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The impact of the global financial crisis on the efficiency of Australian banks

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ABSTRACT

The objective of this study is to measure the efficiency levels of major Australian banks and some regional banks before, during and after the Global Financial Crisis (GFC) by examining their pure technical and scale efficiencies obtained from the bootstrap Data Envelopment Analysis (DEA). The adopted bootstrap approach enables us to conduct statistical inferences regarding scale efficiency estimates of individual banks. We visualize bootstrapped results using an efficiency matrix to present the results of confidence intervals of pure technical and scale efficiency estimates. This novel approach facilitates efficiency comparison across the chosen sample banks for which consistent input and output data were available. This paper provides a useful benchmarking framework for individual banks to assess and identify their likely sources of technical inefficiency. The empirical results reveal that the global financial crisis had an adverse effect on the pure technical efficiency of Australian banks. In addition, the bootstrapped results indicate that small banks mostly operate in the region of increasing returns to scale while medium-sized banks are scale efficient. The results support the view that only smaller banks can enhance their efficiency from possible future mergers with other smaller-medium size banks. Any mergers involving the Big 4 banks are likely to lower the overall efficiency of the banking system and lead to anti-competitive behavior.

1. Introduction

The global financial crisis (GFC) in 2008 was the most significant economic event since the 1970s and had a major impact on the financial systems of many countries (Quiggin, 2011). Unlike banks in many other OECD countries, Australian banks demonstrated a great deal of resilience during this period. In Australia, the GFC has led to the need to ensure that the banking sector operates in an efficient manner.

For many years, the banking sector in Australia has continued to be dominated by the existence of the 'four pillar policy' or dominance of the banking sector by four big banks (the Commonwealth Bank of Australia, the National Australia Bank, Westpac Banking Corporation and the Australia New Zealand Banking Group Limited). There also exist a few smaller regional banks. KPMG (2012) reported that during the GFC, the Big 4 Australian banks remained among the top 25 banks in the world by market capitalisation. Blejer (2006) advances that countries with well-functioning and efficient financial systems are less likely to be adversely affected by tumultuous events during financial crises. Vu and Turnell (2011) attribute the success of Australian banks to higher efficiency levels prevailing in the pre-GFC era.

The banking sector plays an important role in the economic development of Australia and an evaluation of its continued efficiency is of utmost significance. Despite the importance of the banking industry to the economy, there are limited Australian banking efficiency studies and those that do exist mostly cover the periods before 2005 (e.g., Kirkwood and Nahm, 2006; Neal, 2004; Paul and Kourouche, 2008; Sathye, 2002). The majority of earlier studies use Data Envelopment Analysis (DEA) as a linear programming technique to investigate the efficiency level of Australian banks (Kirkwood and Nahm, 2006). Due to the deterministic nature of non-parametric methods such as DEA, these earlier studies suffer from a lack of statistical precision, which may cause biased and misleading results. Additionally, Australian banking efficiency studies that do examine the impacts of the 2008 global financial crisis are limited and cover only the period up to the year 2010 (e.g., Avkiran and Thoraneenitiyan, 2010; Foroughi and De Zoysa, 2012; Shamsuddin and Xiang, 2012; Vu and Turnell, 2011). These recent studies do not cover the post financial crisis periods of 2011 and 2012 which essential in providing a full picture of Australian banks' performance.

The above issues motive the present research. Our aim is to investigate the efficiency levels of Australian banks prior to, during and in the post GFC period. This study makes several contributions to the existing literature. Firstly, it is the first Australian banking efficiency study which covers the periods prior to, during and post the GFC. Secondly, this study utilizes bootstrap DEA in examining the efficiency level of Australian banks to provide statistical properties of

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efficiency estimates, neglected in the earlier Australian banking efficiency literature. Thirdly, the study offers a methodological contribution by applying the bootstrap method to provide statistical properties of scale efficiency and to test the returns to scale hypothesis for individual banks. Fourthly, in order to visualize the results, the study introduces a novel efficiency matrix to demonstrate the confidence intervals of both pure technical and scale efficiency estimates. This assists the comparison of bank efficiency and helps identify the sources of technical inefficiency. We advance that such analyses that present the results of complex techniques in a simple and coherent manner are essential for policy development as decision makers and bank managers are often looking for reliable, practical and comprehensible methods in determining the sources of poor efficiencies.

This article is organized as follows. Section 2 reviews the literature and highlights the gaps. Section 3 discusses the bootstrap DEA models and introduces the sample banks. Section 4 presents the empirical results, and Section 5 provides a summary and concluding remarks.

2. Literature review

Past studies have utilized parametric and non-parametric methods to analyze banking efficiency. Among parametric approaches, Stochastic Frontier Analysis (SFA) is the most commonly used method. While the SFA has been used in a limited number of Australian banking efficiency studies, this method suffers from two main disadvantages. It imposes a functional form on the production technology and also requires a larger sample size than DEA, which is the most commonly used non-parametric method. In contrast, the main drawback of the DEA method is its deterministic nature and inability to provide statistical precision of efficiency estimates (Emrouznejad et al., 2010). Notwithstanding these limitations, Kirkwood and Nahm (2006) highlight that due to limited number of banks in Australia, the majority of banking efficiency studies use DEA method.

