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BANK PRODUCTIVITY IN CHINA 1997-2007: AN EXERCISE IN MEASUREMENT

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Bank Productivity in China 1997-2007: An Exercise in Measurement

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Abstract

This study examines the productivity growth of the nationwide banks of China and a sample of city commercial, banks for the eleven years to 2007. Estimates of total factor productivity growth are constructed with appropriate confidence intervals, using a bootstrap method for the Malmquist index. The study adjusts for the quality of the output by accounting for the non-performing loans on the balance sheets of the banks and tests for the robustness of the results by examining alternative sets of outputs. The productivity growth of the state-owned commercial banks (SOCBs) is compared with the joint-stock banks (JSCBs) and city commercial banks (CCBs). The weak average growth of TFP of the SOCBs disguises strong technical innovation. As a result, the inefficient banks have a greater efficiency gap to make up. This picture is similar but to a lesser extent for the JSCBs. In contrast the CCBs show strong TFP growth driven by efficiency gains and less so by technical innovation.

Keywords: Bank Efficiency, Productivity, Malmquist Index, Bootstrap

JEL Classification: D24, G21

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1. Introduction

Banking sector reform in China has been a gradual and on-going process since 1978. A further stage of reform was announced in 1993 with the objective of creating an efficient commercial banking sector. Following the conditions of the WTO, the Chinese banking market has been open to foreign competition since the end of 2006. Chinese banks have been encouraged to allow foreign banks and investors to take minority shareholding positions. The listing of four of the big five banks on the international exchange during 2006-7 is supposed to usher in, not only foreign capital but also foreign managerial expertise to improve bank management, performance and productivity. Given the acceptance of larger stakes by foreign banks in the smaller commercial banks (to a specified limit of 25% share); it is no surprise that Chinese bank productivity has become a popular topic of research in recent years.

There have been a number of studies of Chinese banking productivity that have been published in Chinese scholarly journals,[1] but to date only a few studies are available to non-Chinese readers.[2] The gradualist reforms of the banking sector and the potential of foreign competition would be expected to improve efficiency and productivity in the banking sector. Evidence of improved performance has begun to emerge.

This paper is an exercise in measurement. It attempts to measure the productivity of the commercial banks in China for the period 1997-2007. Two issues are addressed in this paper, namely measurement and modeling strategy. First, the measurement of output (and input) of banks is not a simple matter. We therefore consider several alternative measures of output as a means of obtaining robust results. Second, we use the Malmquist index of total factor productivity (TFP) as a means of translating inputs and outputs into a measure of productivity growth (TFP). The Malmquist index has the advantage of being able to decompose productivity growth into technological change which captures any expansion in the production frontier, from efficiency improvement, which captures the movement towards the efficient frontier.

One of the problems associated with this approach is that it is constructed within the framework of Data Envelope Analysis (DEA), which is a non-parametric linear programming method that applies observed input and output data to create a 'best practice' frontier. The main drawback of the DEA approach is that it assumes the inputs and outputs are measured without error and therefore do not permit statistical evaluation. This paper aims to provide an inferential capability to the point-estimates of productivity through the use of non-parametric bootstrapping methods.

1 See the appendix for a full list.

2 A recent exception is a study using non-parametric methods by Matthews *et al*. (2009) and parametric methods by Kumbhaker and Wang (2007).

This paper poses the four following questions. What has been the total factor productivity (TFP) growth of Chinese banks over the period 1998 – 2007? What have been the driving factors in TFP growth? Has there been a significant improvement in TFP growth in the second half of the period consistent with an increase in the pace of reform prior to the opening up of the banking market according to the WTO treaty. Finally, what is the effect on the measurement of TFP if non-performing loans are treated as 'bad' outputs?

The paper is organized on the following lines. The next section outlines the background to the Chinese banking system. Section 3 discusses the methodology and literature relating to the Malmquist method of estimating bank productivity. Section 4 presents the banking data. Section 5 discusses the results and section 6 concludes.

2. Chinese Banking

In 2007, the Chinese banking system consisted of 8,877 institutions, including 3 policy banks, 5 large state-owned commercial banks (SOCB), 12 joint-stock commercial banks (JSB), 124 city commercial banks (CCB), 29 locally incorporated foreign bank subsidiaries and the rest made up of urban and rural credit cooperatives and other financial institutions.[3]

Like many economies that have undeveloped financial and capital markets, the banking sector in China plays a pivotal role in financial intermediation. Table 1 shows that the ratio of total bank assets to GDP has increased from 125%, in 1997, to 213% in 2007. The market is absolutely dominated by the four state owned banks, although their share of the market has been decreasing steadily through competition from the other commercial banks (JSB and CCB).

Return on average assets (ROAA) and net-interest margins (NIM) of the SOCBs are respectable by western standards but are well below levels that would be consistent with economies in the same stage of development (as for example India where NIM would be in the region of 3.5%). Part of the reason is that interest rates were heavily controlled during this period and the remaining reason is the large amount of non-performing loans on the books of the commercial banks. The non-performing loans (NPL) ratio of the SOCBs has been falling from 52% in 1997 to around 2% in 2007.

With the encouragement of the regulatory authorities, Chinese banks have in recent years, had to restructure their balance sheet, develop modern risk management methods, improve capitalization, diversify earnings, reduce costs and improve corporate governance and disclosure.[4]

3 CBRC Annual Report 2007.

4 CBRC Annual Report 2006 http://www.cbrc.gov.cn/english/home/jsp/index.jsp

Up until 1995, control of the banking system remained firmly under the government and its agencies.[5] Under state control, the banks in China served the socialist plan of directing credits to specific projects dictated by political preference rather than commercial imperative. Since 2001 foreign banks and financial institutions were allowed to take a stake in selected Chinese banks. While control of individual Chinese banks remain out of reach for the foreign institution,[6] the pressure to reform management, consolidate balance sheets, improve risk management and reduce unit costs has increased with greater foreign exposure. Table 2 shows the extent of foreign strategic investment in individual Chinese banks.

The theory of market contestability (Baumol, 1982) suggests that incumbent banks will restructure weak balance sheets, reduce costs, and improve efficiency in preparation for the threat of entry. In their annual report on foreign banks in China, Pricewaterhouse-Coopers[7] refer to the China Bank Regulatory Commission report on the opening up of the banking sector. The CBRC divide the pace of reform and innovation into three stages; 1980-1993, 1993-2002 and 2003-2006. In the third stage, more of the domestic banking business was opened up to external competition. Foreign banks were allowed to expand RMB business from the four major cities of Shanghai, Shenzhen, Tianjin and Dalian which existed at the time of accession to the WTO, to the rest of the country. RMB business activity was extended from foreign enterprises and individuals to cover domestic firms and residents. Quantitative restrictions on foreign banks RMB liabilities were lifted and capital requirements were brought into equality with domestic banks. Various restrictions on branch development were removed and branches were particularly encouraged in the under-banked geographical regions outside the east coast. The upshot of these and a number of other reforms is that Chinese banks should exhibit less inefficiency, and strong productivity improvements in this period, with marked improvements in the latter years as competition with foreign banks intensify.

3. Methodology and Literature

Data Envelope Analysis (DEA) can be used to evaluate the efficiency of a firm by comparing it with a ‘best practice’ or output efficient firm. An output efficient firm is one that cannot increase its output unless it also increases one or more of its input, whereas an output inefficient firm is one that can increase its output without increasing its inputs. An output efficient firm would have a score of 100% as being located on the output efficient frontier whereas an output inefficient firm would be inside the frontier and have a score of less than 100%. Similarly an input efficient firm is one that cannot reduce its inputs without reducing its output whereas an input inefficient firm can.

5 According to La Porta, *et al*. (2002), 99% of the 10 largest commercial banks were owned and under the control of the government in 1995.

6 There is a cap of 25% on total equity held by foreigners and a maximum of 20% for any single investor, except in the case of joint-venture banks.

7 Pricewaterhouse Coopers (2007).

The major drawback of the DEA approach is that the efficiency scores obtained from a particular sample are confined to that particular sample and cannot be compared with another sample in a different time period. This limitation does not allow the measurement of productivity growth, which allows for improvement in efficiency as well as technical progress.

The idea of comparing the input of a decision making unit over two periods of time (period 1 and period 2) by which the input in period 1 could be decreased holding the same level of output in period 2 is the basis of the Malmquist Index.[8] Färe *et al*. (1994) developed a Malmquist productivity measure using the DEA approach based on constant returns to scale. The Malmquist productivity index (M) enables productivity growth to be decomposed into changes in efficiency (catch-up) and to changes in technology (innovation).[9]

An illustration using the one input one output case is shown in Figure 1.

