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How relevant is the choice of risk management control variable to non-parametric bank profit efficiency analysis? The case of South Korean banks

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Abstract Adopting a profit-based approach to the estimation of the efficiency of South Korean banks over the 2007Q3 to 2011Q2 period, we systematically analyse, within a non-parametric DEA analysis, how the choice of risk management control variable impacts upon such estimates. This is in recognition of previous findings that such estimates are dependent on the choice of risk management control variable and the lack of guidance from such studies on the optimal choice of risk control variable. Using the model of Liu et al. (Ann Operat Res 173:177–194, 2010), we examine the dependency of the estimated efficiency scores on the chosen risk control variables embracing loan loss provisions and equity as good inputs and non-performing loans as a bad output. We duly find that, both for individual banks and banking groups, the mean estimates are indeed model dependent although, for the former, rank correlations do not change much at the extremes. Based on the application of the Simar and Zelenyuk (Econom Rev 25:497–522, 2006) adapted Li (Econom Rev 15: 261–274, 1996) test, we then find that, if only one of the three risk control variables is to be included in such an analysis, then it should be loan loss provisions. We also show, however, that the inclusion of all three risk control variable is to be preferred to just including one, but that the inclusion of two such variables is about as good as including all three. We therefore conclude that the optimal approach is to include (any) two of the three risk control variables identified. The wider implication for research into bank efficiency is that the optimal choice of risk management control variable is likely to be crucial to both the delivery of risk-adjusted estimates of bank efficiency and the specification of the model to be estimated.

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1 Introduction

The dependency of bank efficiency estimates within a data envelopment analysis (DEA) on the specification of the input/output relationship is well known (see, for example, Drake et al. 2009 for analysis of the issue within a Japanese context). Moreover, there is wide awareness within the research community—see below at Sect. 2—of the need to incorporate risk management control variables within such models if risk-adjusted efficiency estimates are to be produced. However, little empirical research has been undertaken to examine the sensitivity of such estimates to the choice of risk control variable.[1] Accordingly, this study, as far as we are aware, represents the first to systematically address this issue, within a Korean context, using a recently released rich data set covering the development of the South Korean banking industry during the period 2007Q3 to 2011Q2. This period, of course, traverses the pre, actual and post—Global Financial Crisis (GFC) eras, thus allowing for interesting inter-temporal comparisons.

In terms of the input/output specification, we have opted for the 'profit-based' approach, pioneered by Berger and Humphrey (1997) and Berger and Mester (1997, 2003), in preference to the so-called 'production' and 'intermediation' approaches developed by Benston and Smith (1976) and Sealey and Lindley (1977), respectively. The profit-based approach is a relevant approach for banking systems that are open, highly-developed and competitive, as in South Korea (see Hall and Simper 2013; Doh 2012; Ree et al. 2012). Moreover, as argued by Berger and Mester (1997), the profit-based approach might be viewed as superior to other approaches because it takes account of inefficiencies on both the input and output fronts. Note that while Berger and Humphrey (1997) and Berger and Mester (1997) designed their profit-based approach in the context of parametric stochastic frontier analysis, we use an adaptation of this approach within a DEA (non-parametric) setting that was first used by Drake et al. (2006).

The need to include risk control variables within an analysis of Korean bank efficiency was highlighted by Korea's experience with the GFC. Given the Korean banks' dependence on overseas markets for the funding of domestic loans[2] and the deterioration in asset quality,[3] management control of interest rate, exchange rate and liquidity risks was at a premium alongside credit risk management.

As for the selection of risk management control variables to be included in the analysis, the standard variables available from the banks' published reports and accounts embrace:

[1] One such study was undertaken by Hadad et al. (2012) who examined the sensitivity of bank efficiency scores to the choice of risk control variable (i.e., loan loss provisions or equity) within an Indonesian context.

[2] During the GFC, long-term overseas borrowing by Korean banks declined dramatically as international funding markets dried up, falling from US \$11.3 billion in 2007 to US \$6.23 billion in 2008 and then to US \$4.25 billion in 2009.

[3] Korean banks' 'substandard' loans rose from 0.72 % of total loans in December 2007 to 1.9 % by December 2010. This subsequently led to the establishment of a government bank recapitalisation fund with an endowment of 20 trillion Korean Won (KRW) (US \$13.5 billion) and the provision of a government guarantee to over US \$100 billion of banks' overseas borrowings.

'Loan Loss Provisions' (LLP),[4] which directly affect profits through the banks' income statement; 'Equity', which is accumulated on the liabilities side of the balance sheet and directly affects the cost of banks' risk-taking; and, finally, 'Non-performing Loans' (NPL), for which accounting definitions differ across financial systems worldwide.[5] Like most other authors—see Sect. 2—we focus on these three variables in our analysis, but use a relatively-new non-parametric model proposed by Liu et al. (2010) that allows for the inclusion of both 'desirable' inputs (i.e., LLP and Equity) and 'undesirable' outputs (i.e., NPL) within a profit-based approach to efficiency estimation.

By way of comparison with earlier related papers, Chiu and Chen (2009) include the summation of different internal risks by incorporation of a risk variable directly into the DEA programme as an input as well as external risk through a 3 stage approach. Our study differs in that we include all these different internal risks separately and then determine which variable should be included when considering the final optimal model in relation to the efficiency of Korean banks. (Indeed, the authors' modelling technique follows closely the 3-stage slacks-based DEA programme advanced by Drake et al. (2006) using Tobit to include different external risk factors to adjust the inputs. However, it has been noted in the literature that such a procedure can introduce bias into the new re-calculated efficiency scores (see, for example, Simar and Wilson 2007). In a more recent study, Sun and Chang (2011) again extended the modelling procedure by incorporating three different risk variables (loan loss reserves, ROA volatility and equity) in the estimation of four different models. Of these models, three include these risk variables separately and then a final model jointly includes all three variables. Interestingly, they find that all four models affect bank efficiency in potentially different ways but cannot tell us which model is the most preferred and therefore which risk variable(s) should be included. Furthermore, whether other risk variables, for example, non-performing loans (see Barros et al. 2012), could be included not as standard inputs/outputs but under the guise of a bad output is also an important consideration when modelling banks. Hence, the aim of our paper is to answer the above questions in addition to using an innovative nonparametric programme allowing these risk variables to enter as either bad/good inputs/outputs separately or in different combinations.

Finally, using a version of the Li (1996) test (adapted to DEA by Simar and Zelenyuk 2006), we are able to get statistical evidence on whether the different models, reflecting the different input/output specifications, produce significant differences in X-efficiency distributions, which in turn helps decide which variables to exclude/include in our systematic modelling strategy.

The paper is organised as follows. In Sect. 2 we briefly discuss the background to the inclusion of risk management control variables in bank efficiency studies. Section 3 describes our non-parametric modelling methodology which allows all and sub-sets of the risk management control variables to be included in efficiency estimation and also how we distinguish between the different estimated modelling distributions. Section 4 presents the results of

[4] "The amount of losses which have been specifically identified is recognized as an expense and deducted from the carrying amount of the appropriate category of loans and advances as a provision for losses on loans and advances. The amount of potential losses not specifically identified but which experience indicates are present in the portfolio of loans and advances is also recognized as an expense and deducted from the total carrying amount of loans and advances as a provision for losses on loans and advances" (International Accounting Standard IAS 30).

[5] An NPL under Basel II (Committee 2004) is any loan that is past due for more than 90 days, but it is subject to wide national variation. If we consider how many days a bank has to allow for a 100 % consumer loan write-down as a non-performing loan in South America, it is 366 days in Argentina, 180 in Chile, 90 in Columbia, 120 in Ecuador, 126 in Mexico and 120 in Peru (for more details see Galindo and Rojas-Suarez 2011).

our analysis of South Korean banking profit efficiency, looking at how scores change (if at all) under the different postulated specifications. Finally, in Sect. 5 we summarise and conclude.

