Two-stage DEA-Truncated Regression: Application in banking efficiency and financial development

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ARTICLE INFO

Article history:
Received 13 June 2017
Revised 6 September 2017
Accepted 6 December 2017
Available online 8 December 2017

Keywords:
Data envelopment analysis
Truncated regression
Bank efficiency
Financial development

ABSTRACT

This study evaluates the efficiency of peripheral European domestic banks and examines the effects of bank-risk determinants on their performance over 2007–2014. Data Envelopment Analysis is utilised on a Malmquist Productivity Index in order to calculate the bank efficiency scores. Next, a Double Bootstrapped Truncated Regression is applied to obtain bias-corrected scores and examine whether changes in the financial conditions affect differently banks’ efficiency levels. The analysis accounts for the sovereign debt crisis period and for different levels of financial development in the countries under study. Such an application in the respective European banking setting is unique. The proposed method also copes with common misspecification problems observed in regression models based on efficiency scores. The results have important policy implications for the Euro area, as they indicate the existence of a periphery efficiency meta-frontier. Liquidity and credit risk are found to negatively affect banks productivity, whereas capital and profit risk have a positive impact on their performance. The crisis period is found to augment these effects, while bank-risk variables affect more banks’ efficiency when lower levels of financial development are observed.

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1. Introduction

Data Envelopment Technique (DEA) is a non-parametric linear programming technique, which extends the idea of estimating efficiency by comparing each Decision Making Units (DMUs) with an efficient production frontier (Farrell, 1957). As introduced by Charnes, Cooper, and Rhodes (1978), DEA defines the set of best-practice observations for the DMUs under study and produces a convex production possibilities set by connecting the best-practice observations with a piecewise linear frontier. This principle is the basis of the traditional DEA and its applications are spread across different scientific disciplines (Chiang & Che, 2015; LaFante & Paradi, 2015; Lee, 2010; Serrano-Cinca, Fuertes-Cañón, & Martín-Moliner, 2005).

The banking sector plays a crucial role in the development of any financial system. Consequently, identifying ways to analyse the efficiency of banks has been in the centre of policy makers’, economists’, institutions’ and academics’ research. For that reason, the DEA literature on banking efficiency is voluminous. Nonetheless, it is characterised by different methodological approaches and mixed results. Most studies traditionally focus on US and European markets, as illustrated by the cornerstone survey work of Berger and Humphrey (1997). The scope in later years shifts primarily in the European setting. For example, Altunbas, Evans, and Molyneux (2001) analyse the efficiency of German banks in relation with their type of ownership types and they claim that there is no significant evidence to suggest that privately owned banks are more efficient than their mutual and public sector counterparts. Maudos and Pastor (2003) control for cost and profit efficiencies for the Spanish and Italian banks respectively and they note that most efficient and profitable institutions are able to better control costs. Chortareas, Girardone, and Ventouri (2009) examine the case of Greece with several metrics of banks’ efficiency and they conclude that controlling for risk preferences is important in determining bank efficiency.

The above studies follow a single-country DEA approach. The rationale behind this choice is that the cross-country banking sector cannot be considered homogeneous due to national variations in legal tradition, regulatory frameworks, culture and religion (Berger, 2007). Lately, vast numbers of studies knuckle down to European comparative studies. This cross-country shift is driven
mainly by two factors. Firstly, the introduction of the Single Market in the European Union over the nineties raised the expectations for higher financial integration and bank efficiency convergence within Europe (Bos & Schmiedel, 2007; Weill, 2009). Secondly and most importantly, the Global Financial and Eurozone sovereign debt crises demonstrated the need for a tighter banking sector union, especially in the Eurozone periphery (Casu, Ferrari, Girardone, & Wilson, 2016).

One such example is the work of Casu, Girardone, and Molyneux (2004) who evaluate the productivity changes in European banking between 1994 and 2000. Their results imply that productivity growth is brought through improvements in technological change, rather than technical efficiency. Altunbas, Carbo, Gardener, and Molyneux (2007) conclude that there is a clear relationship between capital, risk and efficiency, as European inefficient banks tend to hold more capital and take on less risk. Brissimis, Delis, and Papanikolau (2008) evaluate the banking efficiency across newly acceded EU countries and they find that the banking sector reform and competition impact positively the bank efficiency, while capital and credit risk negatively affect bank performance. Finally, Casu and Girardone (2010) discuss how integration and efficiency convergence appears in EU banking markets. Their results indicate that there is a level of convergence towards a European efficiency average, but this pattern does not lead to efficiency improvements across all countries.