Points A and B represent observations in periods t and t+1 respectively. The rays from the origin S_t and S_{t+1} represent frontiers of production for periods *t* and *t+1* respectively. Relative efficiency is measure in one of two ways. The relative efficiency of production of a firm at point A compared to the frontier S_t is described by the distance function $d_t(y_t,x_t)$ = 0a/0b. But compared with the period *t+1* frontier S_{t+1}, it is $d_t(y_t,x_t)$ = 0a/0c. The relative efficiency of production of a firm at point B compared to the period *t+1* frontier S_{t+1} is $d_{t+1}(y_{t+1},x_{t+1})$ = 0d/0e. Compared with the period *t* frontier S_t, the relative efficiency is $d_t(y_{t+1},x_{t+1})$ = 0d/0c. The Malmquist index (*M*) of total factor productivity (TFP) change is the geometric mean of the two indices based on the technology for periods t+1 and t respectively. In other words:

$$M = \left[\frac{d_{t+1}(y_{t+1}, x_{t+1})}{d_{t+1}(y_t, x_t)} \frac{d_t(y_{t+1}, x_{t+1})}{d_t(y_t, x_t)} \right]^{\frac{1}{2}} \tag{2}$$

In their study of productivity growth in industrialised countries, Färe *et al*. (1994) decompose (2) for changes in efficiency (catch up) and changes in frontier technology (innovation). This can be seen by expressing (2) as:

$$M = \frac{d_{t+1}(y_{t+1}, x_{t+1})}{d_t(y_t, x_t)} \left[\frac{d_t(y_{t+1}, x_{t+1})}{d_{t+1}(y_{2t+1}, x_{t+1})} \frac{d_t(y_t, x_t)}{d_{t+1}(y_t, x_t)} \right]^{\frac{1}{2}} \tag{3}$$

8 Grosskopf (2003) provides a brief history of the Malmquist productivity index and discusses the theoretical and empirical issues related to the index. For the decomposition of Malmquist productivity index, see Lovell (2003).

9 A further decomposition can be conducted by separating the change in efficiency into the change in pure efficiency x change in scale efficiency. The change in efficiency is constructed under CRS while the change in pure efficiency and scale efficiency is constructed under VRS.

or $$M = E_{t+1}T_{t+1}$$

where

M = the Malmquist productivity index
E_{t+1} = a change in relative efficiency over the period t and t+1 (catch-up)
T_{t+1} = a measure of technical progress measured by shifts in the frontier from period t to t+1

When $M > 1$ it means that there has been a positive total factor productivity change between period t and t+1. When $M < 1$ it means that there has been a negative total factor productivity change.

The use of the Malmquist method of evaluating productivity performance of banks has been a growth area of academic enquiry. Berg *et al.* (1992) examined Norwegian banks 1980-89 and found productivity regress prior to deregulation and strong productivity gains due to catch-up after deregulation. The Malmquist decomposition was used by Wheelock and Wilson (1999) to examine bank productivity in the USA for the period 1984-93. They report a general drop in average productivity caused by failure to catch-up with outward shifts of the production frontier. Alam (2001) found that the deregulation period resulted in a productivity surge in the first half of the 1980s followed by a productivity regress in the second half for large US banks. These results were confirmed by Mukherjee *et al*. (2001) who also uses panel estimation to explain productivity growth in terms of bank size, product-mix and capitalisation.

Other studies of bank productivity using the Malmquist method have been Drake (2001) for the UK, Grifell-Tatjéand Lovell (1997) for Spain, Canhoto and Dermine (2003) for Portugal, Noulas (1997) for Greece, Fukuyama (1995) for Japan, and Isik and Hassan (2003) for Turkey. A pan-European study was conducted by Casu *et al*. (2004) who compare parametric with the Malmquist method. There finding is that productivity growth in European banking has been largely brought about by technological change rather than efficiency improvement. Outside Europe, Worthington (1999) finds that Australian Credit Unions exhibited strong technological progress after deregulation and Neal (2004) found that productivity improvements were mostly shifts in the frontier with the majority of banks having negative catch-up over 1995-99.

The productivity of Chinese banking has also been the subject of numerous studies by Chinese scholars. Chen (2002), Zhang and Wu (2005) and Tang and Wang (2006) use the Malmquist method to examine the productivity trend of Chinese banks over the 1994-1999, 1999-2003 and 1997-2003 periods respectively. Their basic findings were that the large state-owned banks exhibited lower average growth compared with the joint stock banks. In general average productivity growth was dominated by catch-up rather technical innovation but that there had been in a marked improvement in Total Factor Productivity

(TFP) in the latter years.[10] In contrast Ni and Wan (2006) found strong productivity improvement led by technical improvement rather than catch-up, whereas Sun and Fang (2007) pose the question, whether foreign banks have stimulated an improvement in Chinese bank productive efficiency? Sun and Fang (2007) find that average TFP improved during the period 2001-2004 consistent with the hypothesis that the threat of entry has had significant efficiency effects on incumbent banks. Appendix 1 provides a brief tabulated summary of studies of bank productivity uses the Malmquist method.

However, all these studies are limited by the lack of statistical inferential capability and therefore it is difficult to evaluate the sensitivity of the estimates obtained relative to sample variation. In other words, the deterministic estimates of the Malmquist index cannot assign confidence levels to the measures of growth. The estimates obtained in the above studies represent measures of performance relative to an estimate of the true but unobserved frontier. Since these estimates are based on finite samples, they will be subject to sampling variation of the frontier and subject to finite sample bias. The bootstrap reduces finite sample bias and reduces, or even eliminates finite sample errors in the rejection probability of statistical tests (see Horowitz, 2001).

Simar and Wilson (1998, 1999, 2000) propose a smooth bootstrapping methodology to examine the sensitivity of the DEA scores and Malmquist indices to sampling variations with the aim of assigning confidence intervals.

The application of bootstrapping methods to the Malmquist productivity index remains an ongoing area of research (Lőthgreen and Tambour, 1999). Relatively few studies have applied bootstrapping methods to measuring banking productivity. Gilbert and Wilson (1998) calculate confidence intervals for estimates of productivity in Korean banks in 1980-94 and conclude that the period had experienced significant productivity growth against the null hypothesis of no change between periods. Tortosa-Ausina *et al*. (2008), applies bootstrapping to Spanish savings banks over 1992-1998 and confirm the common finding that productivity growth is dominated by technological progress in the post deregulation period. Murillo-Melchor *et al*. (2005) conduct a European wide study of bank productivity over the period 1995-2001 using bootstrap techniques. They confirm the basic finding of Casu *et al*. (2004) that productivity gains were driven by technological progress but find significant differences in inter-country performance.[11]

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[10] See also Hou (2006) which uses a two-stage panel estimation to explain productivity but inappropriately uses operating expenses as an explanatory variable when it is also an input in the construction of the M index.

[11] Alam (2001) also uses bootstrap confidence intervals to provide ain inferential capacity to the point estimates of productivity of large US banks.

4. Banking Data

This study employs an unbalanced panel of annual data (1997-2007) for the 5 state-owned or state-controlled commercial banks (SOCB), 9 joint-stock commercial banks (JSCB) and 49 city commercial banks (CCB). The total sample consisted of 323 bank-year observations. The main source of the data was Fitch/Bankscope, and individual annual reports of banks.

Two approaches are normally taken in determining what constitutes bank input and output. The intermediation approach developed by Sealey and Lindley (1977) recognises the main function of the bank is to conduct financial intermediation. Under the intermediation approach, bank assets measure outputs and liabilities measure inputs. In contrast, the production approach recognises that the bank provides intermediation services and payment services to depositors. In the production approach, physical entities such as labour and capital are inputs while deposits are a measure of output.[12] Goldschmidt (1981) argues that deposits are both inputs and outputs depending on its use in intermediation services or payments services and suggests a weighting mechanism similar to the divisia approach of Barnett *et al*. (1984). Such a separation would need information about the term maturity of deposits. This information is not easily available for banks in China and in any case up until very recently deposit interest rates were regulated and did not reflect market fundamentals.

A further issue is the problem of non-performing loans which have been treated as an undesirable output in a number of studies. Park and Weber (2006) consider loans less non-performing loans (NPLs) as well as deposits as a valid output of the bank in their study of bank productivity in Korea, where NPLs are viewed as an undesirable output. Stripping out non-performing loans from the stock of loans for each bank creates a new output variable which replaces the stock of total loans and following Scheel (2001) we treat the inverse of NPLS as a positive output.[13]

Another argument for adjusting loans for NPLs is to mitigate the effect of the large loan portfolios held by the SOCBs on the efficiency calculation. The unadjusted loan portfolio would bias the efficiency score upwards for the SOCBs which have the largest share of loans but also the highest proportion of NPLs.