2 Risk management control variables used in the bank efficiency empirical literature

Taking each of the three risk management variables commonly used in the literature in turn, the use of Loan Loss Provisions (LLP) as a risk control variable can lead to problematic modelling if one is considering diverse banks with large differentiated outputs and also if making a cross-country comparison of banks. In the latter case, differing corporate governance, tax and supervisory issues in each financial jurisdiction govern how directors of the banks are able to adjust LLP and hence, by definition, manipulate profits. However, there is some confusion in the literature on whether LLP is a bad or good input. Our position that it is a good input is based upon the three main theories as to why banks utilise LLP (in which the calculation of LLP is comprised of both specific and general provisions (based on estimates of losses yet to be identified—see Bikker and Metzemakers 2005). The first, 'capital management', concerns managers increasing LLP to increase loan loss reserves and the capital position (Tier II) of the bank to cover possible future loan losses, hence bringing capital stability to the bank through the use of a capital buffer (see, for example, Ghosh 2007). The second, 'cyclical management', posits that banks can use LLP as a procyclical capital buffer, whereby in booms LLP is used to manipulate retained earnings leading to increases in the capital account (Tier I), a process followed by all Spanish banks (under the term 'dynamic provisioning'); see Mann and Michael (2002) and Wezel et al. (2012). Thirdly, LLP can be used for 'income smoothing' purposes, thereby reducing the negative impacts of asset volatility across the business cycle on bank capital (see Borio et al. 2001; Anandarajan et al. 2007). Indeed, reporting stability in income streams can signal X-efficiencies and could affect stock price stability and external rating performance, as well as lowering funding costs and increasing management bonuses and salaries (Bikker and Metzemakers 2005). Furthermore, banks with less fluctuating incomes are less susceptible to regulators' attention and strict monitoring (Anandarajan et al. 2007), thereby again rendering LLP a good input.

With respect to equity, Berger and Mester (1997, 2003), Fan and Shaffer (2004), Park and Weber (2006), Akhigbe and Stevenson (2010), Han et al. (2012) and Wheelock and Wilson (2012) all include this as an input to account for a bank's solvency, which is routinely subject to regulatory scrutiny and control.[6] The equity to total assets ratio has also been widely used in European cross country bank studies, including those by Bos and Schmiedel (2007) and Kosak and Zoric (2011), and, in a study concerning central and Eastern European banks, by

[6] One of the first bank efficiency studies to include equity as a risk variable was that of Hughes and Mester (1993), who argued that, "recognizing that financial capital is an input but omitting it in the cost function is equivalent to assuming that the unit price of financial capital is perfectly correlated with one of the other input prices or is the same for all banks (and so its price need not be included separately in the cost function), and that the level of financial capital is determined endogenously as that level which minimizes cost. If we believed that the bank were operating with the cost-minimizing level of financial capital but that the price of financial capital and price of deposits differed, we would include the unit price of financial capital in the cost function. However, there is good reason to suspect that the level of financial capital a bank holds may not be explained entirely by cost minimization. First, regulators set a minimum capital-asset ratio for banks and this may constrain banks from operating at the cost-minimizing financial capital level. Second, if the bank exhibits some risk aversion, then, because lower capital implies higher probability of default (capital acts as a cushion for losses), banks may choose a noncost-minimizing level of financial capital" (pp. 295–296).

Koutsomanoli-Filippaki et al. (2009) who argue that "another issue in the efficiency literature is the treatment of financial capital, which accounts for different risk preferences. If financial capital is ignored, the efficiency of banks that may be more risk averse than others and may hold a higher level of financial capital would be mismeasured, even though they are behaving optimally given their risk preferences" (p. 561). And, with respect to an analysis of 55 Gulf Cooperation Council banks, Ramanathan (2007) denotes equity as an input in his non-parametric specification.

Finally, use of Non-performing Loans (NPL)[7] as a risk control variable also creates difficulties as this variable does not directly affect profits and is just an accounting measure. As such, Berger and Mester (2003) treat it as an environmental variable calculated as the "market-average of nonperforming loans (past due at least 90 days or on a non-accrual basis) divided by total loans"—hence being common across all banks.[8] Studies that endogenise NPL in the production programme include Akhigbe and Stevenson (2010), who argue that it is a measure of the current operating environment and "accounts for negative (and positive) external shocks to the Bank Holding Company's (BHC's) operating environment not under the control of the BHC's management" (p. 135). While Fan and Shaffer (2004) note that NPL are "included as a measure of credit risk, which could reflect a combination of exogenous environmental (market) characteristics, variations in the quality of banks' management and shirking, and strategic decisions to accept and price differing levels of credit risk" (p. 6).[9]

3 Modelling methodology and data

3.1 DEA models with undesirable inputs and outputs

To facilitate our analysis of the technology of South Korean banking, let x and y represent vectors of inputs and outputs, respectively, pertinent to the production technology of banking services in South Korea and assume that this technology can be characterised by the technology or Production Possibility Set (P),

$$P \equiv \{(x,\ y) : x \text{ can produce } y\}. \tag{1}$$

This set is unobserved to a researcher but can be estimated using the actual data on inputs and outputs via Data Envelopment Analysis (DEA), which is a non-parametric method to identify the 'best-practice' frontier rather than the central-tendency. The DEA can directly use input/output data to evaluate the relative efficiencies of decision-making units (DMUs)

[7] One of the first bank efficiency studies to include non-performing loans was Mester (1996) who argued that "while the macroeconomy can affect nonperforming loans, it is felt equally across banks. It is the differences in nonperforming loans across banks that capture differences in quality across banks" (p. 1035). The inclusion of nonperforming loans was therefore included, along with equity, in a stochastic cost frontier model to account for bank risk.

[8] In another study, "the bad output of non-performing loans is defined as the sum of problem loans, which are part of the total loans. Problem loans are computed by adding the balance of loans to bankrupt borrowers and the balance of non-accrual delinquent loans" (Fukuyama and Weber 2008, p. 1860).

[9] Indeed, when undertaking a single country efficiency analysis utilising risk control variables, NPL could be a better risk indicator then either LLP or equity—see also Barros et al. (2012). However, in future, this condition could change as, under Basel III, banks are able to decrease NPL as borrowers begin to repay loans, even though the bank had previously classified the loan as bad. These new rules have not, as yet, been implemented by Korea and, as such, and as such have no effect on banks' calculations of NPL across our sample period.

using piecewise linear approximation of the frontier of technology set (1) presumed to have generated the data. The DMUs that appear on the estimated DEA frontier are classified as efficient units. Since its introduction by Charnes et al. (1978), the Charnes, Cooper and Rhodes (CCR) model has become a popular tool of performance evaluation in many areas, and research on performance in banking in particular, and we follow this paradigm.

Recently, many researchers have proposed different types of DEA models to deal with undesirable inputs and/or outputs when evaluating the performance of DMUs with such characteristics. The existing models can be broadly categorized into two types. One type applies transformations, such as the so-called 'ADD' approach, proposed by Koopmans (1951), the linear transformation (adopted by Ali and Seiford 1990; Pastor 1996; Scheel 2001; Seiford and Zhu 2002), and the 'multiplicative inverse' (adopted by Golan and Roll 1989; Lovell et al. 1995).[10] The other type uses a type of assumption on disposability, such as 'Weak Disposability' (see Färe and Grosskopf 2004) and 'Extended Strong Disposability' in the case of undesirable inputs and outputs (see Liu et al. 2010).

In terms of theory, loans that were made some time ago but thought to be defaulted on, but now are being repaid (due to positive external factors affecting the borrower, such as obtaining employment after a spell of unemployment), are a desirable output; whereas, for a borrower who is still in default, the loan is an undesirable output—leading to a decrease in or an increase in the level of specific LLP, respectively. This is deemed 'free disposability', as reducing LLP frees up funds to create more outputs (loans). In the case of Extended Strong Disposability, again using loans as an output, Equity can be linked to loan losses and also good risk management. That is, loans can be increased if the bank holds sufficient equity to absorb the potential extra loan losses. The latter situation is different to that discussed in Färe et al. (1989), where they assume that strong disposability is not possible with respect to bad outputs (in the general case, studies in the literature concern energy generation with the bad output being pollution)—implying they cannot be freely disposed of. In our example, as the bank has already provisioned for the bad output (loans) in a previous period, it has no effect on the current balance sheet of the bank involved in the disposal of the bad loan.

However, it should also be noted that, even though Extended Strong Disposability is assumed to be bounded in non-banking industries, this might not be true in the banking world. That is, if bounded, this implies that loan losses are limited to equity reserves, when the bank subsequently enters bankruptcy. But, with respect to South Korean banks, the Global Financial Crisis (GFC) saw the government create the Bank Recapitalisation Fund with KRW20 trillion (US \$13.5 billion) of funding, 4KRW trillion of which was used to buy subordinated and hybrid securities from 8 banks. Given the increasing NPL from household loans and loans to Small and Medium Enterprises (SMEs) in 2009/2010, the government also guaranteed all SME loans made by banks through the Korea Credit Guarantee Fund, meaning that no bank failed. Indeed, guarantee schemes were common across many countries as they stabilised banking systems to ensure that the 'too-big-to-fail' banks were still operational. For example, in the US, \$250 billion of the \$700 billion of the 'Troubled Asset Relief Program'(TARP) funding was used to recapitalise the US banking system, with Citigroup and Bank of America subsequently receiving additional TARP funding. Assuming, however, 'possible' bounded limits on the undesirable inputs and outputs and variable returns to scale technology, the estimated technology set can be written as follows:

[10] See Liu and Sharp (1999) for further discussions.

$$\hat{P} = \left\{ \left(x^D, x^U, y^D, y^U\right): \right.$$
$$x^D \geq \sum_{j=1}^{n} \lambda_j x_j^D, x^U \leq \sum_{j=1}^{n} \lambda_j x_j^U, y^D \leq \sum_{j=1}^{n} \lambda_j y_j^D, y^U \geq \sum_{j=1}^{n} \lambda_j y_j^U,$$
$$\left. \sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \geq 0, \forall j = 1, \ldots, n \right\} \tag{2}$$

where $x_j = (x_j^D, x_j^U)$, $y_j = (y_j^D, y_j^U)$ are (vectors of) desirable and undesirable inputs and outputs of the jth DMU, respectively; see Liu et al. (2010).

By assuming Extended Strong Disposability, we can regard the undesirable inputs as desirable outputs, and/or the undesirable outputs as desirable inputs, and then use the standard Strong Disposability assumption (Liu et al. 2010). From this point of view, we can derive DEA models of radial type efficiency for undesirable inputs and outputs, and the extra performance of a decision making unit with allocation (x_0, y_0) can be found by solving the following CCR-type input-oriented DEA model:

$$\begin{aligned}
&\hat{E}(x_0, y_0) = \min \quad \theta \\
&\text{subject to:} \quad \sum_{j=1}^{n} \lambda_j x_{ij}^D \leq \theta x_{i0}^D, \quad i = 1, \ldots, m_D, \quad \sum_{j=1}^{n} \lambda_j x_{ij}^U \geq x_{i0}^U, \quad i = 1, \ldots, m_U, \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj}^U \leq \theta y_{r0}^U, \quad r = 1, \ldots, s_U, \quad \sum_{j=1}^{n} \lambda_j y_{rj}^D \geq y_{r0}^D, \quad r = 1, \ldots, s_D, \\
&\qquad \theta \geq 0, \quad \lambda_j \geq 0, \quad j = 1, \ldots, n.
\end{aligned} \tag{3}$$

This model presumes constant returns to scale (CRS) technology and relates to what we will refer to as CCR-efficiency. By adding the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ to the optimization problem (3), we obtain the so-called BCC-type efficiency scores that allow for variable returns to scale (VRS) technology. To save space, we will focus here on the BCC-efficiency, since most of the conclusions are the same for both approaches for our sample (see note 15 below).

3.2 Adapted Li test for analysing the different models

There are different ways of making formal comparisons or tests between results from different models. The simplest, perhaps, is the comparison of the means (i.e., first moments of distributions) and another simple and popular approach is the comparison of variances (i.e., second moments). The approach we take here as the main tool is to compare the distributions of efficiency scores from different models by estimating the corresponding densities and testing their equalities. For this purpose we use the testing ideas of Li (1996, 1999), based on kernel-density estimators and bootstrap, and in particular, its adaptation to DEA context from Simar and Zelenyuk (2006). Note that this test is often used to test the equality of distributions from different samples, but it is general enough to test the equality of distributions of a variable from the same sample that passed through different estimators. The idea of such an application is similar in spirit to many statistical tests, where different estimators are used for estimating the same target in different ways and the question is whether the difference they yield for a particular sample is due to the estimation noise or is systematic.

To be precise, let $\left\{\xi_j^A : j = 1, \ldots, n\right\}$ be a set of efficiency scores obtained using DEA for a model, call it model A, for a given sample of observations on banks $\left\{\left(x_j, y_j\right) : j = 1, \ldots, n\right\}$ and let $\left\{\xi_j^Z : j = 1, \ldots, n\right\}$ be another set of efficiency scores obtained using DEA with the same sample but for a different model, call it model Z.

Let f_A and f_Z be the two probability density functions corresponding to $\left\{\xi_j^A : j = 1, \ldots, n\right\}$ and $\left\{\xi_j^Z : j = 1, \ldots, n\right\}$, respectively with distribution functions F_A and F_Z, respectively, that are absolutely continuous with respect to the Lebesgue measure. We are interested in testing the null hypothesis H_o: $\Pr\{f_A(\xi) = f_Z(\xi)\} = 1$ (i.e., $f_A(\xi) = f_Z(\xi)$ almost everywhere) against the alternative $H_1 : f_A(\xi) \neq f_Z(\xi)$ on a set of positive measure.[11] In our analysis we wish to examine if any of the eight different model variations discussed below result in significantly differing distributions. We will adopt Algorithm II from Simar and Zelenyuk (2006) where any DMU that scores one and hence is deemed to be on the frontier has its score 'smoothed' away from the frontier by the addition of small noise. That is, more formally, when we have desirable and undesirable inputs and outputs, $x_j = (x_j^D, x_j^U)$ and $y_j = (y_j^D, y_j^U)$, then the original estimates in each model permutation for the efficiency scores $\hat{E}(x_j, y_j)$ are smoothed in the following ways:

$$\hat{E}^*\left(x_j, y_j\right) = \begin{cases} \hat{E}\left(x_j, y_j\right) + \varepsilon_j & if\ \ \hat{E}\left(x_j, y_j\right) = 1 \\ \hat{E}\left(x_j, y_j\right) & otherwise \end{cases} \tag{4}$$

where the smoothing parameter, ε_j is selected as described in Simar and Zelenyuk (2006).

The next section presents our preferred banking model and the different risk variables and model permutations estimated to analyse whether the use of different risk control variables makes a significant difference to the results.

3.3 Data choice and banking model motivation

With the profit-based approach in mind, we specify eight different models (each using 272 bank observations)—see Table 1—which use a combination of traditional inputs/outputs, potentially including up to two 'good inputs' and one 'bad output'. Our choice of inputs follows Berger and Mester (1997), Drake et al. (2006) and Wheelock and Wilson (2012), where Korean banks utilise 'general admin and other expenses' ('Input 1' in our models) and, due to the international nature of their banking model, 'fee and trading expenditure' ('Input 2') to produce outputs. As Filardo (2011) notes when commentating on the South Korean banking system during the GFC, "one interesting feature of the international financial crisis was the severe disruption in international, especially US-dollar-denominated, money and capital markets. The disruptions raised financing costs faced by borrowers in Asia and the Pacific, which intensified the impact of the break in confidence. Huge gross U.S.-dollar-denominated exposures in economies such as Korea proved very costly as Asian currencies depreciated. The disruptions happened in three ways: by directly reducing the availability of offshore credit to Asia-Pacific residents; by increasing demand from non-residents to borrow in Asia-Pacific markets; and by leading market-makers to scale back their activities" (p. 10). That is, before the GFC, the loan-to-deposit ratio was particularly high, as domestic lenders sought out investments that offered higher returns than the domestic banks. The domestic banks therefore relied on non-deposit funding, which saw increases pre-GFC from 103 % (in December 2005) to 127 % in December 2007 but, after the implementation of new

[11] We also assume the regularity conditions from Li (1996, 1999) and Simar and Zelenyuk (2006) are satisfied.

