On the Sources of Heterogeneity in Banking Efficiency Literature

Aiello, Francesco and Bonanno, Graziella

Department of Economica, Statistics and Finance, Unical, Italy, Royal Docks Business School, University of East London, London

12 September 2014

On the Sources of Heterogeneity in Banking Efficiency Literature[•]

Francesco Aiello[a], Graziella Bonanno[a,b]
francesco.aiello@unical.it - graziella.bonanno@unical.it
[a] Department of Economics, Statistics and Finance, University of Calabria
I-87036, Arcavacata di Rende (CS), Italy
[b] Royal Docks Business School, University of East London, Docklands Campus
4-6 University Way, London E16 2RD, UK

Abstract One learns two main lessons from studying the great quantity of banking efficiency literature. These lessons regard the heterogeneity in results and the absence of a comprehensive review aimed at understanding the reasons for this variability. Surprisingly, although this issue is well-known, it has not been systematically analyzed before. In order to fill this gap, we perform a Meta-Regression-Analysis (MRA) by examining 1,661 efficiency scores retrieved from 120 papers published over the period 2000-2014. The meta-regression is estimated by using the Random Effects Multilevel Model (REML), because it controls for within-study and between-study heterogeneity. The analysis yields four main results. Firstly, parametric methods yield lower levels of banking efficiency than nonparametric studies. This holds true even after controlling for the approach used in selecting the inputs and outputs of the frontier. Secondly, we show that banking efficiency is highest when using the value added approach, followed by estimates from studies based on the intermediation method, whereas those based on the hybrid approach are the lowest. Thirdly, efficiency scores also depend on the quality of studies and on the number of observations and variables used in the primary papers. As far as the effects of sample size, dimension and quality of papers are concerned, there are significant differences in sign and magnitude between parametric and nonparametric studies. Finally, cost efficiency is found to be higher than profit and production efficiency. Interestingly, MRA results are robust to the potential outliers in efficiency and sample size distributions.

JEL classification: C13, C14, C80, D24, G21, L25
Keywords: Banking industry, Frontier Models, Efficiency, Meta-analysis, Study design

1. Introduction

The understanding of how, or indeed whether, banks are efficient is one of the most intriguing fields of research in economics. The reason for this lies mainly in the fact that banking fosters economic growth (Bumann et al., 2013; Pagano, 1993; Raghuram et al., 1998) and, thus, studying efficiency becomes a crucial issue in the discipline. Furthermore, the demand for

[•] The authors would like to thank Kristiaan Kerstens, Sergio Destefanis, Giovanni D'Orio, Damiano Silipo and the participants of the EWEPA 2013 Conference held in Helsinki for very useful comments and suggestions on earlier versions of this paper. Editorial assistance by Martin Brimble is also acknowledged. Usual disclaimer applies. At the of writing this paper, Graziella Bonanno was post-doc visiting student at the Royal Docks Business School, University of East London, Docklands Campus, London. She received a Research Fellowship from the Regione Calabria and EU Commission. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of EU Commission and Regione Calabria.

efficiency studies has increased over time because the results inform policy decisions and influence individual behavior. Within the context of our subject, this implies that stakeholders (policy-makers, regulators, investors and private agents) wish to know how banks could perform better, remain on the frontier and ensure financial market stability. To some extent, these reasons explain why, since the 1990s, many countries have regulated their national banking systems with the aim of increasing banks' efficiency. From this point of view, banking has become an interesting case-study for evaluating the effectiveness of any restructuring process, such as deregulation or M&A. On this basis, efficiency is the main concern in many policy-oriented papers.

Moreover, the growing attractiveness of efficiency studies is also driven by various methodological concerns. The theory of production clearly explains whether a decision unit is efficient or not. Farrell (1957) conceptualized technical (TE) and allocative efficiencies (AE) as part of overall efficiency (EE), with EE=TE*AE. In our case, TE represents banks' ability to produce maximum output given a set of inputs and technology, while AE measures banks' success in choosing their optimal input combinations. However, controversy has surrounded the empirics of many efficiency papers, with the result that the question, "What is the best banking frontier and how can it be properly estimated?", still awaits a conclusive answer. This is due to the fact that the frontier is unknown and that estimating approaches differ from one another in several ways, with no consensus on the superiority of one method over the others (Berger and Humprey, 1997; Coelli and Perelman, 1999; Fethi and Pasourias, 2010).

This said, the main consequences of the increased interest in banking efficiency are (a) an impressive proliferation of empirical research and (b) a relevant heterogeneity in results, even for narrowly defined topics. The highly mixed evidence is due to the variety of study designs underlying each work: researchers have to choose between parametric and nonparametric methods, stochastic and deterministic approaches, functional forms to be assigned to the frontier, and distributions for errors and efficiency. Variability is further caused by the econometrics used in estimating the frontiers and also depends on sample size and the number of inputs and outputs. Another factor explaining differences relates to the spam-period covered in the study. While the above remarks are valid for all works on efficiency, whatever the industry, a sector specific source of heterogeneity exists in banking literature. This regards how deposits are treated: the extreme options are the value added and the intermediation approaches which basically differ in that the former considers deposits as output, while the latter considers them as input. In short, it is not surprising that all this heterogeneity in the empirical setting of each paper translates into heterogeneity in efficiency scores.

These arguments necessitate a better understanding of the sensitivity of results to the choice of methods and frontier specifications, an issue which is addressed in several individual studies. For instance, Resti (1997) generates six-samples of data and compares the cost efficiency obtained from simulations with those estimated through the Stochastic Frontiers Analysis (SFA), Data Envelopment Analysis (DEA) and Distribution Free Approach (DFA). He concludes that there is no clear advantage of one method over the others. Similar arguments are also found in Berger and Humphrey (1997). Weil (2004) applies SFA, DEA and DFA to data from five countries (France, Germany, Italy, Spain and Switzerland) and concludes that banking efficiency scores are not comparable, even when considering similar approaches, such as the parametric. Beccalli et al. (2006) investigate the relationship between banks' efficiency and stock performance in the EU and suggest that efficiency is more heterogonous in DEA than in SFA. By analyzing the bank cost efficiency in Latin America over the 1985-2010 period, Goddard et al. (2014) estimate fixed and random effects models and find that the two methods provide efficiency scores which have statistically different means. Other valuable descriptions of how efficiency scores are sensitive to estimation methods are provided by Casu and Girardone (2004), Huang and Wang (2002), Kumar and Arora (2010), Mobarek and Kalonov (2014) and Yildirim and Philippatos (2007).

Besides the single studies which have tried to compare the results that different methods yield from a fixed sample of banks, some authors have reviewed the literature (Berger, 2007; Berger and Humphrey, 1997; Fethi and Pasiouras, 2010; Paradi and Zhu, 2013). While these surveys offer detailed and extremely valuable arguments about the reliability of results and why they may differ, none of them quantifies the impact of methodological choices on the variability of efficiency scores. A response to this issue may be provided by Meta-Analysis (henceforth MA), which is a statistical method used to collect and integrate the results from individual papers with the aim of evaluating whether, and to what extent, the features of each work (i.e. estimation method, year of publication, functional form assigned to frontier, sample size, and dimension) affect the findings (Stanley, 2001). As Glass (1976) says, MA "connotes a rigorous alternative to the casual, narrative discussions of research studies which typify our attempt to make sense of the rapidly expanding research literature" (Glass, 1976, 3).