Finally, a variant of the production approach is to recognise that the services provided to depositors and loan obligors are reflected in the net flows of income to the bank. So services to the consumers of banking products whether it is intermediation services or other financial services, will be reflected in the net interest earnings to the bank and net non-interest earnings.

12 Freixas and Rochet (1997) propose a third approach that recognises the specific activities of banks such as risk management and information processing.

13 See Thanassoulis (2008) for a discussion.

In this study, we adopt a hybrid between the intermediation and production approaches. We also recognise that deposits may be viewed as an output or as an input. We therefore consider five types of models, which can act as boundaries for the intermediation and production approaches including undesirable outputs. Model 1 is one where there are three inputs; bank deposits and borrowed funds, fixed assets and operational costs, and three outputs; total loans, other earning assets, and non-interest income. Although non-interest income remains undeveloped in China, it is selected to reflect the growing contribution of this area to banks' total income. Model 2 separates NPLs from Loans and treats NPLs as an undesirable output. Model 3 recognises deposits as an output and Model 4 allows deposits as an output and treats NPLs as an undesirable output. Model 5 has only fixed assets and overheads as inputs but has net interest income and non-interest income as outputs. Model 5 is the closest to the concepts of the neo-classical production function which uses stocks of capital and labour to produce a flow of output. In this study overheads acts as a proxy of labour and the outputs are the revenues generated from balance sheet and off-balance sheet business, which also subsumes the lower gross interest income generated by NPLs. Table 3 summarises the input/output structure of each model.

As an indicator of scale and evolution of the variables over the period, Table 4 presents the summary statistics of the input and output data by bank group for 1999 as representative of the first half of the period and for 2007 as representative of the second half. Since we are examining the movements in productivity over a period of nine years, the nominal values of data were deflated by the consumer price index.

The groups represent collectively the five state-owned or controlled banks (SOCB), the joint stock commercial banks (JSCB), and the city commercial banks (CCB).

The table highlights the rapid growth in the average loan book over this period, particularly for the SOCBs and JSCBs. The table also shows the decline in the average level of NPLs for the SOCBs in the eight years between 1999 and 2007. In part this represents the transfer of tranches of NPLs from the big-4 to the Asset Management Companies in 1999-2000 and in 2003. It also shows that the average rate of decline of NPLs by the CCBs were relatively faster. The figures for the CCBs are not strictly comparable between the two periods given the unbalanced nature of the sample. While the summary statistics for the SOCBs and JSCBs are comparable, the number of CCBs in the sample for 1999 was 9 whereas in 2007 it was 43.

5. Empirical Results

Positive productivity growth is measured by an estimate greater than unity. Productivity regress is indicated by an estimate of less than unity. We conduct three exercises in the measurement of bank productivity. First we estimate the standard Malmquist measure based on the deterministic Data Envelope

Analysis, however this will be a biased estimate. Second, a bootstrap estimate of the median of 2000 bootstrap simulations is examined. Third, where the estimate of productivity growth is not significantly different from unity as given by the 95% confidence intervals of the bootstrap, the figure is constrained to the null of unity.

The purpose of constraining the median estimate to the null is to differentiate between the 'classical' approaches to statistical measurement from the 'Bayesian' approach. The classical approach would suggest that if an estimate was not significantly different from the null, the null is not rejected, whereas the Bayesian philosophy would suggest that the point estimate of the median is appropriate because of the frequency of its occurrence. In reality there was little numerical difference between the unconstrained and unconstrained estimates. In this particular case, the methodological difference between the classical and Bayesian approaches do not produce estimates are distinct from each other. However, for completeness we report both results.

In all three cases a constant returns to scale technology was assumed. If the production technology is variable returns to scale (VRS), the Malmquist TFP index can be further decomposed into frontier shift, pure efficiency change and scale efficiency.[14] The bootstrap algorithm of Simar and Wilson (1999) uses the conical hull of the observed data to estimate the production set, which amounts to assuming CRS. However, the Malmquist index provides consistent estimates of the true value irrespective of the returns to scale assumption but may give inconsistent results regarding the sources of productivity in the decomposition.[15]

Table 5 shows the sample mean of the weighted (by group asset share) average of TFP and decomposition for each of the five models discussed above using the three alternative estimates;

- the unconstrained median bootstrap value
- the median bootstrap value constrained to the null of zero growth (index = unity) if the null is not rejected
- the pure DEA estimate.

The TFP productivity growth is decomposed into technical progress and efficiency gains (catch-up) for each of the models. A number of points can be made about the results of Table 5. First, the results are qualitatively similar for all three estimates but the bootstrap results are markedly different quantitatively from the DEA estimates, indicating significant bias in the raw DEA results.[16] Second, the SOCBs have had significant TFP regress over this period and only moderate growth in the case of model 3, where

[14] See also Ray and Desli (1997).

[15] In a previous study looking at the productivity growth of the national banks of China for a shorter time period Matthews *et al*. (2009) used the third test of Banker (1996) on selected years and found that the null of CRS could not be rejected.

deposits are considered as an output and NPLs an undesirable output. Third, in general the main driver of TFP growth for the national banks has been technical progress defined by the 'best practice' banks. In most cases the best practice (benchmark) banks have shifted the frontier outwards leaving the average banks behind and further to catch up. However, the main driver of TFP growth for the CCBs has been catch-up (models 2, 3, and 4). Technical progress as the driver of TFP is particularly pronounced in the case when NPLs are treated as an undesirable output (models 2 and 4). Fourth, the bootstrap estimates show strong TFP growth for the CCBs and unlike that of the other two bank groups, also strong efficiency gains (catch-up). This means that the CCBs are converging on each other (peer group) at a faster rate than the SOCBs and JSCBs are within their own groups. Finally, the results show that the TFP growth of the CCBs and JSCBs was higher relative to SOCBs in the case of Model 2 and 4 where NPLs are treated as undesirable outputs but that the technical innovation was stronger in the SOCBs. The reason for this is possibly because the distribution of NPLs is concentrated in the state-owned banking sector but also that the best practice banks in this group have had strong success in reducing their NPL ratios thus reducing their bad output at a faster rate.

Using the unconstrained estimates, Figure 2a – 2c show the decomposition of TFP growth for the three banks groups within each model.

Figure 2a shows that TFP growth for the SOCBs have been at best moderate (model 5) and at worse negative. A similar picture emerges in the case of the JSCBs with moderate growth measured by model 2 and 4 and productivity regress measured by models 1 and 3. Spectacular growth has been measured for the CCBs with all five models. Figure 2b shows strong measured innovation effects defined by the best-practice banks that have worsened the relative positions of the rest in the group. The SOCBs have on average performed particularly well by measuring strong technical innovation effects in all five models. It is likely that the benchmark banks have provided a better service to depositors and therefore attracted more than the non-benchmarks banks in the group and have succeeded in reducing NPLs at a faster rate. The benchmark banks have also defined shifts in the frontier by recording strong technical innovation when output is defined as the real revenue flows. A less striking but similar picture emerges for the JSCBs particularly when NPLs are treated as an undesirable output (Models 2 and 4).

However, the striking picture is what emerges for the CCBs. Strong TFP growth is driven by moderate innovation effects (excepting model 5) and spectacular efficiency gains (catch-up), suggesting that simply emulating best-practice without strong innovation was sufficient to generate strong productivity gains in the CCBs. The average for all 5 models for each bank group is an indication of a robust measure of overall TFP growth and its drivers.

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[16] Appendix 3 provides an example of the magnitude of bias correction for two models in the case of a single year 2006/7, however the frequency of the bias varies from year to year.

Figure 3 shows that taking all five models to obtain a robust measure, TFP growth by the SOCBs and the JSCBs has on average been zero but productivity growth of the CCBs has been 15% a year. However this verdict belies sharp differences in the drivers between the bank groups. In the case of the SOCBs, technical innovation has been equally offset by regress in efficiency. This means that the best practice SOCBs have shifted the frontier widening the gap between them and the remaining SOCBs. A similar but much more moderate picture emerges for the JSCBs. With the CCBs both technical innovation and efficiency gains contribute to the strong TFP growth. However, efficiency gains dominate suggesting that emulating the best practice banks have contributed the most to productivity growth.

The boundary is made up of the benchmark or best practice banks. The banks that make up the benchmark and define the extent of technical innovation may change from year to year and by model. However, it is instructive to identify the benchmark banks within each bank group as the bank that has the most frequent display of technical innovation and with highest average growth due to technical innovation. Table 6 presents the benchmark banks for each bank group.

Increasing deregulation as suggested by the CBRC and the opening up of the Chinese banking market post 2006 would suggest that the second half of the sample period examined should see a significant improvement in TFP growth. To test for this, the sample was split into two periods 1998-2002 and 2003–2007. Table 7 shows the annual weighted average of TFP growth in both periods for all four models.