Table 1 Summary statistics and model specifications (KRW millions)

	Input 1 General admin and other expenses	Input 2 Fee and trading expenditure	Good input 1 Loan loss provisions	Good input 2 Equity	Bad output 1 Non performing loans	Output 1 Net interest revenue	Output 2 Fee and trading income	Output 3 Other operating revenues
Minimum	10,447	430	26,058	142,831	14,498	17,204	1,057	287
Mean	1,885,352	93,546	654,655	3,573,595	912,627	311,233	1,721,623	1,508,540
Maximum	30,370,602	6,327,362	66,188,273	20,231,684	11,807,233	1,935,890	29,707,369	29,467,597
Std dev	3,907,277	471,881	13,088,737	5,752,583	2,123,081	451,664	3,892,166	3,851,159
Model 1	Input 1	Input 2	Good input 1	Good input 2	Bad output 1	Output 1	Output 2	Output 3
Model 2	Input 1	Input 2			Bad output 1	Output 1	Output 2	Output 3
Model 3	Input 1	Input 2	Good input 1	Good input 2		Output 1	Output 2	Output 3
Model 4	Input 1	Input 2	Good input 1		Bad output 1	Output 1	Output 2	Output 3
Model 5	Input 1	Input 2		Good input 2	Bad output 1	Output 1	Output 2	Output 3
Model 6	Input 1	Input 2		Good input 2		Output 1	Output 2	Output 3
Model 7	Input 1	Input 2				Output 1	Output 2	Output 3
Model 8	Input 1	Input 2	Good input 1			Output 1	Output 2	Output 3

'CAMEL'[12] regulations on the banks, non-deposit funding dropped to 112 % in December 2009 and then to 98 % in December 2010 (Korean Financial Supervisory Service (FSS) Annual Report 2010). Thus, there is an obvious need to include 'fee and trading expenditures' in our model specification, especially given the South Korean banks' need to engage in foreign currency hedging; see Ree et al. (2012).[13] The summary statistics of the variables utilised in the respective profit approach models are given in Table 1.

Following Drake et al. (2009), on the output side we allow South Korean banks to gain profits from the 'net interest revenue' ('Output 1') on intermediated funds, 'fee and trading income' ('Output 2') and, finally, from 'other operating revenues' ('Output 3'), the last-mentioned relating to the increasing importance of off-balance-sheet trading in Korean banking. Finally, as part of our addition to the literature concerning the nature of risk management in banking and how this should be taken into account when modelling banks, we use different permutations of good inputs—'loan loss provisions' ('Good Input 1') and 'equity' ('Good Input 2')—and the bad output of 'non-performing loans' ('Bad Output 1'), including the case where none of the risk management control variables is included (Model 7). In Model 1, for example, both good inputs and the bad output are included; whilst 'Good Input 1' also features in Models 3, 4 and 8. Meanwhile, 'Bad Output 1' features in Models 1, 2, 4 and 5; and 'Good Input 2' features in Models 1, 3, 5 and 6. The next section presents our results.

4 Results

4.1 Analysis of the efficiency scores of the South Korean banking industry

The mean radial BCC—efficiency estimates for all banks and groups across the sample period 2007Q3 to 2011Q2 are presented in Table 2. Given that these scores are averaged before, during and after the Global Financial Crisis (GFC), they offer a simple, yet informative narrative on which banks and groups performed relatively-well compared to their competitors and also whether there were any dramatic changes in ranks or scores across the eight models. As can be seen from Table 2, SC First Bank was consistently the most efficient across all models (apart from Model 7), followed by the Korea Exchange Bank, and the least efficient were the National Federation of Fisheries Cooperative and Kwangju Bank (15th or 16th). It is also apparent overall that the most efficient sector was that of the Commercial Banks, followed by the Specialist Banks, and then by the Regional Banks (excluding an outlier 'best' performer, Jeju Bank). Finally, in relation to the average individual bank efficiency rank correlations, all are significant at the 1 % level across all the models. An indication of robustness in individual ranks with respect to small changes in specification is usually a good sign in empirical modelling. As Bauer et al. (1998) point out "efficiency estimates derived from different approaches should be consistent in their efficiency levels, rankings and identification of best and worst firms, consistent over time and with competitive conditions in the market" (p. 87). The results presented in this paper therefore comply with these consistency conditions and, as such, we are satisfied with well specified models whichever risk variable we include in the specification.

12 Denotes capital adequacy (C), asset quality (A), management skill (M), earnings (E) and liquidity (L).

13 The need to include 'fee and trading income' was also noted by Doh (2012). He observes that South Korean capital flows were the most volatile in Asian countries pre and post-GFC, equalling +US \$78 billion between Jan 1995 and Oct 1997, −US \$21 billion between Nov 1997 and April 1998, −US \$70 billion between Sept 2008 and Dec 2008 and −US \$ 82 billion between Jan 2009 and Mar 2010.

Table 2 South Korean banks' mean efficiency scores and ranks over the sample period 2007Q3 to 2011Q2

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Commercial Banks								
Citibank Korea	0.9389 (4)	0.9205 (6)	0.9359 (4)	0.9389 (4)	0.9209 (6)	0.9122 (7)	0.8991 (7)	0.9359 (4)
Hana bank	0.9109 (9)	0.8699 (9)	0.9105 (9)	0.9109 (9)	0.8758 (10)	0.8743 (11)	0.8655 (9)	0.9103 (9)
Kookmin bank	0.9277 (7)	0.9271 (3)	0.9263 (6)	0.9273 (7)	0.9275 (3)	0.9260 (3)	0.9254 (2)	0.9259 (6)
Korea exchange bank	0.9551 (2)	0.9393 (2)	0.9530 (3)	0.9551 (2)	0.9399 (2)	0.9335 (2)	0.9315 (1)	0.9530 (2)
SC first bank	0.9602 (1)	0.9423 (1)	0.9602 (1)	0.9600 (1)	0.9459 (1)	0.9430 (1)	0.9194 (4)	0.9599 (1)
Shin Han bank	0.9327 (5)	0.9234 (4)	0.9303 (5)	0.9327 (5)	0.9235 (5)	0.9228 (4)	0.9226 (3)	0.9303 (5)
Woori bank	0.9323 (6)	0.9207 (5)	0.9251 (7)	0.9299 (6)	0.9247 (4)	0.9188 (5)	0.9123 (5)	0.9215 (7)
Mean	0.9368	0.9205	0.9345	0.9364	0.9226	0.9187	0.9108	0.9338
Regional Banks								
Daegu bank	0.7644 (13)	0.7132 (13)	0.7638 (13)	0.7640 (13)	0.7310 (12)	0.7280 (13)	0.6982 (13)	0.7633 (13)
Jeju bank	0.9535 (3)	0.8925 (8)	0.9531 (2)	0.9421 (3)	0.9098 (8)	0.9054 (9)	0.8723 (8)	0.9409 (3)
Jeonbuk bank	0.6016 (15)	0.5442 (16)	0.6016 (15)	0.6012 (15)	0.5563 (16)	0.5454 (17)	0.5272 (16)	0.6012 (15)
Kwangju bank	0.5906 (16)	0.5606 (15)	0.5903 (16)	0.5905 (16)	0.5687 (15)	0.5658 (16)	0.5574 (15)	0.5902 (16)
Kyoungnam bank	0.7407 (14)	0.7007 (14)	0.7386 (14)	0.7407 (14)	0.7056 (14)	0.6998 (15)	0.6857 (14)	0.7385 (14)
Pusan bank	0.7741 (12)	0.7219 (12)	0.7731 (12)	0.7739 (12)	0.7305 (13)	0.7257 (14)	0.7038 (12)	0.7729 (12)
Mean	0.7375	0.6889	0.7367	0.7354	0.7003	0.6950	0.6741	0.7345
Specialist Banks								
Industrial bank of Korea	0.8446 (11)	0.8182 (10)	0.8444 (11)	0.8429 (10)	0.8245 (11)	0.8242 (12)	0.8142 (10)	0.8413 (10)
Korea development Bank	0.9145 (8)	0.9122 (7)	0.9135 (8)	0.9129 (8)	0.9145 (7)	0.9121 (8)	0.9098 (6)	0.9119 (8)
National agricultural coop fed	0.8946 (10)	0.7923 (11)	0.8938 (10)	0.8196 (11)	0.8946 (9)	0.8938 (10)	0.7899 (11)	0.8186 (11)
National fed of fisheries coop	0.5434 (17)	0.5243 (17)	0.5434 (17)	0.5342 (17)	0.5359 (17)	0.5359 (17)	0.5243 (17)	0.5342 (17)
Mean	0.7993	0.7617	0.7988	0.7774	0.7924	0.7915	0.7595	0.7765