Even though MA was originally applied to other disciplines, such as medicine and psychology (Egger et al., 1997; Hedges and Olkin, 1985; Rosenthal, 1984), it has recently been used in a number of papers covering a very wide spectrum of economic subjects (cfr. footnote 2). As far as efficiency literature is concerned, the prevalent interest is in summarizing the case of efficiency in agriculture, as in Bravo-Ureta et al. (2007), Thiam et al. (2001) and Kolawole (2009). Other excellent applications of MA to efficiency include those carried out by Brons et al. (2005), focusing on urban transport, and Odeck and Bråthen (2012), who summarize the technical efficiency literature regarding seaports. Nguyen and Coelli (2009) analyze the health sector.

Given the increased interest in MA and the fact that the literature on banking industry efficiency lends itself well to being summarized through this approach (the richness of sources behind the great heterogeneity in results is extremely high), it is noteworthy that no exhaustive work has explored the "banking efficiency-study design" nexus. In attempting to fill this gap, this paper considers large sample of efficiency studies and tests the robustness of results to different specifications of MA regressions.

A broadly similar study to ours is that by Iršová and Havránek (2010), which, however, focuses exclusively on the US banking system. Their MA refers to the period 1977-1997 and considers 32 papers, yielding a maximum of just 59 observations for some regressions and even fewer for others. Despite the limited sample size, they argue that the methodology adopted affects the efficiency scores. However, they realize that their "findings still need to be verified by future research using a broader sample of empirical studies" (Iršová and Havránek, 2010, 319).

Bearing in mind that some key elements (the number of studies covered, heterogeneity detection in results and the sensitivity analysis) have to be controlled for when performing a MA, we start with what Iršová and Havránek said and go on to introduce several contributions to the debate regarding the origins of heterogeneity in banking literature. Data used in this paper come from different sources with no restriction on the countries covered in the original studies. Our meta-data set comprises 1,661 observations from 120 papers published from 2000 to 2014 (which were available in April 2014). By applying the MA approach to such a wide coverage of relevant studies, we ask several questions that are relevant for both academic research and policy making. The issues that we raise relate to the size and the sign of the impact on the estimated efficiency scores brought about by different methodological choices made by authors of primary papers. The general question we ask is how much the efficiency scores are systematically influenced by the study design in the original papers. To be more precise, the scope of the research is to address these main issues. Whether parametric studies yield different results from nonparametric studies. Whether different approaches regarding the variables to be included into banks' frontiers have an impact on the average level of efficiency. Whether the impacts differ when considering cost instead of profit or production efficiency. Whether results change over time. What the consequences are of country-specific factors on national banking systems.

The rest of the paper is organized into 7 sections. Section 2 summarizes the methods most commonly used to estimate efficiency. Section 3 briefly presents MA, while section 4 reviews MA applications to economics and efficiency. Section 5 describes the criteria adopted to create the meta-dataset and highlights the efficiency heterogeneity of primary studies. Section 6 presents and discusses the results. Section 7 concludes.

2. Measuring efficiency: main features

While the concept of efficiency is subject to different interpretations (Aigner et al., 1977; Battese et al., 2005; Farrell, 1957), there is consensus in considering efficiency to be the degree of proximity of an actual production process to a standard of optimality. Efficiency can be thought of as the ability of a decision unit to minimize the amount of input for the production of a certain output (input-oriented TE) or to maximize the amount of output given a certain amount of input (output-orientated TE), for any level of technology. Furthermore, efficiency may be evaluated and interpreted from different perspectives, depending on whether the focus is on production, profits, costs or revenues.

Since efficiency is evaluated in relation to the best-practice, the key concerns in this field of research come from the methods applied to estimate the frontier. Table 1 summarizes these methods. The proposed classification reports, method by method, the requirements regarding the functional form to be assigned to the frontier, the assumptions regarding the disturbances (existence and composition) and some specificities of the efficiency scores (time-invariant, punctual estimates). A number of advantages/caveats are highlighted for each technique.

A common criterion of classification distinguishes between parametric and nonparametric approaches. Parametric methods assign density functions to the stochastic component of the model, while nonparametric methods only define the deterministic part. The SFA, the DFA and the Thick Frontier Approach (TFA) are parametric methods and are all based on a specific functional form of the output-variable (i.e. production, profit, cost or revenue), assign a distribution to the error term and allow to do inference. The DEA and the Free Disposal Hall Approach (FDH) are nonparametric methods. The group name refers to the fact that these methods do not assign a distribution function to the error term. Another criterion is based on how the distance from the frontier should be understood. In this respect, we have stochastic or deterministic methods. The first group admits that a bank may be far from the frontier due to randomness and/or inefficiency. In other words, a stochastic method, such as the SFA, allows the decomposition of the error into two parts, one attributable to inefficiency and the other to random error. On the other hand, when using a deterministic approach, the distance from the frontier is seen as being entirely due to inefficiency. In other words, the determinist approach ignores the existence of pure random disturbance, which may be, for example. due to measurement errors or unforeseen events. This issue can be illustrated using the graphical example proposed in figure 1. For the sake of simplicity, we refer to banking industry by considering a cost function C(y,w) to produce output y at some price of input w. There are two banks, A and B, for which we observe the costs C_A and C_B of producing Y_A and Y_B respectively. When analyzing bank A by using a deterministic method, DEA for instance, the level of inefficiency is given by $u_A + v_A$, the entire distance from the frontier, while SFA admits randomness, e.g. v_A, and, therefore, yields an inefficiency score of just u_A. In this case, DEA over-evaluates inefficiency. In the case of bank B, an unforeseen positive disturbance, v_B, makes the inefficiency obtained by applying SFA equal to u_B, i.e. higher than that obtained through DEA. From this discussion, the crucial point to be emphasized is that the sign of random errors may be negative, a situation that is not taken into account when using DEA. Figure 1 makes it clear that it is not certain that DEA will underestimate efficiency with respect to SFA, as is intuitively to be expected, since DEA treats the distance from the frontier as inefficiency, while SFA allows for noise. The final net result depends on the type of adjustment made for the erratic component (see also Nguyen and Coelli, 2009).

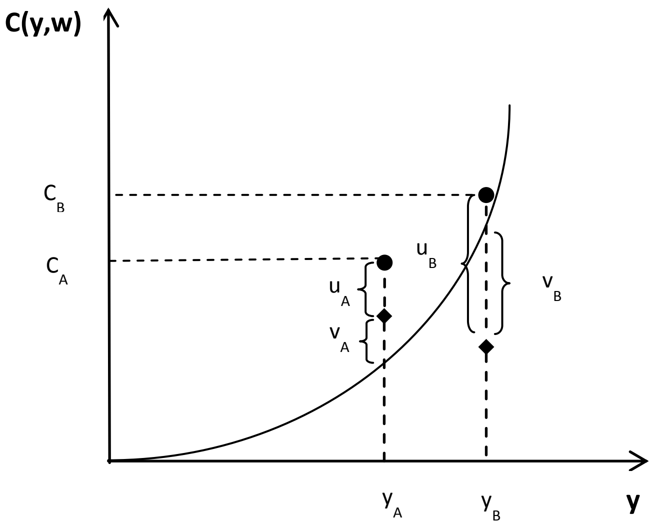
Table 1 highlights the fact that there are numerous different ways to perform an efficiency study and that, despite the high degree of specialization in the use of various methods, the effect of some methodological choices is still not certain. For example, we learn from figure 1 that the estimated efficiency scores in stochastic methods may be higher or lower than those obtained using the deterministic approach. Similarly, much may be said with regards other options to be made. The following brief considerations come from in-depth discussions concerning the advantages and limitations of the methodological choices to be made when measuring efficiency (Berger and Humphrey, 1997; Coelli, 1995; Fethi and Pasourias, 2010; Nguyen and Coelli, 2009). For instance, the orientation of deterministic models (input versus output-oriented) and the distribution of efficiency in stochastic parametric models are two additional factors with an uncertain impact on efficiency. On the other hand, the use of panel data would generate higher efficiency levels than those from cross-section. An analogous impact is expected when using second order functional forms instead of the Cobb-Douglas. Finally, efficiency would increase with the number of variables included in the frontier, while it would decrease with small sample-size and the assumption of constant returns to scale. However, while the theory predicts the likely impact of any choice, the actual measure of how the results are sensitive to the study design is an issue to be addressed empirically. To this end, this paper focuses on banking efficiency literature.

Table 1 A breakdown of some methods used to estimate efficiency

	Nonparametric and determinist approaches		Parametric and stochastic approaches		
	DEA	**FDH**	**SFA**	**DFA**	**TFA**
Functional Form of the Frontier	Not specified	Not specified	To be specified	To be specified	To be specified
Erratic Disturbance	Not allowed	Not allowed	Composite term - inefficiency - random error	Composite term - inefficiency - random error	Composite term - inefficiency - random error
Efficiency	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Only general estimate
Advantages	- No constraint to assign a functional form to frontier - No constraint regarding error distribution - Point estimates of each DMU	- No constraint to assign a functional form to frontier - No constraint regarding error distribution - Point estimates of each DMU - No assumption of production set convexity	- Composite error split into a component relating to efficiency and another due to randomness - Point estimates of each DMU	- Composite error split into a component relating to efficiency andanother due to randomness - Point estimates of each DMU	- Composite error split into a component relating to efficiency and another due to randomness
Caveats	- No randomness - No parametric test for inference	- No randomness - No parametric test for inference	- Arbitrary choice of distribution for the error tem - Arbitrary choice of functional form of frontier	- Arbitrary choice of functional form for the frontier - Efficiency is assumed to be time-invariant	Arbitrary choice of functional form for the frontier Arbitrary choice of distribution for the error tem - No point estimates - Arbitrariness in the division of the distribution in quartiles

Legend: DEA = Data Envelopment Analysis; FDH = Free Disposal Hall; SFA: Stochastic Frontier Approach; DFA = Distribution Free Approach; TFA = Thick Frontier Approach.

Figure 1 The distance from the frontier: comparing SFA and DEA



3. The Meta-Analysis in a nutshell

The difficulty of comparing the results of empirical works is a common caveat in economics because studies differ in several ways. As discussed above, the main source of heterogeneity is the study design, but differences also depend on time periods covered, samples and data source used in each analysis. Another source of heterogeneity in final outcomes lies in the changes to contextual and institutional factors that potentially affect any decision unit.

One approach which deals with this heterogeneity in results is the Meta Regression Analysis (Glass, 1976; Glass et al., 1981; Stanley and Jarrell, 1989). MA is a statistical method which reveals more about a significant phenomenon that has been studied in a large set of empirical works. It investigates the relationship between the dependent variable (i.e. the principle finding of the primary studies covered in the MA) and some features of every paper. By modeling all of the relevant differences across studies of a given subject, MA allows us to assess the role of each varying factor in determining the variability in outcomes. In other words, MA provides a systematic synthesis of a substantial number of studies and stresses the quantitative effect of various relevant characteristics in the original papers in explaining the variability of results. In detecting the main sources of variability, MA offers the opportunity to direct future research.

In its essence, MA offers some advantages with respect to the standard qualitative literature surveys. Indeed, it does not suffer from potential bias in selecting the studies to be reviewed because it covers all of the relevant literature without restrictions accruing from the reviewer's judgments. As an extreme solution, when complete (or relatively wide) coverage is not feasible, MA mitigates any bias relating to the researcher's preference by performing inferential analysis on a relatively representative randomized sample of the papers of interest. Our MA utilizes an exhaustive sample of papers and, therefore, ensures an ample coverage of the literature on banking efficiency (details on the original papers selected are in section 5).

However, it has been suggested that there are three main limits to MA. According to Glass et al. (1981), the first shortcoming of MA is that it brings together studies which are very different from one another. This is a sort of "*apples and oranges problem*" that can be addressed by refining the identification of the problem to be studied in order to focus attention on the specific factors that are assumed to be important in explaining differences in results. In this respect, this study only focuses on the few elements that are considered to be significant sources of variability in the estimations of banks' efficiency. For instance, the main point of interest is to understand how the use of nonparametric or parametric methods affects efficiency scores. One issue to be addressed regards whether banks perform better when maximizing profits than when controlling costs and whether results are statistically different when using the intermediation approach instead of the value added approach or a combination of both (the so-called hybrid approach).

Another potential limit is that MA assigns the same weight to the results of different works regardless of the quality of the studies. In this respect, it is also necessary to point out that one must also include working papers in order to obtain an appropriate coverage of studies and enrich the heterogeneity in results. Including all the literature makes sense because important information regarding the topic in question may be retrieved from unpublished, as well as published, papers. With the aim to address this issue, a binary variable for study quality is included, as in Disdier and Head (2008).[1] We will control for quality of publication by (i) using a dummy variable to distinguish between journal papers and works published as working papers and by (ii) using a continuous variable which we create by referring to the Impact Factor (IF) of each journal at the time of the publication of a primary paper.

Finally, MA may suffer from publication bias, in the sense that final results may reflect the fact that journals tend to publish papers whose evidence is robust in statistical terms. In order to control for this issue, many scholars weight the observations by using appropriate measures of the estimates' variability (Bumann et al., 2013; Cipollina and Salvatici, 2007; Doucouliagos and Stanley, 2009; Feld et al., 2013; Stanley, 2008). From an empirical perspective, these studies indicate that the Random Effect Multilevel Model (REML) and the weighted-cluster data analysis (WLS) are robust to publication bias. After controlling for publication bias in our sample, we will proceed by using the REML technique because it controls not only for within-study variability, but also for between-study heterogeneity (cfr. 6.1).

4. Meta-Analysis in efficiency literature

The use of MA is increasing in economics and is applied to a very wide range of areas. Poot (2012) counts 626 papers which applied MA to economics between 1980 and 2010, with an exponential growth in the 2000s. About three quarters of these MA applications were published in field-specific journals, several appeared in "top" journals (*The American Economic Review*, *Journal of Banking and Finance*, *Journal of Political Economy*, *Review of Economics and Statistics, and The Economic Journal*), whilst the remaining were disseminated across working papers or book chapters. Among other things, Poot (2012) shows that scholars have only paid attention to publication bias in the most recent MA studies.

Although there has been a widespread use of MA in many areas of economics,[2] it is worth noting that few papers deal with efficiency and, when they do, most consider the

[1] Disdier and Head (2008) introduce a dummy variable equal to 1 if the study is published in one of the following top three journals: the *American Economic Review*, the *Journal of International Economics* and *Review of Economics and Statistics*.

[2] With regards to the topics under review, agricultural and environmental economics are the field of research with the highest proportion of MA papers, followed by industrial economics, labor economics

agricultural sector. For instance, Bravo-Ureta et al. (2007) examine the efficiency data collected from 167 farm level studies (569 observations) published over the last four decades. Their main results indicate that nonparametric deterministic models yield higher estimates of efficiency levels than stochastic frontier models do, whereas parametric deterministic frontiers yield lower estimates. Furthermore, the role of functional form is vague, while a significant effect is found for the structure of data used in the original papers, in the sense that cross-sectional data produce lower estimates than panel data. This is also found in Thiam et al. (2001), who review 34 articles covering agricultural efficiency in developing countries. The authors find that no effect on efficiency is exerted by the number of variables in the model, crop type, stochastic versus deterministic frontiers and sample size, while efficiency in agriculture increases with the number of fixed inputs and the number of inputs. Kolawole (2009) focuses on Nigerian agriculture[3] and performs an MA covering 64 studies and 86 observations for the period 1999-2008. He shows that the sample size, the number of inputs used and the aggregate output variable (i.e., single output variable) are the main sources of variability in efficiency in Nigerian agriculture. The author also finds that crop and livestock production perform better than other agricultural sectors and that studies on the northeast and southeast regions of the country yield lower scores of efficiency. It is important to point out that the MA performed by Kolawole (2009) lacks, as the author acknowledges, "published information on the study specific characteristics used as explanatory variables in the regression" (p. 14).

While Brons *et al*. (2005) focus on urban transport, finding that there is no statistical difference in efficiency scores between parametric and nonparametric studies, Odeck and Bråthen (2012) analyze the variations in the technical efficiency of seaports using 40 published papers (127 estimates) and show significant differences between results obtained by using a variety of methods. One of the main findings is that the random effects model outperforms the fixed effects model in explaining variations in efficiency. Moreover, the estimated efficiency of recent studies is low compared with earlier published papers. Interestingly, DEA yields, on average, higher estimations of efficiency than SFA. Finally, efficiency increases when moving from studies based on panel data to cross-sectional analyses. Another MA is that carried out by Nguyen and Coelli (2009), who focus on hospital efficiency. They use 253 observations obtained from 95 primary studies published between 1987 and 2008. Their paper explains the differences in efficiency with respect to sample size, number of variables, parametric versus nonparametric method, returns to scale, functional

---

and consumer economics. In order to give an idea of the wide spectrum of recent MA applications in economics, it is sufficient to say that they have been used with regard such topics as the tax impact on corporate debt financing (Feld et al., 2013), the financial liberalization-growth nexus (Bumann et al., 2013), misalignments in real exchange rates (Ègert and Halpern, 2006), the demand for gasoline (Havranek et al., 2012), labor supply elasticities (Chetty et al., 2011), the relationship between FDI and taxation (Feld and Heckemeyer, 2011), the effect of active labor market policies (Card et al. 2010), aid effectiveness (Doucoliagos and Paldam, 2009), the role of distance in bilateral trade (Disdier and Head, 2008), the 2% β-Convergence (Abreu et al., 2005) and a variety of other environmental and transport issues (summarized in van den Bergh and Button, 1997).

[3] According to the author, the decision to consider a single country helps to overcome the weakness relating to the fact that, in Thiam et al. (2001) and Bravo-Ureta et al. (2007), "each cited study is treated as an experiment based on a sample from a single population by implicitly assuming a common benchmark for the comparison: i.e., the existence of a population Is implicit in these studies. ……….. the advantage (*to focus on a single country*) is, in our view, more than outweighed by the easier interpretation of efficiency" (pages 3-4).

form, error distribution form, cost versus technical efficiency and cross-sectional versus panel data. The authors find that, in hospital efficiency literature, sample size and constant returns to scale have a negative effect on efficiency, while the number of variables exerts a positive effect. None of the other individual study features have an impact on efficiency.

A very similar research question to ours has been addressed by Iršová and Havránek (2010) who review US banking efficiency literature covering the years from 1977 to 1997. Their dataset comprises 32 papers and 53 observations. By applying several estimators (OLS, Tobit, Iteratively re-weighted least squares method, and Random-Effect), they show that US banks are less efficient when generating profits than when controlling costs. Interestingly, when referring to the translog functional form, the estimated efficiency scores are high compared with the Fourier specification. In the words of Iršová and Havránek (2010):

> " … the functional forms generally operate in opposite directions (translog functional form positively and Fourier functional form negatively), which contradicts the results in Berger & Mester (1997) who favour an insignificant difference between these two forms. According to our results, the translog parametric choice does not return significantly different results from the nonparametric approaches. Therefore, when researchers happen to find different results between parametric and nonparametric approaches, it is mainly due to the usage of a Fourier-flexible production function" (p. 319).

The paper by Iršová and Havránek (2010) is the only MA which has been conducted to review the efficiency studies in banking. However, it covers just one country, uses a sample of just a few papers and observations and the surveyed literature only considers papers focusing on US bank efficiency up to 1997, when in studying this literature we have observed, over the 2000s, a proliferation of scientific contributions employing a very wide spectrum of methods and focusing on very different samples of banking industry. Again, scholars refer to very different frameworks of analysis and use various econometric methods in order to address the research question. The choice of the estimation method is a key aspect in this class of study. In fact, the signs of the results and the existence of actual efficiency gains are not uniform. However, different works come to different conclusions, even when using the same type of estimation approach and, sometimes, when considering the same time period. Having said this, the lack of a systematic and quantitative survey on banking efficiency is surprising because MA fits the banking sector very well . The hypothesis that the heterogeneity in results may depend on the methodological choices of each study remains an interesting issue to be addressed empirically.

5. The Bank-Efficiency Meta Dataset

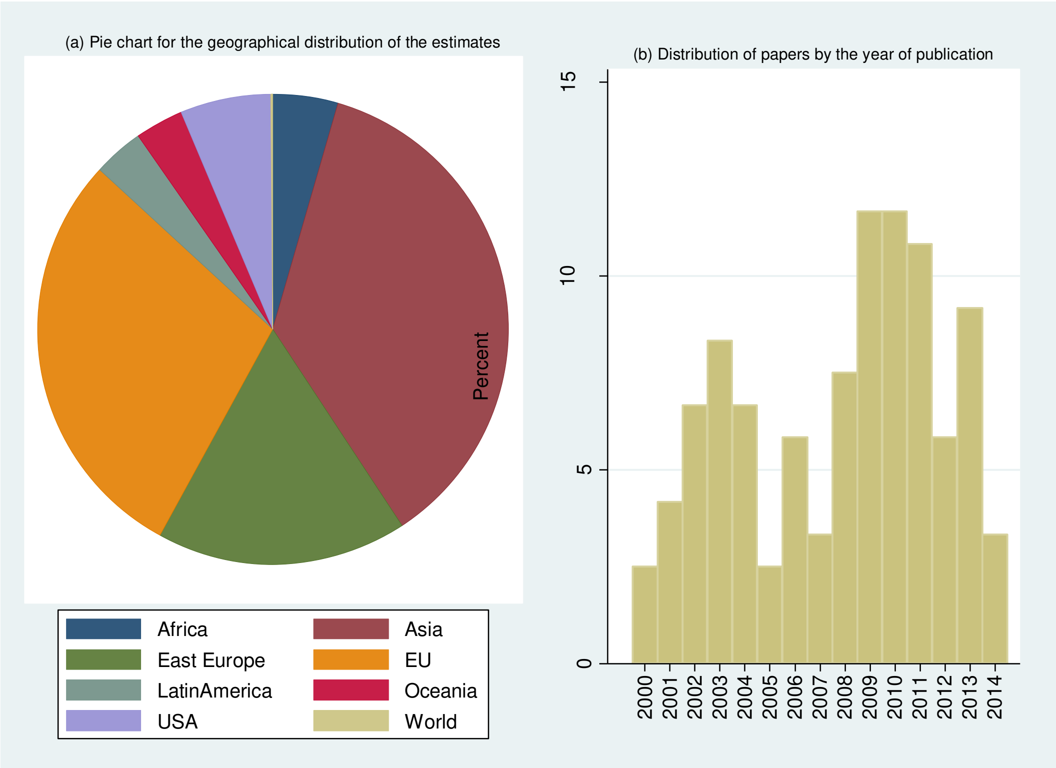
A delicate phase of an MA is the creation of the database. The number of potential papers in banking literature is impressive: for instance, when searching through Google for "banking efficiency", one obtains more than 45,000 results (as of 24th April, 2014). This diminished to 10,800 after controlling for "frontier". Therefore, in order to collect a representative sample of works, we employ some criteria to identify relevant academic studies from the large pool of papers on bank efficiency. The search was conducted in two phases.

Firstly, we refer to the EconBiz, Repec, ScienceDirect, IngentaConnect and Econlit archives. The key-words used in the baseline search in the title, abstract or keywords are "bank", "efficiency" and "frontier". At the beginning, the search was not restricted and provided a sample of 1,322 published works and working papers that encompass a very broad set of hypotheses and empirical works. Before filtering this sample of works, we ensured that they (a) focused on bank efficiency; (b) included sufficient information for the performing of an MA (efficiency scores and standard deviations); (c) ran specific models for estimating the frontier (DEA, SFA, others); (d) were written in English; (f) were published in a journal or as working papers after 2000; (g) conducted analysis at bank (not branch) level. In this phase, we excluded the papers with the same efficiency score result as were reported in other papers by the same author/s and papers that do not report efficiency estimates.

Secondly, we (a) manually consulted the principal field journals (the *Journal of Banking and Finance*, *Journal of Productivity Analysis*, *Review of Financial Studies*, *Journal of Financial Economics*, *European Journal of Operational Research*, *Applied Financial Economics* and *Journal of Business Finance & Accounting*); (b) explored additional databases such as the Google Scholar and Social Science Research Network (SSRN) and (c) verified that we had not overlooked efficiency studies by scanning the references of qualitative surveys dealing with issues strictly relating to our research question that were published after 2000, i.e., Berger (2007), Fethi and Pasiouras (2010), Paradi and Zhu (2013). The second round of the search yielded twenty-nine additional studies. The dataset was concluded on the 24th April, 2104 with a set of 120 papers and 1,661 observations.

Table A1 in Appendix A presents the list of the studies which make up the meta-dataset, including the authors' name, the year of publication, the type of publication, the journal, the number of estimates, the average efficiency and some measure of variability (standard deviation, maximum and minimum values). In order to save space in the table, we just display the average for the primary studies reporting different measures of efficiency (i.e., profit or cost efficiency) . Nevertheless, the econometric analysis uses all the information from every paper. As can be seen, the number of estimated efficiency scores varies greatly from one study to another, ranging from 1 to 162 estimates. Similarly, the average value of the efficiency is extremely variant, falling in the range between 0.279 and 1.025. Figure 2a presents the distribution of observations by geographical area. Note that the number of efficiency score varies widely across the areas: there is a high frequency of primary studies which investigate the case of Asia (37% of the entire sample refers to Asian countries), followed by the EU (29%), Eastern Europe (17%) and the USA (6%). The others have a minor frequency. Figure 2b shows that that 41 (34% of the entire sample) studies appeared over the three-year period 2009-2011, 11 (9%) papers were published in 2013 while few works, that is to say fewer than 5 (4%), appeared in 2000, 2005 or 2007. The year 2014 is represented by 4 (3% of the sample) papers.

Figure 2 Efficiency scores by geographical area and papers by year of publication



A synthesis of the collected estimates is reported in table 2, where different sub-samples of scores have been considered according to the approach used in estimations (parametric or nonparametric), the approach followed in selecting the variable for the frontiers (intermediation, value added or hybrid approaches), the structure of data (panel or cross-section), the functional form of the frontier (Cobb-Douglas, translog or Fourier) and, finally, on the basis of the hypotheses regarding returns to scale (constant or variable).

Overall, the sample of 1,661 observations yields an average efficiency of 0.69. Some differences emerge by efficiency type: the average of the 726 cost-efficiency scores is 0.73, while it is 0.62 for 288 observations based on profit frontiers. In the case of the 647 observations of efficiency in production, the average is 0.69. data also highlight that the overall mean of the 872 observations from parametric studies is always lower than that of the 789 observations of nonparametric papers: the difference in mean is 0.0599 (0.7313-0.6714) and is statistically significant.[4]

Differences between the efficiency of nonparametric and parametric studies remain positive and significant, whatever type of efficiency we refer to (cost, profit or production). Again, there are 907 observations referring to studies using the intermediation approach, more than 50% of the entire sample, while the dataset includes 361 observations from studies using the value added approach. Between these two extremes, there is the hybrid approach, which differs in that researchers consider deposits either as input or output. The hybrid approach is made up of 391 observations. The difference in means is only high when

[4] We implement a test of differences in means for each sub-group. We always reject the null hypotheses of equality in means, except for two cases which regard (1) the panel data versus cross section data (p-value is equal to 0.1726) and (2) the intermediation approach versus the added-value approach (p-value is equal to 0.2072). Data are available on request.

considering the cost-frontier where the production approach yields a higher (0.7913) average efficiency than the intermediation (0.7238) and the hybrid (0.7039) choices. With regards the structure of data used in primary studies, the analysis shows that about two-thirds of the observations come from estimations obtained from panel data and the other one-third refers to cross-section data. What clearly emerges is that there is no difference in means when considering the entire sample of observations, while cost and profit efficiency scores are higher, on average, when using cross-section instead of panel data. The opposite holds for the other measures of efficiency. Furthermore, in the sample of parametric studies, another difference is that few (111 in the full sample) observations refer to a Cobb-Douglas specification of the frontier, while the majority use more flexible functional forms (526 adopt a translog frontier and 235 a Fourier one). While Cobb-Douglas specifications yield a higher level of efficiency when studying cost efficiency (0.8246 compared with 0.6731 from translog and 0.7746 from Fourier), the translog form applied to profit frontier yields a higher value of efficiency (0.5964 compared with 0.5341 from Cobb-Douglas and 0.5795 from Fourier). Finally, an interesting pattern is observed when referring to the hypothesis of returns to scale of nonparametric-studies. Overall, the assumption of VRS translates to an average level of efficiency (0.7452) which is higher than that (0.7035) associated with the observations using the hypothesis of CRS. However. results differ according to the frontier. For instance, when considering profit frontiers, we find that the average level of efficiency obtained in the primary studies using CRS is 0.8320, that is to say a much higher value than that (0.6675) associated with the studies based on VRS.

A lesson learnt from this discussion is that the study-design of primary papers plays an important role in determining differences in the means of banking efficiency scores. In addition, the heterogeneity in banking efficiency literature is confirmed by figures 3-7, which display the distribution of the estimated scores by group. The exposition of results follows the same strategy in each figure. For instance, panel A of figure 3 refers to the full sample and presents the efficiency scores obtained from parametric and nonparametric methods. It is clear that the density functions have different shapes and forms. The likely effect of choosing to estimate banking efficiency through a parametric or a nonparametric method is even more evident when splitting the sample by cost efficiency (panel b), profit efficiency (panel c) and efficiency in production (panel d). The distributions are more uneven when comparing the intermediation, value added and the hybrid methods (figure 4). The same applies for the remaining cases, except for some overlapping of the distribution of cost-efficiency reported in panel data and cross section studies (figure 5, panel b).[5]

[5] In panel c of figure 6, the density referring to Cobb-Douglas is apart from translog and Fourier because the scale of frequencies is very different.

Table 2 Average, standard deviation and number of observations in bank efficiency literature by group

		All sample	Cost	Profit	Production
All	Mean	0.6999	0.7301	0.6245	0.6995
	SD	0.1820	0.1873	0.1739	0.1696
	Obs	*1661*	*726*	*288*	*647*
Approach					
Parametric	Mean	0.6714	0.7092	0.5892	0.6511
	SD	0.1937	0.1993	0.1611	0.1716
	Obs	*872*	*541*	*221*	*110*
Nonparametric	Mean	0.7313	0.7911	0.7411	0.7095
	SD	0.1626	0.1289	0.1644	0.1676
	Obs	*789*	*185*	*67*	*537*
Variables of the frontier					
Intermediation	Mean	0.7045	0.7238	0.6587	0.6964
	SD	0.1991	0.2058	0.1824	0.1918
	Obs	*907*	*485*	*157*	*265*
Value added	Mean	0.7186	0.7913	0.6414	0.6996
	SD	0.1166	0.1043	0.0747	0.1116
	Obs	*361*	*107*	*51*	*203*
Hybrid	Mean	0.6712	0.7039	0.5467	0.7012
	SD	0.1872	0.1572	0.1790	0.1889
	Obs	*391*	*134*	*80*	*179*
Functional form in parametric studies					
Cobb-Douglas	Mean	0.7132	0.8246	0.5341	0.6460
	SD	0.1712	0.0843	0.0065	0.1767
	Obs	*111*	*43*	*2*	*66*
Translog	Mean	0.6585	0.6731	0.5964	0.7742
	SD	0.2103	0.2202	0.1758	0.1289
	Obs	*526*	*370*	*132*	*24*
Fourier	Mean	0.6807	0.7746	0.5795	0.5201
	SD	0.1593	0.1146	0.1381	0.0688
	Obs	*235*	*128*	*87*	*20*
Data					
Panel	Mean	0.7043	0.7206	0.6144	0.7479
	SD	0.1899	0.1921	0.1847	0.1633
	Obs	*1080*	*574*	*235*	*271*
Cross section	Mean	0.6916	0.7658	0.6695	0.6647
	SD	0.1663	0.1638	0.1042	0.1657
	Obs	*581*	*152*	*53*	*376*
Returns to scale in nonparametric studies					
CRS	Mean	0.7035	0.7935	0.8320	0.6586
	SD	0.1650	0.1592	0.1116	0.1531
	Obs	*263*	*49*	*30*	*184*
VRS	Mean	0.7452	0.7903	0.6675	0.7360
	SD	0.1597	0.1168	0.1644	0.1689
	Obs	*526*	*136*	*37*	*353*

Figure 3 Distribution of banking efficiency by estimating method (parametric and nonparametric)

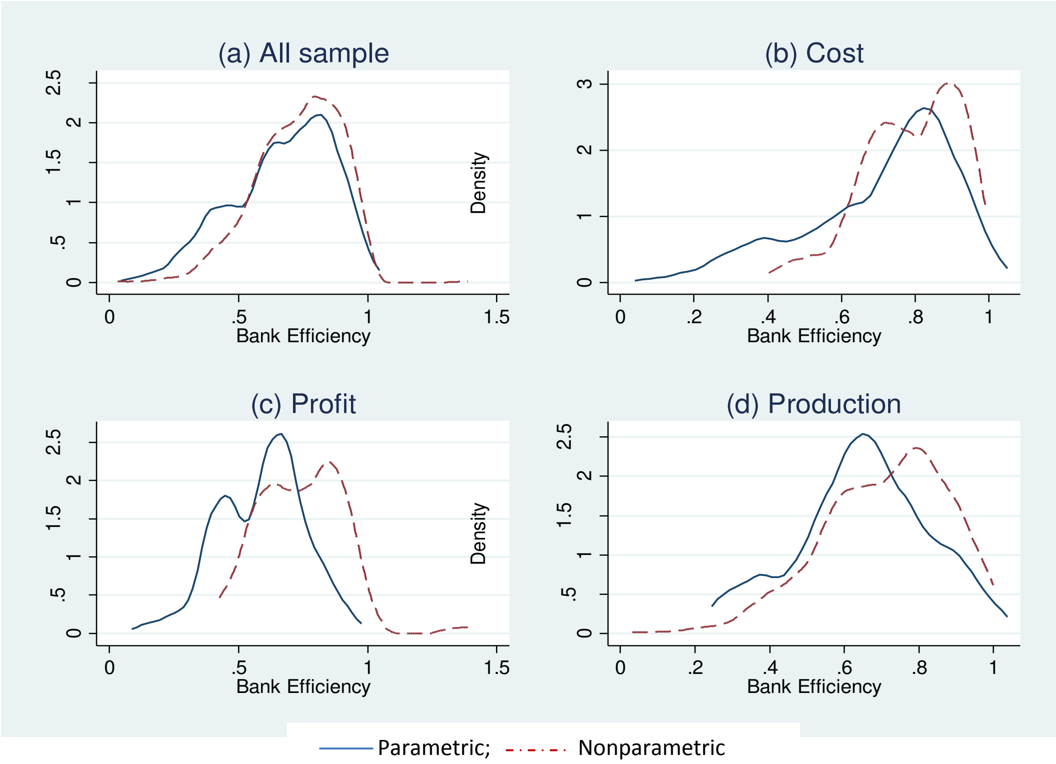


Figure 4 Distribution of banking efficiency by variables approach (intermediation, value added and hybrid)

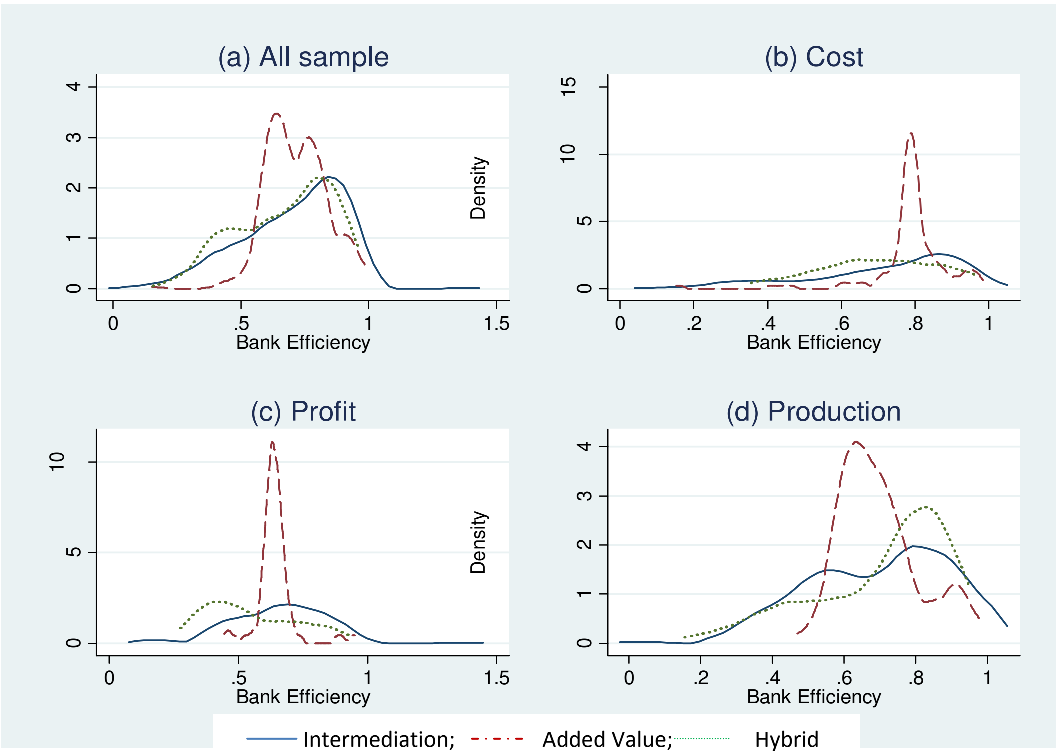


Figure 5 Distribution of banking efficiency by data type (panel and cross section)

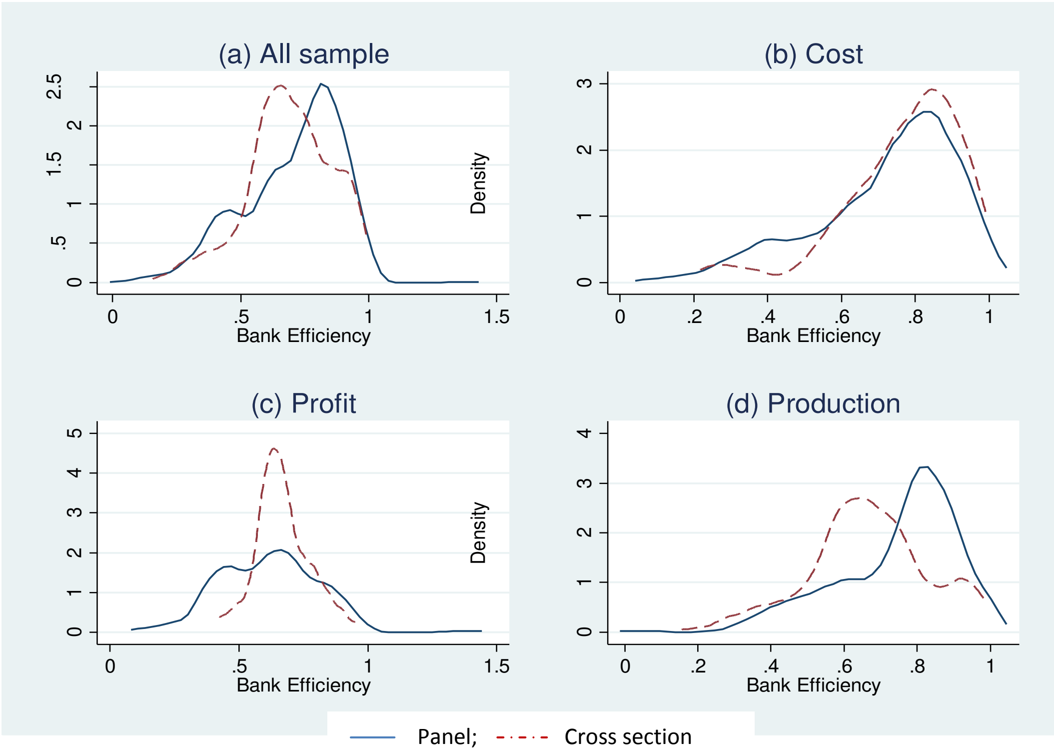


Figure 6 Distribution of banking efficiency by functional form (Cobb-Douglas, translog and Fourier)

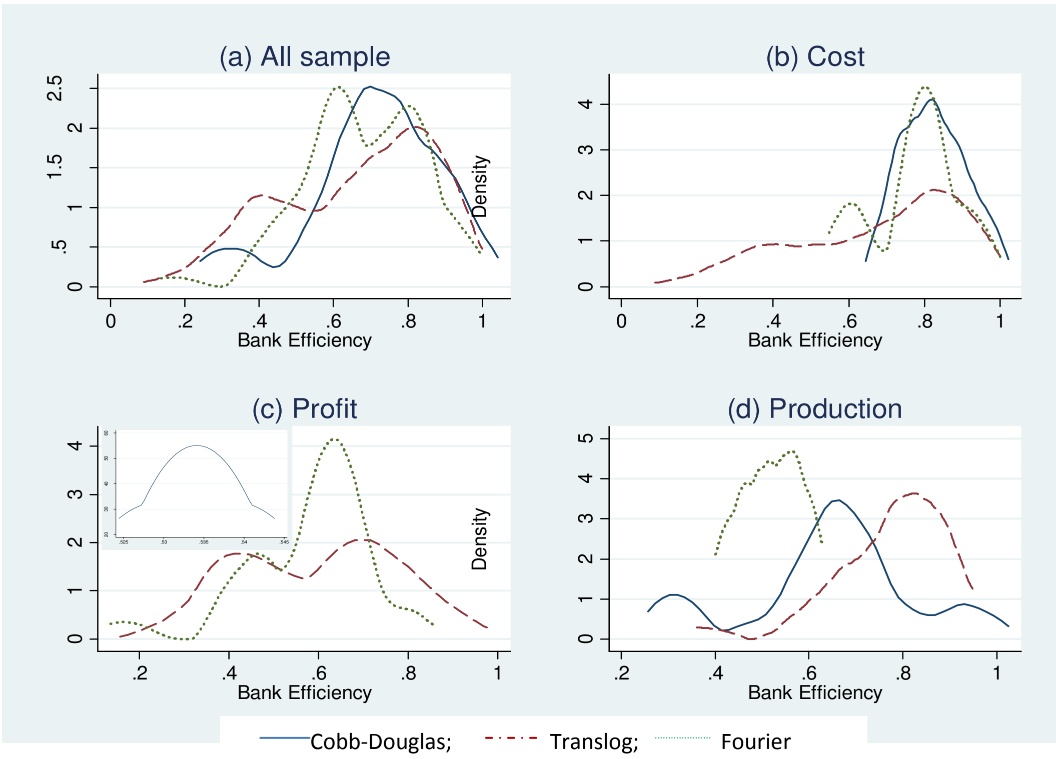
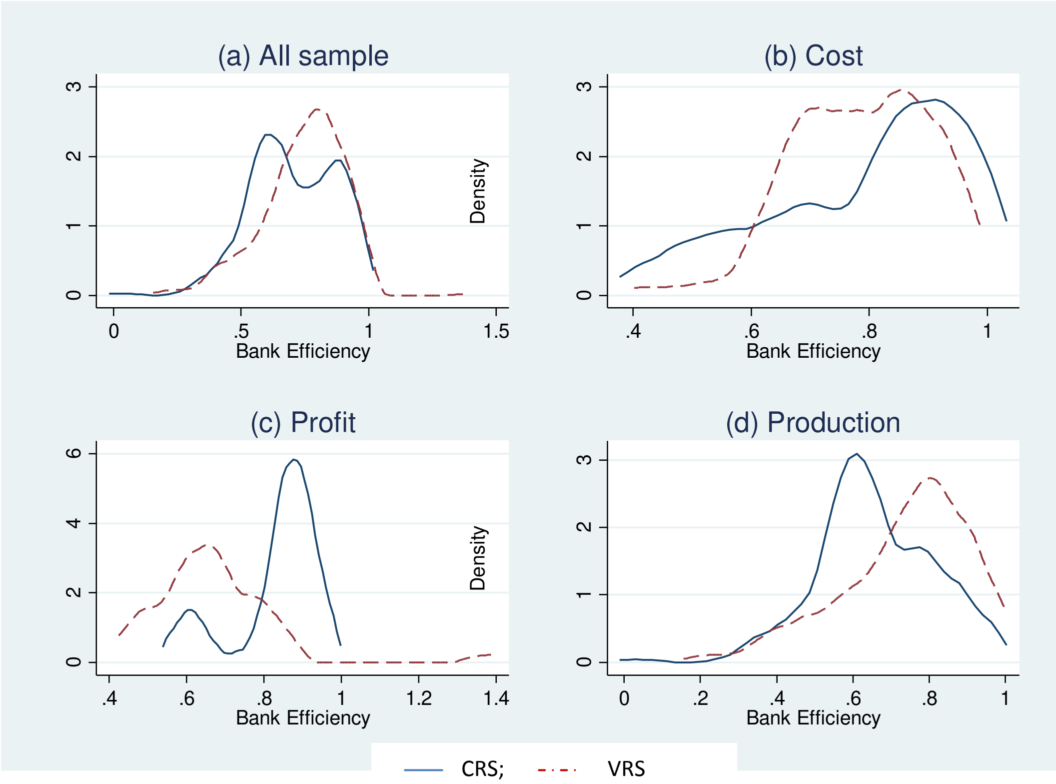


Figure 7 Distribution of banking efficiency by return to scale (CRS and VRS)



6. Meta-analysis regression and results

6.1 The empirical setting

The descriptive evidence indicates that there are relevant differences in means and in the efficiency distributions when grouping observations by different criteria. Given this, providing a systematic explanation of the variability of efficiency becomes an important issue to be addressed on econometric grounds. This section focuses on meta-regression analysis carried out to explain heterogeneity in banking efficiency scores. We proceed by (i) introducing the estimator used in the empirical analysis and presenting the econometric specification of the meta-regression and by (ii) discussing the results.