The table shows that the average TFP growth of the SOCBs ranged from 0.1% a year to 13.8% a year in the first half of the period but was universally negative in the second half. Given that Table 5 indicates the main driver for TFP growth was technical progress, this suggests that the benchmark banks had raced ahead leaving the other banks in the group with more ground to catch-up, leading to an average productivity regress. The results for the first half of the period also confirm the standard finding that the JSCBs outperformed the SOCBs, particularly when NPLs are treated as an undesirable output. But contrary to the findings of some Chinese scholars this performance is not sustained in the second half of the period. The main result is that the TFP growth of the CCBs was stronger than both groups of the national banks confirming the findings of Ferri (2009) that city commercial banks have increased their performance and are challenging the traditional banks.

Using the distance function method of estimating TFP, Kumbhakar and Wang (2007) find that overall TFP growth for the national banks in China over the period 1993-2002 was 4.5% annually with the SOCBs showing an annual growth of 0.7% a year and the JSCBs showing an average growth of 6.1%. The inputs in the Kumbhhakar and Wang (KW) study were labour, fixed assets and deposits and the outputs were loans and other earning assets. The inputs and outputs in this paper do not correspond exactly with the KW study; however model 1 is the closest in proximity where overheads act a proxy for labour as a factor production.

The results reported in Table 7 does not support the estimates found in the KW study although using the different models as a range show that they fall within the band. Furthermore, the results do not support the notion that the second half of the period saw an improvement in TFP growth. Table 8 shows the result of a non-parametric test for the differences in the measures of TFP growth between the two periods. There is no strong evidence (at the conventional 5% level of significance) that the high productivity growth of the first half of the period was improved on in the run-up to the opening up of the banking market to foreign competition. Indeed there is weak evidence to the contrary.

We now turn to an examination of the characteristics of TFP growth as a means of identifying the key bank specific components that might explain productivity performance. Taking the logarithms of TFP we conduct pooled regression.

The bank specific variables that we used were SIZE measured by the log of assets, the cost-income ratio (COST), NPL ratio (NPL) and a measure of revenue diversification given by the proportion of fee income in total revenue (FEE). In addition we also explored the performance of banks that have a foreign stake-holding and we also included a dummy variable to distinguish between the earlier and later periods (DUM) and category of bank (JCSB=1 if joint stock bank, zero otherwise and CCB=1 if City Commercial Bank, zero otherwise). All bank specific variables were lagged one period to account for potential endogeniety. Table 9 summarises the results.

Two consistent characteristics emerge from this analysis. First, higher TFP growth is mostly associated with banks that have lowered their cost-income ratio, and have diversified their revenue sources by developing non-interest income. Second, there is weak evidence that size measured by total assets is positively associated with higher TFP growth.

The determinants of the decomposition of TFP growth into technical innovation (frontier shifts defined by best practice) and efficiency (catch-up) is shown in Table 10.

Table 10 shows more clearly that technical innovation is positively associated with banks that have diversified their revenue sources by developing non-interest income business, whereas efficiency gains (catch-up) has been typically associated with banks that have reduced their cost-income ratio. There is also some weak evidence that banks have been able to generate catch-up efficiencies by lowering the NPL ratio and that size is a positive factor in developing technical innovation. There is consistent evidence that efficiency gains are more prevalent with the CCBs than with the other two bank groups.

6. Conclusion

This paper has used the Malmquist decomposition to quantify the productivity growth of Chinese banks in the period 1998-2007. The advantage of using the Malmquist method is that it separates the diffusion of technology (efficiency gains) from advances in technology (frontier shifts). The paper also applies bootstrapping techniques to evaluate significant changes in productivity, efficiency gains and innovation. Five models were examined to provide a robust measure of bank productivity performance.

In general, average TFP growth has been neutral over the period for the SOBs and JSCBs but positive for the CCBs. However, the weighted average figures mask wide differences in individual performance. The benchmark banks that define the production frontier have generated sharp increases in technical innovation, leaving a wider gap between them and the other banks in their respective groups. The CCBs showed improvements in both technical innovation and efficiency (catch-up) gains.

Once NPLs are treated as an undesirable output the picture becomes even clearer. On average the SOCBs show productivity regress. Technological gains have been swamped by average efficiency regress. However, the JSCBs show strong TFP growth driven by stronger innovation effects. While adopting technologies that improved the productivity of individual JSCBs, other banks in the group failed to keep up with the benchmark banks and slipped back in relative terms.

The CCBs show strong TFP growth driven largely by efficiency gains but also moderate innovation effects. Efficiency gains for all the banks (catch-up) have been obtained through cost reduction. Technical innovation is associated with greater diversification of revenue away from interest earnings and also in a limited way with size of the bank. There is no evidence to support the case that an increase in the pace of innovation and reform in the second part of the sample period, or the opening up of the Chinese banking market has resulted in an improvement in bank productivity. This may in part be due to the fact that foreign banks still only command a small share of the banking market in China. It is also possible that domestic competition is particularly strong between local banks with CCBs challenging the bigger established national banks.

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Table 1. The Chinese Banking Market

Variable	1997	2000	2007
Total Assets to GDP	125.6%	147.1%	213.4%
SOB Employment	1,670.4 thousand	1,540.8 thousand	1,492.1 thousand
SOB Market share % assets	88.0%	71.4%	53.2.0%
NPL ratio SOB only	52.7%	31.5%	2.4%
ROAA SOB*	0.93%	0.78%	1.12%
NIM SOB*	1.8%	1.5%	2.6%
Cost-Income Ratio SOB*	48.2%	59.6%	40.7%

Sources: IMF *International Financial Statistics*, Individual Bank Annual Accounts, China Regulatory Banking Corporation Annual Report, *Almanac of China's Finance and Banking*, Fitch-Bankscope data base, National Bureau of Statistics of China, * weighted average by asset share.

Table 2. Foreign Bank Ownership Stake

Chinese Bank	Foreign Bank	Stake – first acquisition
Bank of Beijing	ING	19.2% - Oct 2005
Bank of Shanghai	HSBC (8%) and other foreign institutions	18.0% - Dec 2001
Shanghai Pudong Development Bank	Citigroup(4.6%), Barclays, J P Morgan, Morgan Stanley	5.3% - Dec 2002
Tianjin City Commercial Bank	ANZ	20% - Dec 2005
Industrial Bank	Hang Seng (12.8%), Tetrad Ventures	20.8% - Dec 2003
Bank of Communications	HSBC (19.9%), Barclays, J P Morgan,	21.5% - June 2004
Xian City Comm. Bank	Scotia Bank	12.4% - Sep 2002
Jinan City Comm. Bank	C Bank of Australia	11% - Nov 2004
Shenzen Develop. Bank	Newbridge Capital (17.9%), Barclays, Nikko Asset Management	19.3% - Jun 2004
China Minsheng Bank	Fullerton (7.9%), Barclays, J P Morgan	8.9% - Jan 2005
Hangzhou City Com Bank	C Bank of Australia	19.9% - July 2006
China Construction Bank	Bank of America (8.5%) Fullerton, Other foreign	15.2% - June 2005
Bank of China	RBS-China(8.3%), Fullerton, Other foreign	20.6% - Aug 2005
ICBC	Goldman Sachs, Allianz, American Express	10% - Sep 2005
Nanjing City Com. Bank	BNP Paribas	19.2% - Oct 2005
China Bohai Bank	Standard Charter Bank	20.0% - Sep 2005
Guangdong Development Bank	Citigroup (20%), IBM	24.7% - Dec 2006
Hua Xia Bank	Deutsche bank (9.9%) Sal Oppenheim Jr	14.0% - April 2006
CITIC Bank	BBVA Bank of Spain	5% - Dec 2006
Shanghai Rural Commercial Bank	ANZ	19.9% - Nov 2006

Source: *Business Week* October 31, 2005, *Fitch Bankscope* and Pricewaterhouse Coopers (2007)

Table 3. Model Structure

Model Type	Inputs	Outputs
1	Deposits (RDEP), Overheads (ROHD), Fixed Assets (RFA)	Loans (RLOAN), Other earning assets (ROEA), RFEE (net fee income)
2	Deposits (RDEP), Overheads (ROHD), Fixed Assets (RFA)	Loans less NPLs (RPLOAN), Other earning assets (ROEA), RFEE (net fee income), RNPLs as undesirable output
3	Overheads (ROHD), Fixed Assets (RFA)	Loans (RLOAN), Other earning assets (ROEA), RFEE (net fee income), Deposits (RDEP)
4	Overheads (ROHD), Fixed Assets (RFA)	Loans less RNPLs (RPLOAN), Other earning assets (ROEA), RFEE (net fee income), RNPLs as undesirable output, Deposits (RDEP)
5	Overheads (ROHD), Fixed Assets (RFA)	Net interest earnings (RNIE), net fee income (RFEE)

Table 4. Output-Input Variables 1999 and 2007 (Million RMB) per Bank/Year Deflated by the Consumer Price Index 1997=1

Variable	Description	Bank Group	Mean	Standard Deviation	Minimum	Maximum
RLOAN	Stock of loans	SOCB	142078	783544	29024	2464455
			2505421	986477	979895	3464731
		JSCB	48577	25186	16643	80603
			386374	141514	194756	590849
		CCB	11239	9611	4420	33094
			18264	28563	553	138379
ROEA	Stock of other earning assets	SOCB	685486	370853	224289	1210672
			2496702	1146125	873945	4025218
		JSCB	42189	24770	15157	74369
			313253	133885	116718	568532
		CCB	11875	13207	2024	38144
			17879	33616	1254	172276
RFEE	Net fees and commissions	SOCB	1664	3496	0	7910
			19834	10308	6403	31032
		JSCB	78	67	15	177
			1691	1648	407	5811
		CCB	11	10	1	28
			35	64	0	277
RNPL	Non-performing loans	SOCB	642448	411000	50705	1090038
			203324	300511	20482	738243
		JSCB	8232	9834	0	31372
			8496	3750	4136	16922
		CCB	1388	880	370	2792
			359	749	4	3947
RDEP	Deposits and other sources of funds	SOCB	2063133	1097080	31830	3249698
			4655574	1956532	1709734	7016662
		JSCB	86105	44388	34818	140688
			616877	265686	233158	1094492
		CCB	23308	23520	5328	69579
			32960	57493	2682	281241
RFA	Fixed assets	SOCB	44935	24472	4856	67995
			62260	22907	29060	88802
		JSCB	2360	951	930	3795
			4574	2006	1800	7620
		CCB	440	237	122	778
			307	462	11	2516
ROHD	Overhead and other non-interest costs	SOCB	25822	12960	6164	38031
			63999	27516	19420	84296
		JSCB	1339	677	584	2616
			7649	3014	3894	13225
		CCB	391	3259	116	1013
			324	457	23	2278
RNIE	Net interest earnings	SOCB	40192	21769	844	64969
			150729	49225	88490	202585
		JSCB	2214	978	957	3913
			21112	11803	8669	48866
		CCB	859	659	297	1615
			936	1424	5	6760

Sources: Fitch/Bankscope, *Almanac of China's Finance and Banking* (various) and author calculations from web sources.

Table 5. Weighted Annual Average of Productivity Growth 1998 – 2007

Model	Group	Bootstrap Unconstrained estimates			Bootstrap Constrained estimates			DEA standard linear-programming estimates		
		TFP	Tech	Catch-up	TFP	Tech	Catch-up	TFP	Tech	Catch-up
1	SOCB	0.997	1.046	0.996	0.997	1.040	0.994	1.005	1.035	0.974
	JSCB	0.975	0.994	0.970	0.969	0.989	0.953	0.980	0.987	0.961
	CCB	1.038	1.019	1.018	1.043	1.023	1.065	1.015	1.010	0.994
2	SOCB	0.992	1.102	0.946	0.996	1.092	0.924	0.997	1.085	0.923
	JSCB	1.052	1.085	0.999	1.051	1.060	0.982	1.032	1.048	0.973
	CCB	1.294	1.087	1.352	1.317	1.015	1.320	1.027	1.029	1.003
3	SOCB	1.006	1.113	0.949	1.004	1.115	0.953	1.009	1.099	0.948
	JSCB	0.952	0.974	1.009	0.952	0.974	0.990	0.967	0.983	0.982
	CCB	1.008	0.979	1.216	1.014	1.000	1.172	1.021	0.993	1.018
4	SOCB	0.996	1.133	0.935	0.993	1.142	0.945	1.008	1.213	0.935
	JSCB	1.038	1.053	1.008	1.036	1.032	0.986	0.999	1.024	0.957
	CCB	1.340	1.048	1.339	1.342	1.016	1.328	1.033	1.011	1.008
5	SOCB	1.054	1.095	0.936	1.055	1.073	0.950	1.053	1.142	0.941
	JSCB	1.019	0.979	0.977	1.016	0.964	0.975	1.022	1.029	0.966
	CCB	1.085	1.206	0.976	1.074	1.209	0.978	1.109	1.146	0.956

Table 6. Best Practice Banks

Bank group	Model 1	Model 2	Model 3	Model 4	Model 5
SOCB	Bank of China	Bank of China	Bank of China	Bank of China	ICBC
	Bank of Communications	Bank of Communications			
JSB	China Minsheng	China Minsheng			
		China Merchant	China Merchant	China Merchant	China Merchant
CCB	Xiamen	First Sino Bank	Xiamen	Xiamen	Shanghai
	Ningbo	Xiamen			

Table 7. Total Factor Productivity Growth in Sub-Samples (Weighted Averages)

Years	Bank Group	Model 1	Model 2	Model 3	Model 4	Model 5
1998 -	SOCB	1.014	1.001	1.027	0.996	1.138
2002	JSCB	1.005	1.132	1.018	1.176	1.141
	CCB	1.047	1.481	0.954	1.359	1.206
2003 -	SOCB	0.979	0.983	0.984	0.996	0.998
2007	JSCB	0.946	0.973	0.886	0.899	0.938
	CCB	1.030	1.107	1.063	1.321	1.007

Table 8. Difference in Performance between Two Periods

Model	**Mann-Whitney z value**			**Probability**		
	SOCB	**JSCB**	**CCB**	**SOCB**	**JSCB**	**CCB**
Model 1	0.38	1.35	-0.39	0.70	0.18	0.70
Model 2	0.13	1.88*	-0.52	0.90	0.06	0.61
Model 3	0.59	0.76	-1.88*	0.55	0.45	0.06
Model 4	-0.03	1.79*	-0.85	0.98	0.07	0.39
Model 5	0.18	1.33	-0.70	0.85	0.18	0.48

* significant at the 10% level

Table 9. Productivity Characteristics (Pooled Regression) – Dependant Variable ln(TFP). Intercept Not Shown

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
COST_1	-0.0016***	-0.0038***	-0.0043***	-0.004***	-0.0012
Ln SIZE_1	0.0138	-	0.0123*	0.0129	0.0115*
FEE_1	0.5548***	0.5166	0.7507***	1.141***	0.8399***
DUM	-0.0520***	-0.0661*	-0.0474	-0.0666*	-
JSCB	0.0686	0.0555	-0.0536*	-	0.0445
CCB	0.0383		-	-	-
Significance of Regression	F(6,316) = 3.42***	F(4,318) = 4.05***	F(5,316) = 6.2***	F(4,318) = 4.87***	F(4,315) = 3.26***

*** 1% level of significance, ** 5% level of significance, * 10% level of significance

Table 10. Characteristics of Technical Innovation and Efficiency Growth

Variable	Model 1		Model 2		Model 3		Model 4		Model 5	
	Tech	Eff	Tech	Eff	Tech	Eff	Tech	Eff	Tech	Eff
COST_1		(-) **		(-)		(-) ***		(-) ***		(-) ***
FEE_1	(+) ***	(-) **	(+) ***		(+) ***	(-) **	(+) ***		(+) ***	(-) ***
Ln(SIZE)-1			(+) ***	(+) ***			(+) ***		(+)	
NPL				(-)	(+) **	(-) **	(+) **	(-) **		
CCB	(-) ***	(+) ***	(-) ***	(+) ***	(-) ***	(+) **		(+) **	(-)	
JSCB			(-) ***	(+) ***	(-) **					
DUM							(-) ***		(-) ***	

Direction showed in parenthesis. *** significant at the 1%, ** significant at the 5%

Figure 1.

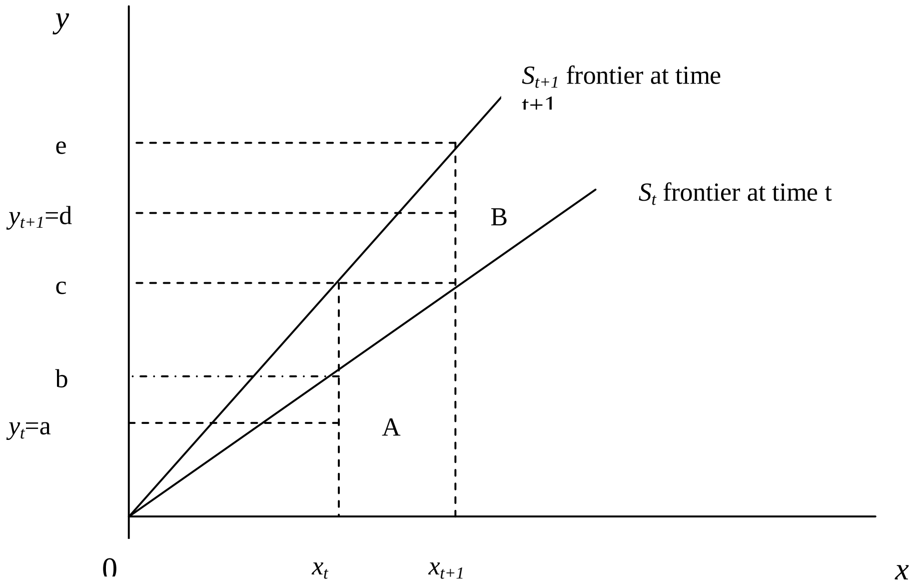


Figure 2a.