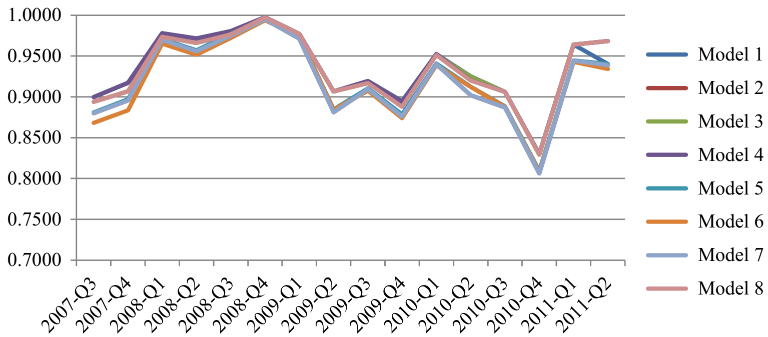

Fig. 1 Commercial banks: mean efficiency scores

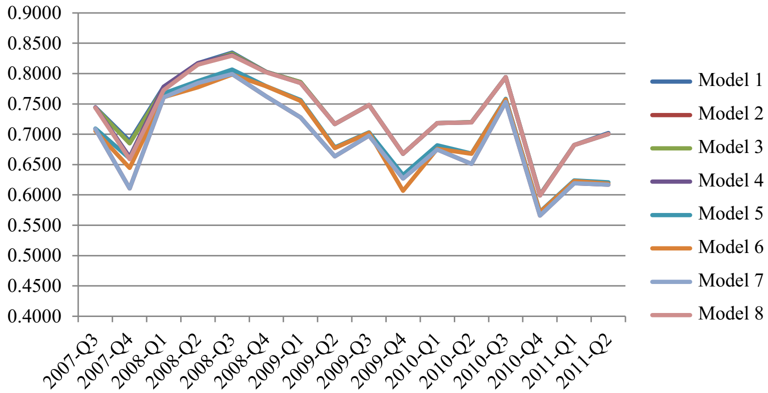

Fig. 2 Regional banks: mean efficiency scores

Figures 1, 2 and 3 present results for the different banking sectors but, instead of averaging over time, we average across each bank within the models. This allows us to determine if there are any differences across models and also how the efficiency scores change before, during and after the GFC. Firstly, there are no appreciable differences across the models in any bank sector, with all within at least a 5 % standard deviation of the scores. In terms of the Commercial and Regional Banks, Models 1 and 8 give the highest and Models 6 and 7 the lowest scores; yet, for Specialist banks, Models 3 and 6 give the highest and Models 7 and 8 the lowest scores. Therefore, the mean BCC—efficiencies of different bank sectors in South Korea are susceptible to which risk management variable(s) is excluded or included in the model, especially in respect of Loan Loss Provisions (LLP), which is included in Models 1, 3, 4 and 8. It also seems that the Specialist Banks do need equity to feature as a risk variable if efficiency scores are to be optimised. These results, if replicated in other countries, pose the question of whether the inclusion of different banking sectors in a complete model is appropriate, given that incorrect (in the sense of not accounting for risk) efficiency scores could be produced.

When we consider how the different models' scores reacted to the GFC, Figs. 1, 2 and 3 show that each sector experienced a profound effect, as seen by the steep falls in efficiency in 2009. The 2008 collapse in the money markets and the subsequent increase in problem loans in 2009 were compounded by increases in the ratio of banks' loans classified as substandard,

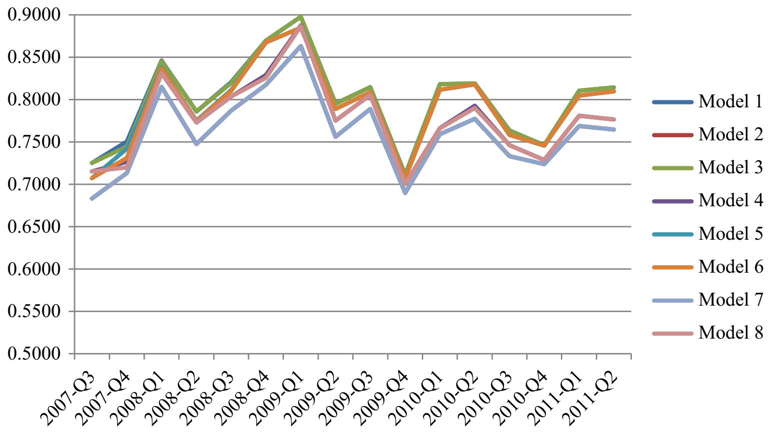

Fig. 3 Specialist banks: mean efficiency scores

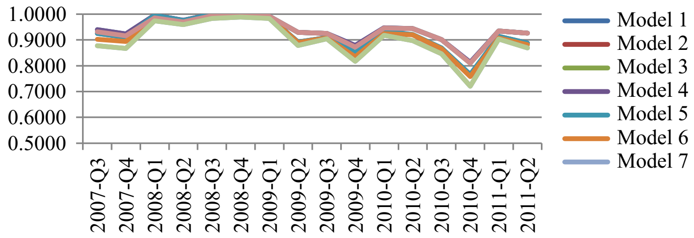

Fig. 4 Citibank Korea

from 0.72 % in December 2007, to 1.14 % in December 2008 and to 1.90 % in December 2010. This subsequently led to the establishment of a KRW20 trillion (US $13.5 billion) government-funded bank recapitalization fund (as noted earlier) and the provision of a government guarantee of US $100 billion covering banks' overseas debts. This restructuring duly led to increases in efficiency from the fourth quarter of 2009.[14] But the turmoil continued due to the on-going bad debt problem in 2010 (for example, 'substandard or below' loans increased from 1.4 % of loans in 2008, to 1.24 % in 2009 and to 1.90 % in 2010 for all banks; FSS Annual Report 2010), leading to significant falls in efficiency for many banks during the latter half of 2010 before recovery ensued.

4.2 Analysis of the efficiency scores of individual South Korean banks

To provide an initial insight into our results we first consider the individual BCC—efficiency scores from the banks in each quarter, covering the period 2007Q3 to 2011Q2, as presented in Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19 and 20 (a full presentation of the results is available from the authors—they are excluded due to space limitations). In terms

[14] Indeed, those banks that sold hybrid and subordinated debt to the bank recapitalisation fund included the commercial banks Woori (KRW1,000 bn), Kookmin (KRW1,000 bn), Hana (KRW 400 bn) and the specialist National Federation of Fisheries (or Suhyup) (KRW100 bn), and the regional banks Kyoungnam (KRW116 bn) and Kwangju (KRW 87 bn). As at end of March 2011, only the commercial banks Woori (KRW300 bn), Kookmin (KRW400 bn) and Hana (KRW100 bn) redeemed the debt from the government as their balance sheets improved post-GFC.

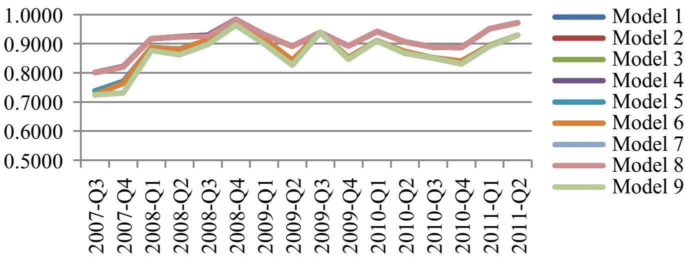

Fig. 5 Hana bank

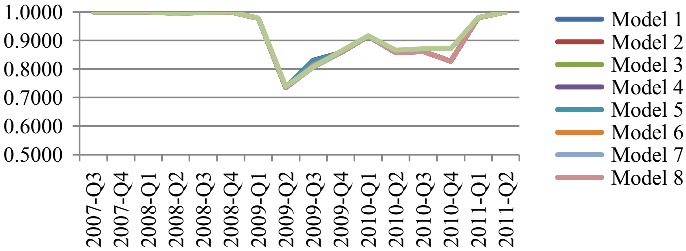

Fig. 6 Kookmin bank

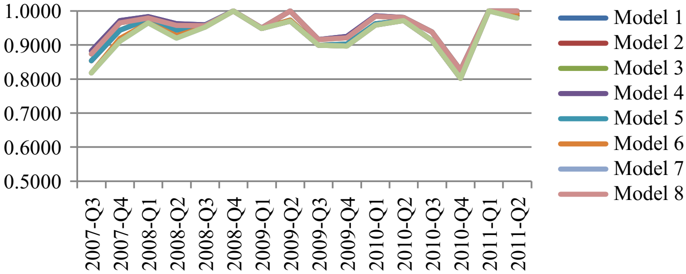

Fig. 7 Korea exchange bank

of the best-performing and most consistent banks in our sample, the Korea Development Bank—a Specialist Bank—stands out as being on or near the frontier during the period 2007Q3 to 2009Q3. However, in 2009Q4, as shown in Fig. 18, there was a quite dramatic collapse in the bank's score, in all models, to between 0.11 and 0.13. In the following year it jumped back to respectable levels, averaging 0.85 (models 1 to 8). This blip is explained by its privatisation where the bank handed over its policy-related assets—mainly equity stakes—and certain liabilities to a new public entity, the Korea Finance Corporation, hence having a profound effect on its balance sheet. The jump back to normality in 2010Q was due to this newly-formed banking entity, 50 %-owned by the Korean government through the Ministry of Strategy and Finance, operating at normal levels relative to its comparators.

The Commercial Banks that exhibited relatively stable scores, averaging over 0.8 in all models and across all quarters apart from a one quarter dip below 0.80, included Citibank Korea (being on or close to the frontier during 2008Q3 to 2009Q1—see Fig. 4), Kookmin Bank (being on the frontier during 2007Q3 to 2008Q4 and in 2011Q2—see Fig. 6), Korea Exchange Bank (being on the frontier in 2008Q4, 2009Q2 and between 2011Q1 to 2011Q2—

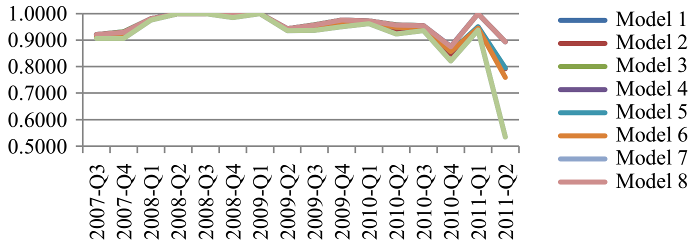

Fig. 8 SC first bank

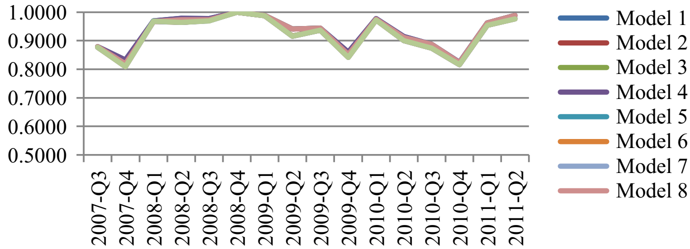

Fig. 9 Shin Han bank

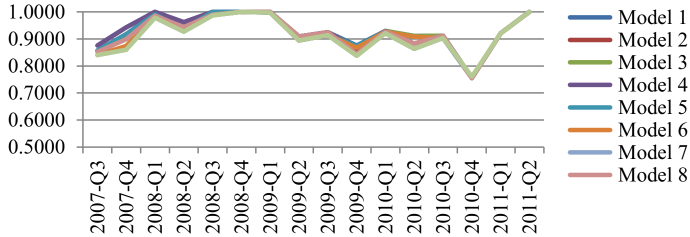

Fig. 10 Woori bank

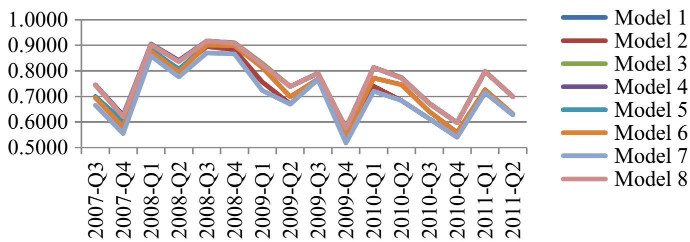

Fig. 11 Daegu bank

see Fig. 7), SC First Bank (on the frontier during 2008Q2 to 2009Q1 and in 2011Q1—see Fig. 8) and Woori Bank (on the frontier during 2008Q3 to 2009Q1 and in 2011Q2—see Fig. 10). Indeed, having weathered the initial storm of the Global Financial Crisis that began in 2008, these commercial banks then found their scores declining due to market turmoil and difficult trading conditions. For example, Kookmin Bank, having been on the frontier during 2007Q3 to 2008Q4, experienced a dramatic decline to 0.7340 in 2009Q2, hovering around an average score equal to 0.85 (across all models) until it picked up again in 2011Q1 to over

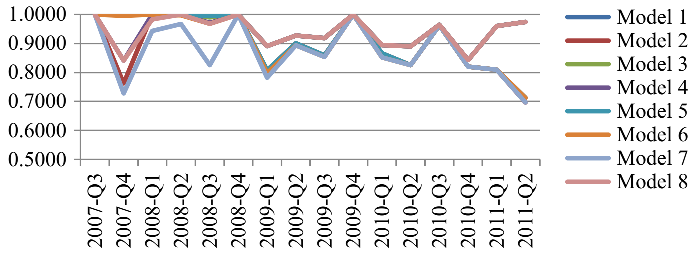

Fig. 12 Jeju bank

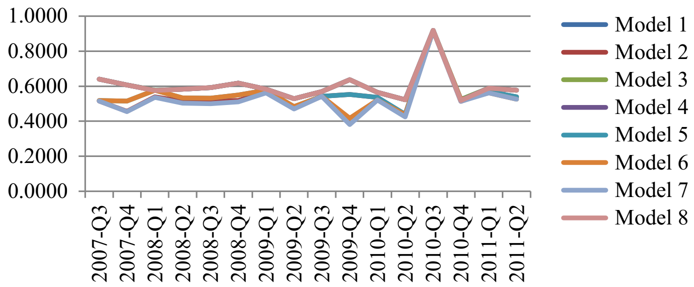

Fig. 13 Jeonbuk bank

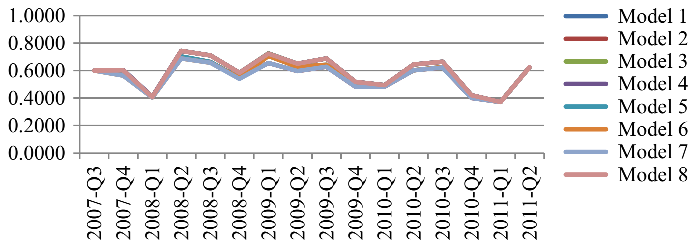

Fig. 14 Kwangju bank

0.9750. In addition, Fig. 8 nicely shows that the results are model dependent, even among these consistently-high performers. That is, SC First Bank's score declines in 2011Q1 from a previous quarterly score of over 0.90 to just under 0.80 in Models 1, 2 and 4 to 8, but falls even more dramatically, from 0.9376 to 0.5352, in Model 3 where NPL are excluded from consideration in the profit function.