Casu et al. (2016) recently evaluate the effect of the Eurozone crisis and observe a structural break in bank productivity growth in the Eurozone countries at the start of the crisis. This is particularly interesting, given that the Eurozone markets have small capital markets. In 2012, Greece, Ireland, Italy, Portugal and Spain (GIIPS) saw their stock market capitalisation to further reduce. During this period, banks faced liquidity shortages and higher credit risk, which led to cuts of their lending conditions up to 47% for Small and Medium Enterprises (SMEs). Logically focusing on the periphery economies should provide further insight on what effect capital markets’ development has on banking efficiency. The intuition behind that is that banks and capital markets can be complementary to one another, as capital market development lowers the cost of bank equity capital. Consequently, this enables banks to raise the extra capital needed to take on riskier loans that they would otherwise reject (Vazquez & Federico, 2015). Other studies show that the sovereign debt crisis adversely affects the European stock markets and as a result, countries with poor credit market regulations and with larger pre-crisis account deficits (Giannone, Lenza, & Reichlin, 2011 and Grammatikos & Vermeulen, 2012). With this in mind, the European Commission (EC) initiatives and vision (BASEL III and Capital Market Union (CMU)) to allow capital markets’ development and deepen the banking integration seem especially relevant for fostering growth in the Eurozone periphery (Darusu-Ciftci, Ispir, & Yetkiner, 2017).

From a methodological point of view, DEA continues to be very popular for practitioners as a technique for evaluating DMUs’ efficiency (Asoseh, Nalchigar, & Jamprazmey, 2010). Its application is easy and interpretable, while it is able to project an efficient frontier formed by linear combinations connecting the set of ‘best-practice’ observations in the dataset. A DEA practitioner does not need to make assumptions about the distribution of inefficiency, while Fethi and Pasiousas (2010, p.190) suggest that DEA ‘does not require a particular functional form on the data in determining the most efficient banks’. Compared to other parametric techniques, DEA is also able to cope with small sample sizes and the application of categorical variables that are commonly used in country-

specific panels of data (Brissimis et al., 2008; Fethi & Pasiousas, 2010).1 This is particularly important for banking datasets that are usually small in nature. In traditional statistical approaches (e.g. regression analysis), small sample size comes at a cost as the average DMU behaviour is of interest. On the other hand, DEA focuses on the performance of each DMU. Therefore, the number of DMUs in a DEA framework could be considered immaterial (see amongst others and Cook, Tone, and Zhu (2014) and Tsolas and Charles (2015)). Finally, most parametric approaches introduce time trends to the data which lead to smoothing out the variation of the productivity changes.

Additionally, there is no consensus around the DEA orientation (Cook et al., 2014). Many researchers advocate the input-oriented approach assuming that bank managers impose control over inputs (e.g. expenses) rather than outputs (e.g. income) (Khodabakhshi, Agharian, & Gregoriou, 2010; Tsolas & Charles, 2015; Wu, Yang, & Liang, 2006). On the other hand, others believe it is more appropriate to answer how can output quantities be proportionally expanded without changing the underlying input quantities used over different time periods (see amongst others Fethi and Pasiousas (2010), Griffel-Tatjé and Lovell (1997)) and Bassem (2014). Although the literature is conflicting, many studies suggest that the choice of orientation has minimum effect upon the actual calculated scores. Therefore, the DEA orientation should not be a point of friction across researchers’ approaches.

Several studies on banking efficiency proceed to a two-stage approach, where efficiency scores are estimated in the first stage and then simply regressed on independent environmental variables (Beccalli, Casu, & Girardone, 2006; Sun & Chang, 2011; Wang, Tseng, & Weng, 2003). This approach is problematic for the following reasons. Firstly, the estimated distances from the DEA frontier can be underestimated when optimal DMUs are excluded from the sample (sample bias). Secondly, traditionally DEA estimates (not incorporating Malmquist index approaches) introduce boundary inefficiencies in the OLS method. Finally, efficiency scores suffer from high serial correlation, which impedes their statistical interpretability and valid estimation. All these disadvantages are clearly explained by the influential work of Simar and Wilson (2007). The authors introduce a Double-Bootstrapped Truncated Regression (DBTR) framework, which copes with the above issues and provides bias-corrected efficiency scores. The benefits of this approach are well-documented in the respective banking literature (see amongst others Assaf, Barros, and Matousek (2011), Chortareas, Girardone, and Ventouri (2013), Feng and Serletis (2010), Wanke and Barros (2014), Wanke, Barros, and Emrouznejad (2016)).

The above background positions this work clearly in the respective literature and clarify its motivation. Firstly, DEA efficiency scores based on a Malmquist Productivity Index (MPI) are calculated on a cross-country level, namely the peripheral economies of GIIPS. This approach, although not the only available for efficiency scores’ calculation, is common in the respective literature (see amongst others Casu et al. (2004), Färe, Grosskopf, Norris, and Zhang (1994), Tortosa-Ausina, Griffel-Tatjé, Armero, and Conesa (2008) and Kevork, Pange, Tzeremes, and Tzeremes (2017)). In our case, efficiency is evaluated based on the five metrics derived from the ‘enhanced decomposition’ proposed by Färe et al. (1994). Secondly, a DBTR framework is adopted in order to reconstruct the initial DEA estimates into bias-corrected ones which are optimised for the second-stage regression.

This study is offering several innovations in terms of the methodological approach undertaken. We further validate the success of the MPI’s ‘enhanced decomposition’ and Simar’s and Wilson’s (2007) approach. In particular, we provide a unique setting to calculate different bank efficiency metrics and evaluate the effects of bank-risk variables and financial development on them through

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1 The corresponded figures for Greece, Italy, Portugal and Spain area are 21.3%, 15.4%, 28.4% and 76% respectively.
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