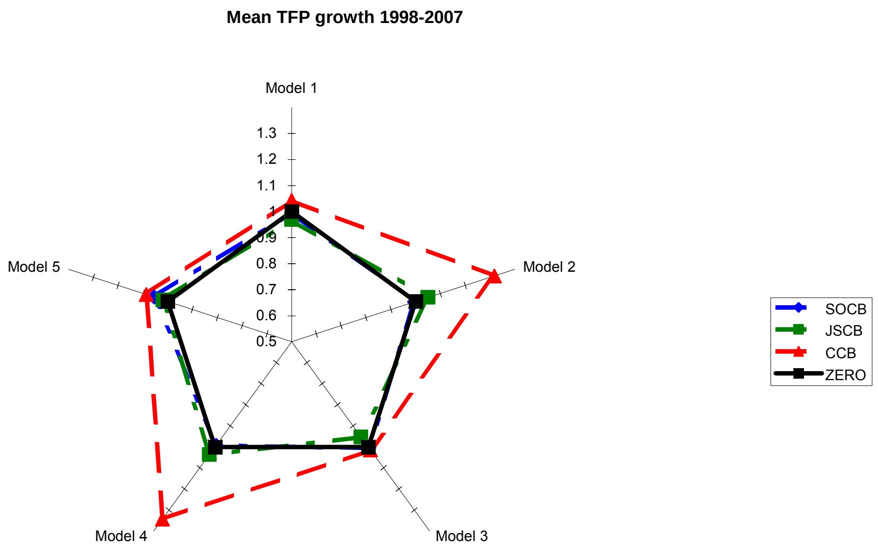


Figure 2b.

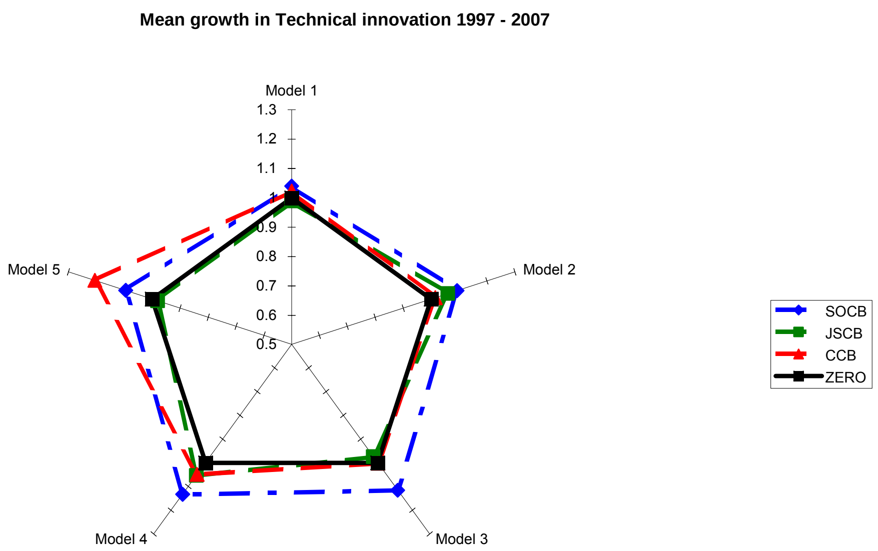


Figure 2c.

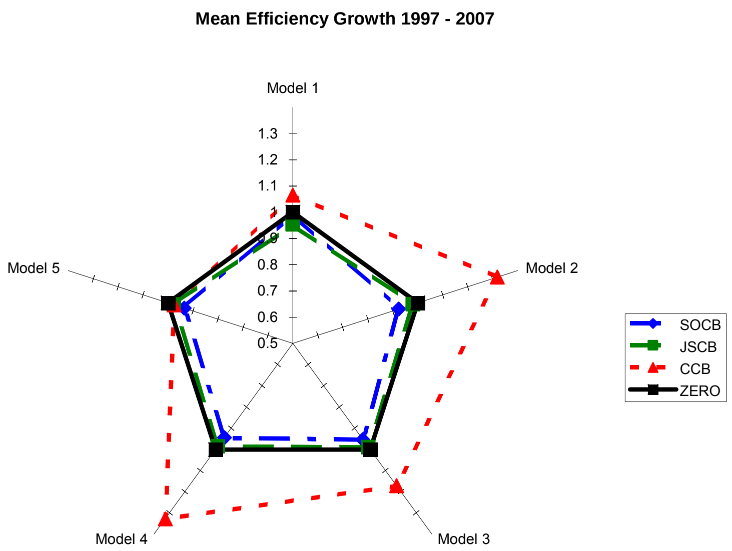
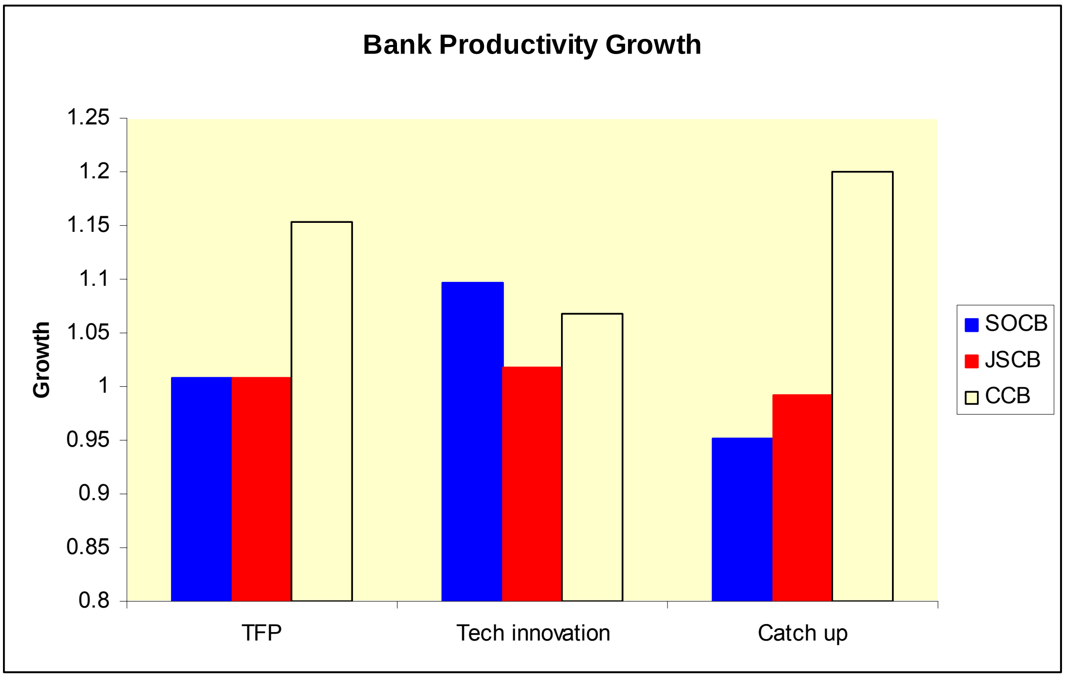


Figure 3.


Bank Productivity Growth
Growth
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
TFP
Tech innovation
Catch up
SOCB
JSCB
CCB

Appendix 1. Summary of Studies on Bank Productivity

Study	Country	Period	Inputs	Outputs	Results
Berg *et al*. (1992)	Norway	1980-89	Labour hours, operational expenses deflated by materials price index	Short-term loans, long-term loans, deposits and loan losses treated as negative output	Low TFP growth but strong catch-up following deregulation. Big banks had stronger productivity growth than smaller banks.
Wheelock and Wilson (1999)	USA	1984-93	Labour, physical capital, purchased funds	Four categories of loans, demand deposits	Decline average productivity over the period. The benchmark banks improved technical productivity through technical innovation but average efficiency declined.
Alam (2001)	USA	1980-89	Two categories of deposits, other purchased funds, capital, labour, equity.	Securities, three categories of loans.	Lag in effect between regulatory reform and growth in productivity. Improvements in productivity obtained from technical innovation rather than efficiency gains.
Mukherjee *et al*. (2001)	USA	1984-90	Labour, physical capital, equity, two categories of deposits.	Three categories of loans, investments, non-interest income	Productivity growth of large banks was generally positive in this period but productivity growth fluctuated with respect to size.
Drake (2001)	UK	1984-95	Physical capital, labour, (deposits)	Loans, Other investments, Non-interest income, (deposits)	Uses both intermediation and production methods. Productivity growth driven by technical progress. Slower TFP under the intermediation approach.
Grifell-Tatjé and Lovell (1997)	Spain	1986-93	Labour, non-labour operating expenses	Loans, Savings deposits, demand deposits (all deflated by CPI)	Savings bank productivity driven by technical progress and catch-up. Commercial bank productivity declined in latter half of period.
Canhoto and Dermine (2003)	Portugal	1990-95	Labour, physical capital	Loans, deposits, securities, interbank assets/liabilities	Strong technological progress following deregulation. Catch-up weakened as benchmark banks grew strongly.
Noulas (1977)	Greece	1991-92	Labour, physical capital, deposits	Liquid assets, loans, investments	State owned banks experienced faster TFP than private banks. Catch-up was faster in private banks. State-owned banks experienced stronger technical progress
Isik and Hassan (2003)	Turkey	1981-90	Labour, physical capital, deposits	Short-term loans, long-term loans, other earning assets, non-interest income	Productivity loss 1982-86. Productivity growth 1987-90. Strong catch-up in 1987-90 following deregulation but low technical progress.
Casu *et al*. (2004)	Europe	1994-00	Wage bill/Assets, deposits, physical capital	Loans, other earning assets, non-interest income.	Productivity growth supported by technological progress rather than efficiency gains, except in the UK where catch-up was stronger.
Worthington (1999)	Australia	1993-97	Labour, physical capital, non-deposit liabilities	Demand deposits, time deposits, three categories of loans, other investments	Technological regress but high variability within credit unions. Technical progress occurred after deregulation. Efficiency gains due to technical efficiency rather than scale efficiency.

Chinese Studies of Bank Productivity

Study	Period	Inputs	Outputs	Results
Chen (2002)	1994-99	Physical assets, operating expenses	Deposits, loans, profit	Technological regress but strong catch-up drives TFP. JSB exhibited higher TFP variation
Ni and Wan (2006)	1998-02	Labour, physical assets, branches, op expenses	Deposits, loans, op revenue	Positive TFP. Joint stock banks more productive than SOB. Productivity growth driven by technical progress.
Tan and Wang (2006)	1997-03	Labour, physical assets, deposits	Profit, gross income	TFP growth negative until final year, driven by technological regress. Efficiency improvements
Hou (2006)	1996-02	Deposits, physical assets, op. expenses	Interest earnings, non-interest earnings	Declining trend in technical efficiency. TFP driven by technological progress
Zhang and Wu (2005)	1999-03	Labour, non-deposit funds	Deposits, Profits	TFP driven by efficiency catch-up. SOCBs driven by technical progress
Xu and Zhong (2005)	2001-02	Capital, net fixed assets, total expenses	Deposits, loans, profit before tax	Adopted bootstrapping method to re-examine the efficiency results. Capital, fixed assets and deposits have significant impact on bank efficiency, while fixed assets, loans and profits have no significant impact.
Zou (2008)	1996-05	Deposits, net fixed assets, Op. expenses	Investments, loans	FTP driven by technical progress. Listed banks are more efficient than non-listed. The latter is better than SOB. Ownership is the key factor. Bank size is positive correlated to technical progress and efficiency catch-up.
Yan (2008)	1995-04	Op. expenses, deposits, number of staff	Loans, profits	Banking market concentration is declining, which caused bank efficiency improvement. Competition level is positively correlated with efficiency,
Sun and Fang (2007)	1996-04	Interest expenses, other expenses, operating expenses, total assets	Interest earnings, other earnings, profit before tax	From 1996 till 2001, TFP was less than 1. Foreign banks entry ha no significant impact on Chinese banking efficiency improvement. 2001-04, TFP, TE is positive greater than 1. As China joined WTO, foreign entry has limited impact on Chinese banking.
Pang (2006)	2000-04	Deposits, net fixed assets	Loans, investments	TFP improved, driven by technical progress. Size matters.
Zhu (2006)	2000-04	Labour, net fixed assets, deposits	Operating income, net income	The average TE is 0.87. SOB less productive than JSB. TFP decreased caused by technical regress.
Tan and Wang (2006)	1997-03	Labour, next fixed assets, deposits	Income, profits	Declining trend in efficiency. TFP driven by frontier shift.
Hou and Wang (2006)	1996-02	Deposits, net fixed assets, operating expenses	Interest earnings, non-interest earnings	TFP is not driven by technical progress.
Ni and Wan (2006)	1998-02	Net fixed assets, number of outlets, labour, operating expenses	Gross income, deposits, loans	Efficiency improved, driven by technical progress. Ownership matters.
Zhang and Wu (2005)	1999-03	Net fixed assets, labour, loanable funds	Deposits, profits	TFP improved. For SOB, driven by AE, whilst technical progress contributed to TFP increase in JSB.

Appendix 2

The estimates of the distance functions for N banks over 2 periods are obtained following the standard method outlined in Färe *et al*. (1992) for $\hat{d}_t\left(y_{i,t}, x_{i,t}\right)$ and $\hat{d}_{t+1}\left(y_{i,t+1}, x_{i,t+1}\right)$. As in Simar and Wilson (1998) a DGP is assumed whereby the N banks randomly deviate from the underlying true frontier in a radial input direction. Bootstrapping involves replicating the DGP and generating 1000 pseudo samples which are used to measure the distance function for either period for each observation in the pseudo sample. This section borrows heavily from Jeon and Sickles (2004)

Step 1: Form (N x 1) vectors $\mathrm{A} = \left[\hat{d}_t(y_{1,t}, x_{1,t}), \hat{d}_t(y_{2,t}, x_{2,t}) \ldots \hat{d}_t(y_{N,t}, x_{N,t})\right]$ and $\mathrm{B} = \left[\hat{d}_{t+1}(y_{1,t+1}, x_{1,t+1}), \hat{d}_{t+1}(y_{2,t+1}, x_{2,t+1}) \ldots \hat{d}_{t+1}(y_{N,t+1}, x_{N,t+1})\right]$. The values in A and B are bounded from below at unity.

Step 2: Reflect these values about the boundaries in two-dimensional space to form (4N x 2) matrix in partitioned form;

$$\Delta = \begin{bmatrix} A & B \\ 2-A & B \\ 2-A & 2-B \\ A & 2-B \end{bmatrix}$$

The matrix Δ contains 4N pairs of values corresponding to the two time periods. The estimated covariance matrix of the columns [A B] is $\hat{\Sigma}$ which is the same as that of the reflected data [2 – A 2 – B], given by the temporal correlation of the original data. The covariance matrix of [2 – A B] and [A 2 – B] is $\hat{\Sigma}_R$, where;

$$\hat{\Sigma} = \begin{bmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} \\ \hat{\sigma}_{12} & \hat{\sigma}_2^2 \end{bmatrix} \text{ and } \hat{\Sigma}_R = \begin{bmatrix} \hat{\sigma}_1^2 & -\hat{\sigma}_{12} \\ -\hat{\sigma}_{12} & \hat{\sigma}_2^2 \end{bmatrix}$$

Let Δ_j denote the jth row of Δ. Then $\hat{g}(z) = \frac{1}{4Nh^2}\sum_{j=1}^{4N} K_j\left(\frac{z-\Delta_j}{h}\right)$ is a bivariate kernel density estimator of the 4N reflected data points represented by the rows of Δ, where *K*(.) is the bivariate kernel function, *h* is a bandwidth set to $(4/5N)^{1/6}$ following Silverman (1986) and *z* is (1 x 2)

$z_i = [\hat{d}_t(y_{it}, x_{it}), \hat{d}_{t+1}(y_{it+1}, x_{it+1})]$ is the ith row of the (N x 2) matrix of the original distance function estimates.

Step 3: Randomly draw with replacement N rows from Δ to form (N x 2) matrix $\Delta^* = [\delta_{i,j}]$, *i*=1,2,….N, *j*=1,2.

Step 4: Compute

$$\bar{\delta}_j = \tfrac{1}{N}\sum_{i=1}^{N}\delta_{i,j} \text{ , } j = 1, 2$$

Step 5: Simulate draws from a bivariate $N\left(0,,\hat{\Sigma}\right)$ and $N\left(0,\hat{\Sigma}_R\right)$ by generating iid pseudo random *N*(0,1) deviates (z_1, z_2) s.t. $(l_1 z_1, l_2 z_2 + l_3 z_2)$ from $N\left(0,,\hat{\Sigma}\right)$ and $(l_1 z_1, -l_2 z_1 + l_3 z_2)$ from $N\left(0,\hat{\Sigma}_R\right)$. Here l_1, l_2, l_3 are elements of a lower triangular matrix

$L = \begin{bmatrix} l_1 & 0 \\ l_2 & l_3 \end{bmatrix}$ obtained from the Cholesky decomposition of the (2 x 2) matrix $\hat{\Sigma}$. These simulated draws form ε^* which is (N x 2) containing independent draws from the kernel function. If Δ^*_j is drawn from [A B] or [2 – A 2 - B], the ith row of ε^* is from $N\left(0,,\hat{\Sigma}\right)$, but if ε^* is drawn from [2 – A B] or [A 2 – B], the ith row of ε^* is from $N\left(0,\hat{\Sigma}_R\right)$.

Step 6: Compute (N x 2) matrix

$$\Gamma = (1+h^2)^{-1/2}\left(\Delta^* + h\varepsilon^* - C\begin{bmatrix} \bar{\delta}_{.1} & 0 \\ 0 & \bar{\delta}_{.2} \end{bmatrix}\right) + C\begin{bmatrix} \bar{\delta}_{.1} & 0 \\ 0 & \bar{\delta}_{.2} \end{bmatrix}$$

where C is (N x 1) of unit values which gives a (N x 2) of bivariate deviates from the estimated density of Δ and ε^* is an (N x 2) containing N independent draws from the kernel function $K_j(.)$.

Step 7: For each element of $\gamma_{i,j}$ of Γ set; $\gamma^*_{i,j} = \gamma_{i,j} \geq 1$ or $2 - \gamma_{i,j}$ otherwise. The (N x 2) matrix $\Gamma^* = [\gamma^*_{i,j}]$ contains simulated distance function values.

Step 8: Pseudo samples ℓ^* are then constructed by setting $x^*_{it,j} = \gamma^*_{i,j} x_{i,t} / \hat{d}_t(y_{it}, x_{it})$ and $y^*_{it,j} = y_{it,j}$ for *i* = 1, 2, ..N and j = 1,2.

Step 9: Compute the four distance functions;

$\hat{d}_t^*(y_{it}^*, x_{it}^*), d_{t+1}^*(y_{it}^*, x_{it}^*), d_t^*(y_{it+1}^*, x_{it+1}^*), d_{t+1}^*(y_{it+1}^*, x_{it+1}^*)$. Repeat steps 3 to 9 B times to get a set of B bootstrap estimates.

Appendix 3

Median Values	Model 1 - 2007/6				Model 5 – 2007/2006			
2000 bootstraps	**TFP**	**Boot**	**L-B**	**U-B**	**TFP**	**Boot**	**L-B**	**U-B**
State Owned Banks								
ICBC	0.94	0.94	0.91	0.96	0.93	0.92	0.91	0.93
CCB	0.81	0.84	0.79	0.91	1.01	1.04	0.96	1.14
ABOC	3.91	2.60*	1.75	3.69	1.12	1.08	1.00	1.12
BOC	0.97	0.95	0.89	1.00	1.02	1.03	0.98	1.09
Bank of Communications	3.09	2.03*	1.35	2.80	0.79	0.78	0.76	0.79
Joint Stock Banks								
China Merchant Bank	0.94	0.94	0.88	1.00	0.97	0.99	0.95	1.03
China Minsheng Bank	0.90	0.87	0.82	0.92	0.95	0.92	0.88	0.96
CITIC	0.85	0.86	0.82	0.91	0.70	0.69	0.66	0.70
SPDB	0.95	0.95	0.89	1.01	0.91	0.87	0.80	0.94
IBC	0.74	0.65*	0.59	0.72	0.88	0.84*	0.82	0.87
EVRBRT	0.89	0.90	0.84	0.95	0.83	0.79	0.72	0.85
HUAXIA	0.79	0.74	0.68	0.81	0.92	0.92	0.88	0.96
GDB	0.92	0.92	0.89	0.93	0.79	0.78	0.73	0.83
Shenzhen Develop Bank	0.97	0.99	0.97	1.02	0.92	0.92	0.89	0.95
City Commercial Banks								
BEIJING	0.70	0.75	0.70	0.79	0.70	0.72	0.67	0.75
SHANGHAI	0.98	0.93	0.87	1.01	0.92	0.92	0.86	0.94
Shenzhen Pin An	0.86	0.97	0.85	1.12	0.81	0.91*	0.85	0.93
TIANJIN	0.63	0.61	0.57	0.65	0.67	0.69	0.64	0.70
NANJING	0.89	0.90	0.85	0.94	0.94	0.96	0.90	1.00
DONGUAN	0.78	0.78	0.75	0.84	0.92	0.89	0.83	0.97
WUXI								
CHONQING	0.80	0.77	0.74	0.81	0.79	0.80	0.79	0.81
XIAMEN	0.97	1.06	0.94	1.21	1.00	1.00	0.90	1.13
NINGBO	0.91	0.94	0.91	0.96	0.98	1.00	0.96	1.05
XIAN								
WUHAN	0.90	0.95	0.92	0.98	0.83	0.90*	0.85	0.91
QINGDAO	0.93	1.03*	0.95	1.11	0.76	0.80	0.75	0.84
JINAN	0.95	1.00*	0.97	1.00	0.76	0.81*	0.77	0.81
DALIAN	0.98	1.09*	1.00	1.18	0.51	0.57	0.51	0.63
HANGZHOU	1.01	1.06	0.99	1.14	0.87	0.88	0.83	0.92

CHANGSA	1.35	1.42	1.33	1.54	0.93	0.98	0.87	1.05
FSB	0.87	1.00*	0.90	1.09	0.84	0.87	0.83	0.92
SHIJIAZHUANG	0.96	1.00	0.94	1.05				
SHAOXING	0.83	0.85	0.81	0.89	0.75	0.76	0.73	0.76
JINZHOU								
LAIWU	0.98	0.94	0.88	0.99	0.73	0.70	0.65	0.73
JIUJIANG	0.82	0.87	0.77	1.00	0.40	0.46*	0.41	0.52
PANZHIHUA	0.92	1.03*	0.93	1.10	0.64	0.64	0.64	0.66
DONGYING	0.88	0.80*	0.74	0.86	0.92	0.82*	0.82	0.87
ZENGZHOU	0.76	0.76	0.75	0.78	1.01	1.03	1.01	1.03
WEIFANG	0.90	0.96	0.87	1.07				
UNITED OVERSEAS	1.29	1.42	1.19	1.84				
LINYI	1.02	1.13*	1.05	1.20	1.18	1.20	1.16	1.22
XINXIANG	0.89	0.88	0.83	0.91	0.86	0.84	0.79	0.88
LIUZHOU	0.86	0.86	0.85	0.88	0.79	0.79	0.75	0.79
HUZHOU	0.87	0.87	0.85	0.89	0.87	0.86	0.84	0.88
KARAMAY	0.85	0.79	0.71	0.89	3.44	2.67*	2.27	3.26
HUANGSHI	0.84	0.84	0.81	0.88	0.76	0.77	0.73	0.78
XUCHANG	0.96	0.97	0.91	1.02	0.97	0.98	0.91	1.01
JINING	1.02	1.07	1.01	1.12	0.78	0.73	0.67	0.80
CHENGDE	0.69	0.72	0.65	0.81	0.61	0.60	0.55	0.64
HENGYANG	1.02	1.12	1.01	1.23	1.40	1.48	1.26	1.68
GANZHOU	0.82	0.82	0.80	0.85	0.68	0.69	0.66	0.70
GUILIN	0.81	0.79	0.76	0.83	0.63	0.63	0.62	0.63
NIANYANG	0.85	0.86	0.83	0.89	0.78	0.80	0.78	0.80
JIAOZUO	3.41	1.58*	1.34	1.99	2.78	1.72*	1.21	2.53
DEYANG	0.77	0.78	0.72	0.86	0.87	0.87	0.84	0.87
ZHEJIANG MINTAI	0.68	0.68	0.62	0.74	0.98	0.98	0.97	0.98
ZHEIJIANG CHOUZHOU	0.90	0.93	0.89	0.99	1.01	1.01	1.01	1.03
ZHANJIANG	0.81	0.87	0.81	0.92	0.56	0.56	0.50	0.62
JIAXING	0.93	0.97	0.92	1.01	0.93	0.91	0.83	0.98
ZHEJIANG TAILONG	0.87	0.88	0.86	0.91	0.81	0.81	0.78	0.82
WEIHI	0.73	2.00*	1.31	2.85	0.41	0.93*	0.69	1.14

* indicates significant bias at the 95% confidence interval