Among recent studies that cover the global financial crisis period include, Vu and Turnell (2011) who investigated the impact of the global financial crisis on the cost and profit efficiency of Australian banks by using the SFA method. The study found that the profit efficiency of Australian banks declined during the crisis with regional banks being hit harder than their major rivals. Surprisingly, it was found that the global financial crisis caused no change in the cost efficiency level of the sample banks. One drawback of using SFA in that study was that it imposed a functional form on the production function, which was problematic when the production function was skewed (Simar and Wilson, 2008). SFA estimates have been based on an unidentified residual, which is another drawback of this method (Simar and Wilson, 2008). In addition, the study did not include the post-crisis period.

Foroughi and De Zoysa (2012) investigated the efficiency level of Australian banks using DEA over the period 2004–2010. Their results showed the adverse impact of the global financial crisis on the efficiency level of sample banks under an intermediation approach. However, it was also shown that the technical efficiency of the sample banks improved throughout the financial crisis when production and value-added approaches were undertaken in choosing variables of models. Since the study used the DEA method, it suffers from a lack of statistical precision of the efficiency estimates, which can lead to biased or misleading results.

Avkiran and Tripe (2011) examined the efficiency level of Australian financial institutions, including banks, credit unions and building societies, over the period 2006–2010. The authors found that the efficiency level of sample institutions deteriorated during the crisis and was at its lowest level in 2009. It was also found that banks performed better than other financial institutions throughout the study period. The authors conclude their study by advancing that using benchmarking tools such as DEA could provide valuable information for regulatory bodies to monitor Australian financial institutions. Notwithstanding their pioneering study, the results of this research can further be improved by relaxing the deterministic assumption of the DEA approach.

Other key studies using DEA and SFA methods in assessing the efficiency of Australian banks are summarized in Table 1:

Earlier Australian banking efficiency studies presented in Table 1 suffer from the imposition of a functional form on the production technology or the lack of statistical precision. To mitigate these drawbacks, Simar and Wilson (1998) proposed a bootstrap procedure. In recent times, the bootstrap DEA method has become more popular and has been used in analyzing banking efficiency in various countries (e.g., Arjomandi et al., 2011, 2012; Lee et al., 2010; Matthews et al., 2009; Moradi-Motlagh et al., 2012a; Tortosa-Ausina et al., 2008). However, none of the earlier banking efficiency studies in Australia have employed this advanced method to remedy the drawbacks of the DEA and SFA techniques — most likely due to the lack of access to user friendly software and the complexity of the bootstrap approach.

3. Methodology and data

Measuring efficiency of large firms is a complicated exercise, involving a complex multi-input/output structure. Data envelopment analysis (DEA) technology, by design, naturally account for such issues efficiently and effectively (Emrouznejad et al., 2008). DEA has been proven to be a powerful benchmarking methodology to measure the relative efficiency of business entities in a wide range of industries, sectors, portfolios, and even economic efficiency of countries (e.g., Arjomandi et al., 2014; Boubakri et al., 2005; Christopoulos, 2007; Emrouznejad, 2003; Emrouznejad and Anouze, 2009, 2010; Khodabakhshi, 2009; Kirigia et al., 2002; Lo, 2013; Lu et al., 2013; Miningou and Vierstraete, 2013; Moffat and Valadkhani, 2011).

DEA was initially proposed by Charnes et al. (1978) as a mathematical programming technique to estimate the relative efficiency of Decision Making Units (DMUs). Pure technical efficiency of a DMU is measured by assuming variable returns to scale in the DEA model to obtain the relative efficiency of a unit in comparison to other units with similar scale of operations. The main drawback of the DEA method is the lack of statistical precision of efficiency estimates as this technique does not take into account measurement errors and random noise (Worthington, 2004). To mitigate this issue, Simar and Wilson (1998, 1999, 2000) proposed a procedure based on the statistical technique of bootstrapping which provides statistical properties of DEA estimators, such as confidence intervals and bias.

Assuming n bank-year observations $\{(x_i, y_i), i = 1, \ldots, n\}$ that use multiple inputs x to produce multiple outputs y, a summary of the Simar and Wilson (1998, 2000) procedure to estimate pure technical efficiency of the sample observations is as follows:

1) For each bank-year observation (x_k, y_k) $k = 1,\ldots,n$ compute $\hat{\theta}_k$ using the following linear program formula:

$$\hat{\theta}_k = \min\{\theta > 0 | y_k \le \sum_{i=1}^{n} \lambda_i y_i; \theta x_k \ge \sum_{i=1}^{n} \lambda_i x_i; \sum_{i=1}^{n} \lambda_i = 1; \lambda_i \ge 0 \forall i = 1, \ldots, n\} \tag{1}$$

where λ is a vector of constant.

2) Draw with replacement from $\hat{\theta}_1, \ldots, \hat{\theta}_n$ to generate $\beta_1^*, \ldots, \beta_n^*$,
3) Smooth the sampled estimates using the following formula:

$$\tilde{\theta}_i^* = \begin{cases} \beta_i^* + h\varepsilon_i^* & if \quad \beta_i^* + h\varepsilon_i^* \le 1 \\ 2 - \beta_i^* - h\varepsilon_i^* & \text{otherwise} \end{cases} \tag{2}$$

where h is the bandwidth of a standard normal kernel density and ε_i^* is a random error drawn randomly from the standard normal distribution. The cross-validation method can be used to determine the bandwidth parameter as detailed by Simar and Wilson (1999).

4) Correct the variance of the bootstrap estimates by computing: