0.4404** (0.014)	-0.781	-0.058	-0.896	0.107	-0.724	-0.128
IB	-0.4528** (0.021)	-0.855	-0.009	-0.935	0.151	-0.800	-0.083
$\hat{\sigma}_{\varepsilon}$	0.6234*** (0.000)	0.509	0.722	0.489	0.766	0.520	0.697

Notes: The regressed variable is the inverse of the MSBM input efficiency score estimates. *,**,*** denote significance at the 10%, 5% and 1% levels respectively according to the frequency of the bootstrapped parameters with the same sign.

Table 7.
Results of Truncated Regression Analysis Using Algorithm 1

(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	1.3523***						
	(0.000)	0.947	1.787	0.822	1.916	1.004	1.719
SIZE^2	-0.0226***						
	(0.000)	-0.031	-0.014	-0.036	-0.011	-0.030	-0.016
LPRIVCONS	-3.8893***						
	(0.000)	-5.954	-1.924	-6.569	-1.354	-5.642	-2.252
LEXPORT	1.7483***						
	(0.000)	0.893	2.676	0.687	2.921	1.059	2.523
LRENT	2.2071***						
	(0.005)	0.470	3.912	-0.038	4.455	0.782	3.627
LEXPORT*	-0.1047***						
SIZE	(0.000)	-0.159	-0.054	-0.175	-0.044	-0.151	-0.061
TIME	0.0334						
	(0.231)	-0.048	0.125	-0.073	0.158	-0.035	0.113
CB	-0.1391*						
	(0.093)	-0.338	0.079	-0.379	0.155	-0.290	0.044
IB	0.0146						
	(0.437)	-0.215	0.251	-0.287	0.318	-0.184	0.206
$\hat{\sigma}_{\varepsilon}$	0.4427***						
	(0.000)	0.389	0.482	0.378	0.495	0.395	0.473

Notes: The regressed variable is the inverse of the MSBM input efficiency score estimates. *,**,*** denote significance at the 10%, 5% and 1% levels respectively according to the frequency of the bootstrapped parameters with the same sign.

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Figure 1
Dynamics of Aggregate Efficiency of Banking Groups (Intermediation Approach)

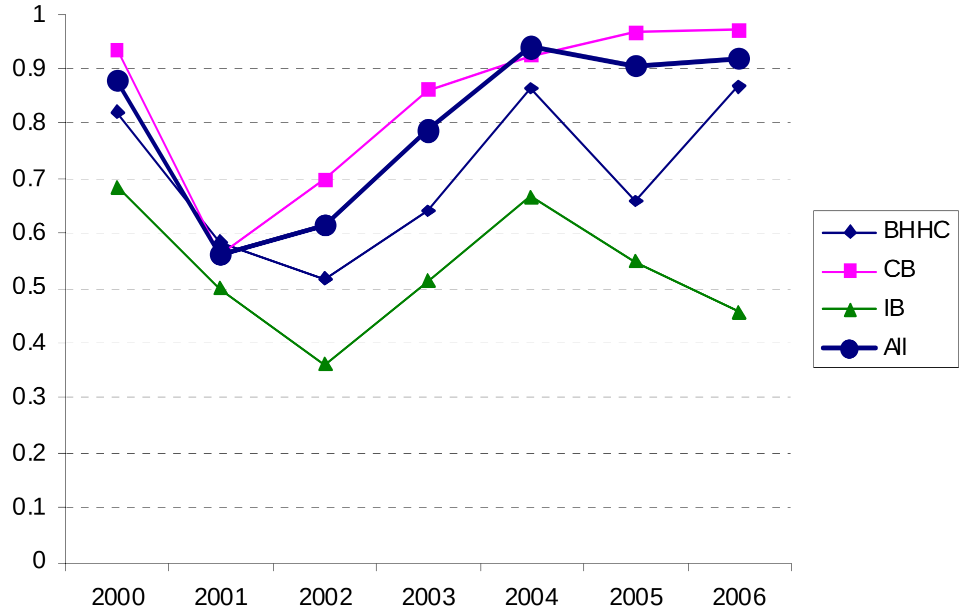


Figure 2
Dynamics of Aggregate Efficiency of Banking Groups (Production Approach)

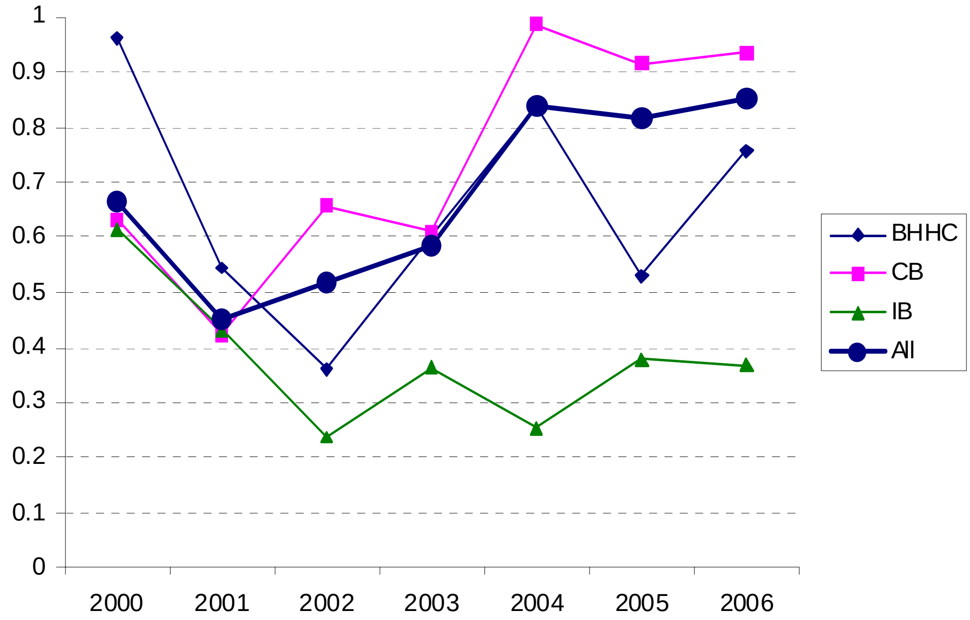
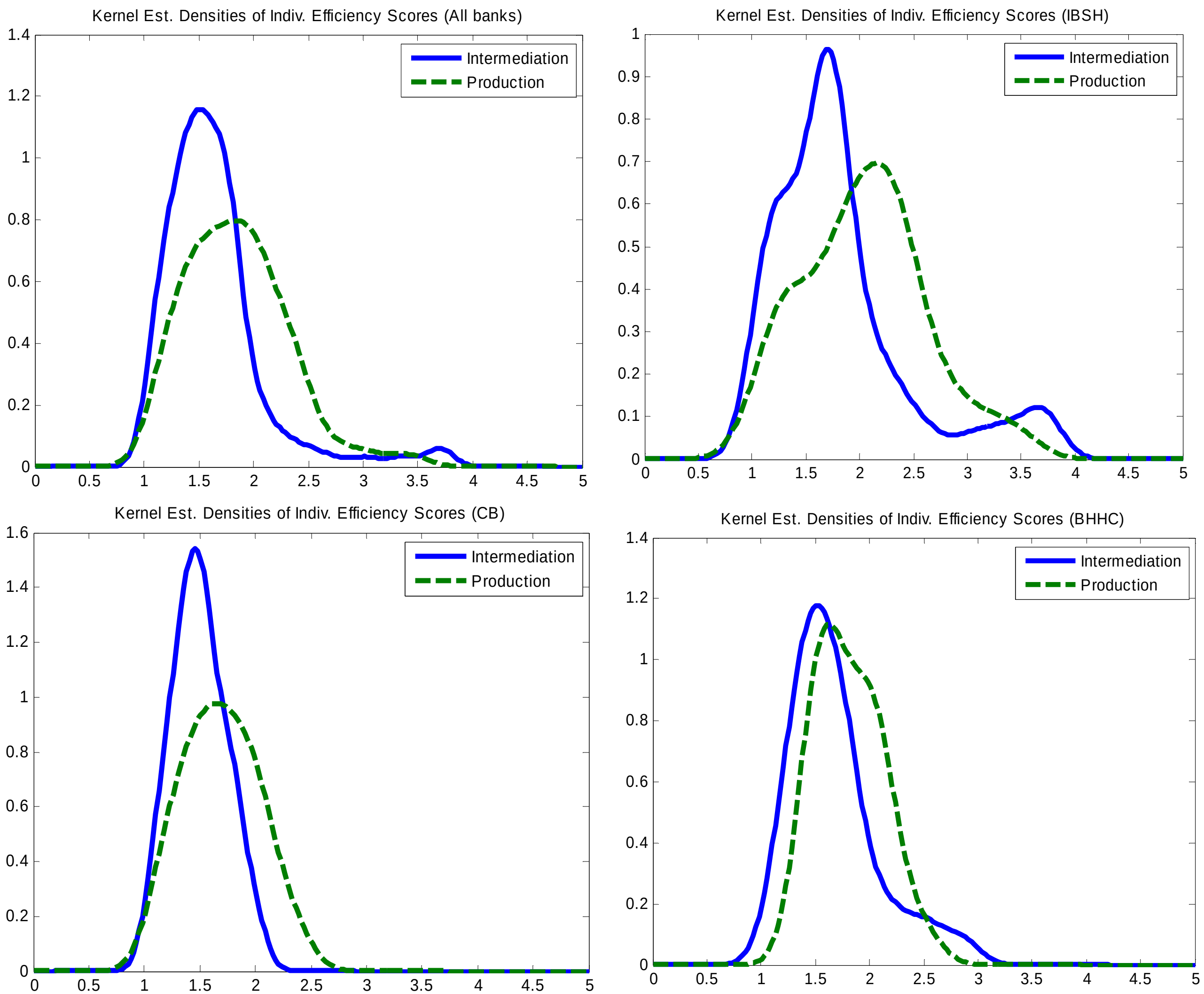


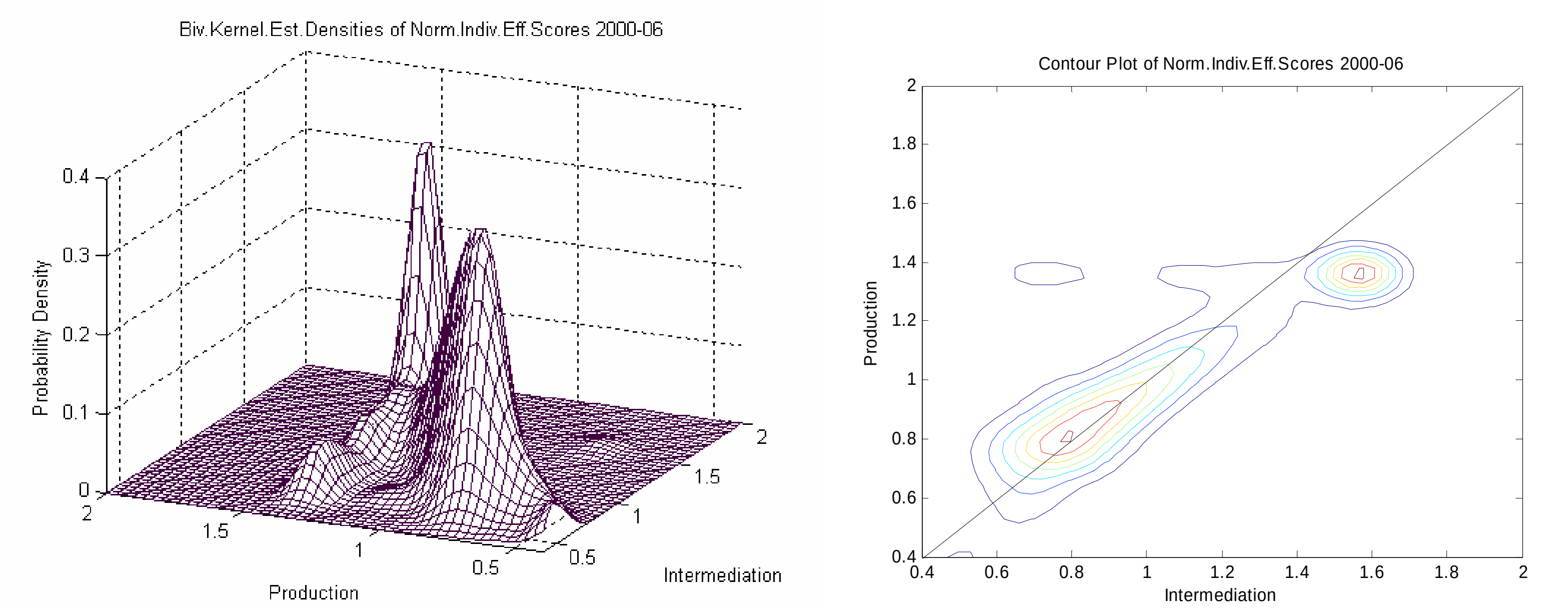
Figure 3.

Distribution of SBM Efficiency Scores by Type of Banking Firm Under the Two Alternative Approaches.



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 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).