With respect to the Regional Banks, only Jeju Bank ever features on the frontier—from 2007Q3 to 2008Q4 and in 2009Q4—with its scores fluctuating in the remaining periods between 0.80 to 0.96 depending on the estimated model used (see Fig. 12). For example, in the last quarter of the sample period, 2011Q2, Jeju Bank had an estimated score above 0.97 in Models 1, 3, 4 and 8, but a score between 0.69 and 0.71 for Models 2, 5, 6 and 7—again showing that model specification can have a significant effect on the results. This model-dependency of the scores was also exhibited by the National Agricultural Cooperative Federation—see Fig. 19—where it was on the frontier under Models 1, 3, 5 and 6 during the period 2008Q4 to 2009Q1 (but Models 2, 4, 7 and 8 had estimated scores averaging 0.92) and during 2010Q1 to 2010Q2 (but Models 2, 4, 7 and 8 had estimated scores between 0.79 and 0.92).

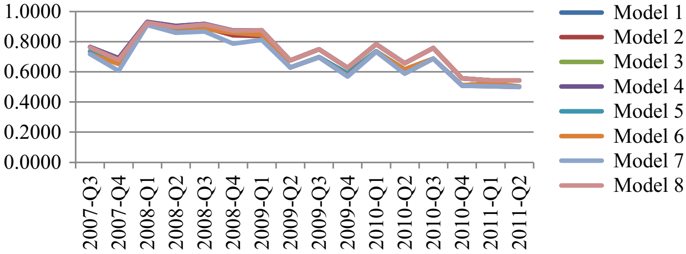

Fig. 15 Kyoungnam bank

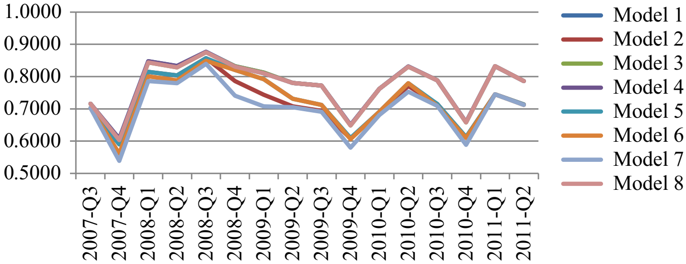

Fig. 16 Pusan bank

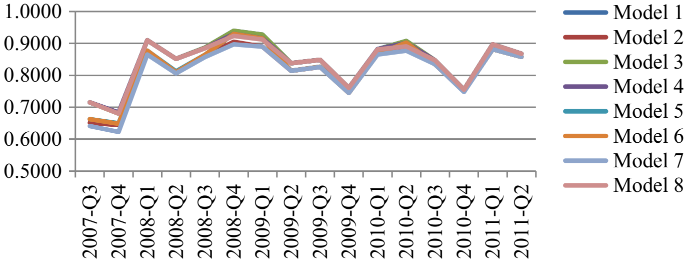

Fig. 17 Industrial bank of Korea

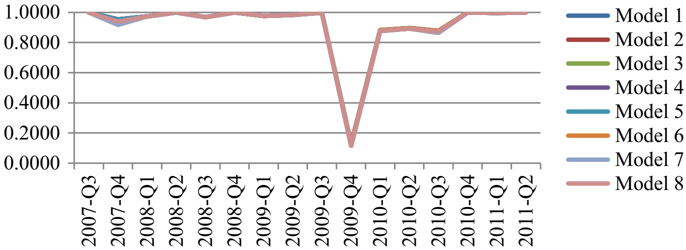

Fig. 18 Korea development bank

Banks which exhibited BCC—efficiency stability around the 3rd quartile (i.e., with average scores from 0.5 to 0.75) across all models only included the Regional Banks i.e., Daegu Bank, Jeonbuk Bank, Kwangju Bank and Pusan Bank. The banks that steadily improved their efficiency scores over the same period comprise Hana Bank (see Fig. 5), the Industrial Bank of Korea (see Fig. 17) and the National Agricultural Cooperative Federation (or Nonghyup)

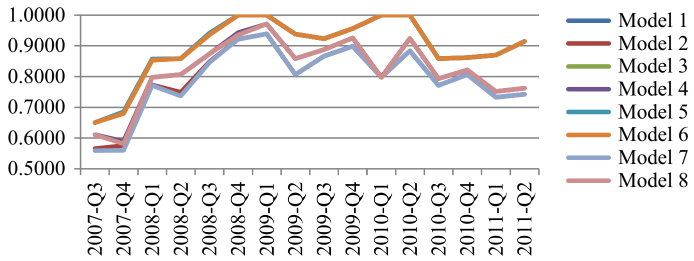

Fig. 19 National agricultural coop federation

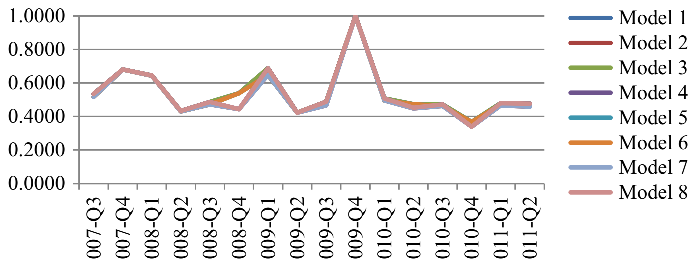

Fig. 20 National federation of fisheries coop

(see Fig. 19). Contrariwise, the bank that stood out as facing a consistent reduction in its scores was the Regional Bank Kyoungnam Bank, with average scores falling from 0.76 to 0.52 over the sample period. Finally, the banks that were consistently the poorest performers comprised the Regional Bank Jeonbuk Bank (±0.15 from 0.55 in all quarters for all models except for a one off jump to around 0.9 in 2010Q3—see Fig. 13) and the Specialist Bank the National Federation of Fisheries Cooperatives, whose scores averaged around the 0.5 mark except for a one off jump to the frontier in 2009Q4 (see Fig. 20).[15]

4.3 Testing significance of the differences between the models

In this section we discuss whether the estimated efficiency scores from the 8 model specifications have significantly different distributional equality. The Simar and Zelenyuk (2006) adapted Li (1996) test results shown in Table 3 indicate that, out of the possible permutations, there are 12 significant differences across the models. Beginning with the base specification, where all risk control variables are excluded (Model 7), we can determine that there is no difference in efficiency scores from models including only NPLs (Model 2) or EQ (Model 6) as risk control variables. It is only when LLP (Model 8) is included as a singular risk management control variable that the efficiency score distributions become different. This gives us our first result. In estimating South Korean bank efficiency, the researcher should always include LLP as the risk management control variable if only one such variable is to be included. Indeed, the exclusion of LLP leads to many banks seeing a reduction in their efficiency scores, with one of the least efficient banks, Jeonbuk Bank, for example

[15] The results (not shown but available from the author) show that there is a close similarity between the CCR and BCC—efficiency scores of banks across all models except for Jeju Bank and Jeonbuk Bank, who suffer a near 50 % collapse in efficiency from one program to the other. This is due to scale inefficiencies—estimated at 0.4761 for Jeju Bank. In general, for all remaining banks and models the scale inefficiencies experienced are less than 0.10—hence the reason why the CCR results are excluded from the current discussion.

Table 3 Simar and Zelenyuk adapted Li test results

Model	*p* value		*p* value
Model 1: LLP, EQ, NPL		Model 2: NPL	
Model 2: NPL	0.009	Model 8: LLP	0.091
Model 1: LLP, EQ, NPL		Model 3: LLP, EQ	
Model 6: EQ	0.059	Model 6: EQ	0.089
Model 1: LLP, EQ, NPL		Model 3: LLP, EQ	
Model 7: Nothing	0.001	Model 7: Nothing	0.003
Model 1: LLP, EQ, NPL		Model 4: LLP, NPL	
Model 8: LLP	0.065	Model 7: Nothing	0.007
Model 2: NPL		Model 5: EQ, NPL	
Model 3: LLP, EQ	0.014	Model 7: Nothing	0.089
Model 2: NPL		Model 7: Nothing	
Model 4: LLP, NPL	0.063	Model 8: LLP	0.014

Only significantly-different results are shown
LLP is Loan Loss Provisions, EQ is Equity, NPL is Non-performing Loans and Nothing denotes no risk control variables included in the model.
The *p* values are computed using the Matlab code from Simar and Zelenyuk (2006), with 5000 bootstrap replications and Gaussian kernel

seeing reductions equalling 0.057 under Model 2, 0.057 under Model 6, and 0.074 under Model 7 relative to Model 8. In comparison, those banks enjoying increased efficiency scores following the replacement of LLP as the risk control variable by another include the National Agricultural Cooperative Federation—from 0.8186 (Model 8) to 0.8938 (Model 6)—and the Kookmin Bank (from 0.9259 (Model 8) to 0.9271 (Model 2)). This implies that Model 8, which includes LLP only, can differentiate itself from models including other risk management control variables when only one risk variable is to be included in the model specification.

Going to the other extreme, involving a comparison of models with the one including all three risk variables—Model 1—we also find some interesting results. The inclusion of only singular risk variables in Models 2, 6, and 8 each gives different efficiency score distributions to the model with all 3 risk variables included so all three should be included, if available. However, Models 3, 4 and 5, which only include 2 risk management control variables, are insignificantly different from Model 1, which includes all three. Hence, we can say that including only 2 of the risk management control variables will give the same results as including all 3. To recap, if 3 is better than 1 (which is better than 0), and 3 is the same as 2, then including 2 risk variables is better than including 1. To finalise, we propose that when modelling South Korean banks a combination of 2 variables from Equity, Loan Loss Provisions and Non-performing Loans be included; it is not necessary for the inclusion of all three, overcoming the problem of the 'curse of dimensionality'.[16]

[16] This type of model-dependency result was also found by Altunbas et al. (2000) where they note for Japanese banks "that financial capital has the most noticeable influence on the scale economy and scale efficiency results. If one excludes it from the estimation the scale economy and scale efficiency estimates are similar (across) years as the cost function which has no risk and quality variables. Non-performing loans and the liquidity ratio appear to have little effect on the results. The result, however, should be treated with caution given that the influence of the financial capital variable (E) may be overstated because this variable is fully interactive with the output and input price variables in the cost function but the non-performing loan ratios and the liquidity

At the theoretical level, a specification that includes all three risk management control variables could lead to a cancelling effect of one variable over another, hence giving the result that the inclusion of the three risk variables is no different from the inclusion of two risk variables. For example, when declaring an increase in NPL, a bank increases its LLP (on the profit and loss account), which then feeds through to Equity capital. This affects the retained earnings and profitability of the bank and hence reduces, next quarter—if, for example, operating under a pro-cyclical LLP strategy—the availability of funds to make loans. Once this happens, the 'net interest revenue' (a good output) decreases. By definition, efficiency also decreases, as good outputs decrease relative to the increase in good inputs (including LLP and Equity).

South Korea also proved to be an interesting case as all banks in our sample had, based on performance evaluation under Basel II, a core equity Tier I ratio in excess of the required 7 %, which increased from, on average, 8 % in 2008 to over 11.5 % in 2010— with Shinhan Bank, Citibank Korea, and KDB maintaining particularly-high standards by running overall risk-adjusted capital ratios in excess of 16 % and Tier 1 capital ratios in excess of 12 % (FSS 2010). Hence, with high overall and Tier I ratios, one could argue whether the use of equity as a risk control management variable in the case of South Korean banks is actually justified, as it proved not to be a powerful discriminatory variable in the determination of bank efficiency. [Note, however, that it has been argued that equity is not only a general risk indicator but also a source of funds for a bank and could thus be included as a relevant input or netput in the bank model, on a theoretical basis (see for example, Berger and Mester 1997; Hughes and Mester 2011)]. It did not offer valuable risk management information as all banks were highly-capitalised, even though some did sell hybrid and subordinated securities to the Bank Recapitalisation Fund. However, the 6 banks that did participate only sold a total of KRW2,206 billion to the available fund of KRW20,000 billion (11 %) and the majority only on a short term basis to weather the GFC storm.

5 Conclusions

Having elected for a profit-based approach to the estimation of South Korean bank efficiency, we then proceeded to provide a systematic study of the choice of risk management control variable in a non-parametric DEA analysis that allows for the inclusion of both 'good' and 'bad' inputs and outputs. Using the model of Liu et al. (2010), we examine the dependency of the estimated BCC-efficiency scores on the chosen risk control variables, embracing loan loss provisions and equity as good inputs and non-performing loans as a bad output.

Averaging over the sample period 2007Q3 to 2011Q2, we first find that the most efficient banks were the Commercial Banks SC First Bank and the Korea Exchange Bank, with the least efficient being the National Federation of Fisheries Cooperative (a Specialist Bank) and Kwangu Bank and Jeonbuk Bank (both Regional Banks). Although the actual efficiency scores were shown to be model dependent, rank correlations, however, were hardly affected by the choice of risk management control variable, with SC First Bank and the National Federation of Fisheries Cooperative ranking first and last respectively in all eight models, for example. As for the banking groups, the Commercial Banks were shown to be the most

Footnote 16 continued
ratio are not (see footnote 3). It could be the case that the inclusion of financial capital impacts the results most because Japanese banks experienced a decline in their capital strength over the period of study whereas changes in provisioning levels were more modest" (p. 1617).

efficient grouping, followed by the Specialist Banks and then by the Regional Banks (Jeju Bank proving to be an outlier), again across all models.

Averaging across the banks for each model, the mean BCC-efficiency scores were also shown to be dependent on the choice of risk management control variable. As for the variability in scores across time, most banks experienced steep falls in efficiency in 2009, as expected given the severity of the Global Financial Crisis which struck in 2007/2008, with recovery for many ensuing in the second half of 2010.

We then find that, using the Simar and Zelenyuk (2006) adapted Li (1996) test, if only one of the three risk management control variables is to be included in such an analysis then it should be loan loss provisions. We also find, however, that the inclusion of all three risk management control variables is to be preferred to just including one, but that the inclusion of two such variables did not produce statistically different results as including all three. We therefore conclude that, given the 'curse of dimensionality', the preferred approach is to include (any) two of the three risk management control variables identified, whichever the experts find most relevant for the context of the study. The wider implication for research into bank efficiency is that the optimal choice of risk management control variable is likely to be crucial to the delivery of both risk-adjusted estimates of bank efficiency and the specification of the model to be estimated. Clearly, it is possible that the results we derive in this study may be specific to Korean (or more generally Asian) banking and so hope it will encourage other researchers to carry out similar investigations for other countries, cultures and regions.

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