There are two main issues to be addressed in our empirical analysis. The first regards heteroschedasticity, while the second relates to publication bias.

The dependent variable of the MA regression is banks' efficiency retrieved from the primary literature. As we have seen before, in creating the meta-dataset we have collected all the information from each paper and many papers provide more than one estimations of efficiency. From an econometric perspective, this means that the unit of observation is the individual value of the estimated efficiency with the result that there is a within study heterogeneity to control for. As for publication bias, the success of a paper depends greatly on the study results, in the sense that the probability of a paper's being published increases the more its conclusions are based on highly significant evidence and thus they are conclusive. A simple method for detecting publication bias is to regress the key-variable of the meta-analysis - banks' efficiency in our case - against its precision in primary estimations (Egger et al., 1997). If this regression yields significant results, then there is evidence of publication bias in the meta-data set which must be controlled for in the meta-regression.

This said , in order to provide answers to the research questions raised throughout the paper, we refer to the following equation:

$$\mathrm{E_i} = \beta_1 + \beta_0 S_i + \sum_{\mathrm{j}} \beta_{\mathrm{j}} \mathrm{X_j} + \varepsilon_i \qquad [1]$$

where the dependent variable E_i is the i-*th* efficiency score. X_j is comprised of the explicative variables that summarize various model characteristics of the primary studies. S_i is a measure of variability of Ei and enters into the meta-regression to control for publication bias as proposed by Egger et. al. (1997) and applied by Bumann et al*.* (2013), Cipollina and Salvatici (2007), Feld et al. (2013) and Stanley (2008). ε is the error of the model, which is clearly heteroschedastic because the variance of individual estimates changes in the sample and the estimates are not independent within the same study (Stanley, 2008). This issue is addressed by weighting the observation through a measure S of the variability of each observation:

$$\begin{aligned} \frac{\mathrm{E_i}}{S_i} &= \beta_0 + \beta_1 \frac{1}{S_i} + \sum_{\mathrm{j}} \beta_{\mathrm{j}} \frac{\mathrm{X_j}}{S_i} + e_i \\ E_i^* &= \beta_0 + \beta_1 S_i^* + \sum_{\mathrm{j}} \beta_{\mathrm{j}} X_i^* + e_i \end{aligned} \qquad [2]$$

where the disturbance $e = \varepsilon / S$ is corrected for heteroschedasticity- The test for publication bias will be carried out on the constant β_0, as in Cipollina and Salvatici (2007), Doucouliagos and Stanley (2009), Fed et al. (2013) and Stanley (2008).

The method to be used in estimating eq. [2] may be a fixed-effects or a random-effects model. While both methods provide results which are robust to publication bias (Stanley 2008), they differ in terms of their treatment of heterogeneity. In particular, a fixed-effects meta-regression assumes that all the heterogeneity can be explained by the covariates and leads to excessive type I errors when there is residual, or unexplained, heterogeneity (Harbord and Higgins, 2008; Higgins and Thompson, 2004; Thompson and Sharp, 1999). Instead, a random-effects meta-regression allows for such residual heterogeneity (the between-study variance not explained by the covariates) and therefore extends the fixed-effects model. Formally, under the random-effects framework, eq. [2] becomes:

$$E_i^* = \beta_0 + \beta_1 S_i^* + \sum_{\mathrm{j}} \beta_{\mathrm{j}} X_i^* + u_i + e_i \qquad [3]$$

where $e_i \sim N(\theta_i, \sigma^2_i)$ is the disturbance and $u_i \sim N(\theta_i, \tau^2)$ is the fixed-effect. The parameter τ^2 is the between-study variance, which must be estimated from the data as in Harbord and Higgins (2008).[6]

The right-hand side of eq. [3] includes X_j which relates to the firm observed characteristics used to explain the variability in banks' efficiency and we have identified on

[6] Technically, REML first estimates the between-study variance, τ^2, and then estimates the coefficients, β, with the weighted least squares procedure and using as weights $1/(\sigma_i^2 + \tau^2)$, where σ_i^2 is the standard error of the estimated effect in study i. The word "multilevel" refers to the structure of the metadata set which combines observations at single estimates level and observations at study level (Harbord and Higgins, 2008; Thompson and Sharp, 1999).

the basis of a systematic comparison of original papers. In selecting the moderator variables, we bear in mind the fact that the focus is to verify whether the methodology choices followed in primary works matter in determining the mean efficiency of the banking industry. The explanatory variables follow.

The first distinguishing element to be considered relates to the approach used to estimate the frontier. We made a broad distinction between papers using a parametric method and papers following a nonparametric approach. To this end, the dummy variable used is *Parametric* (*PA*) which is equal to unity for the first group of studies and zero for the others. As we have already said (cfr. § 5), scholars use deposits as inputs or outputs in banking literature. In this respect, we include the dummies *Intermediation* (*INT*) and *Value added* (*Y*), which are unity when efficiency scores are derived from primary-studies using the intermediation or the value added approach (the controlling group comprises the point-observations from papers using the hybrid approach, *HY*). Furthermore, the entire sample comprises three types of efficiency, cost, profit and production efficiency. To control for this, we include two dummies, *Cost (CE*) and *Profit (PE*), with the value 1 if the efficiency score refers to cost or profit efficiencies (the controlling group is the efficiency obtained a production frontier).

The literature on Meta-Regression helps to select the other controlling variables. A element which should be considered is the time period analyzed. Increasing regulation is expected to gradually lead to improvements in how banks work, other things being equal. This time-effect is meant to be gauged by the dummies $Y_{2000\text{-}2004}$ and $Y_{2005\text{-}2009}$, which are equal to one if the paper was published in the corresponding years and zero otherwise (the controlling group is comprised of the studies published in the years 2010-2014). Another distinction to be made is between the efficiency obtained in papers using cross-sectional data and that derived from studies based on panel data. The dummy variable *Panel* is equal to unity if original works used panel data and zero otherwise. Furthermore, in order to separate estimates reported in published works from others, we use the dummy *Published* which is one for published papers and zero otherwise. In order to better control for any potential quality-effect of primary paper, we also build the variable *IF* which is a continuous variable relating to the Impact Factor of the particular journal at the time of the publication of the paper. IF is equal to zero for journals without impact factor and when the efficiency score comes from book chapters, working papers and unpublished papers. Finally, we consider the variable *Sample Size,* i.e. the number of observations used in estimating the efficiency score. The variable *Dimension* is given by the sum of the number of inputs and outputs of the frontier. There are two other choices in the study design which are related to the functional form of the frontier and the returns to scale. The dummy variable *Cobb Douglas* is unity if the Cobb-Douglas functional form is used in modeling the frontier (the reference category comprises translog and Fourier specifications), while *VRS* is a dummy variable equal to one if the primary study assumes variable returns to scale and zero otherwise. Finally, in order to control for geographical differences, we consider the dummy variables Africa, Asia, East Europe, EU, Latin America, Oceania and the USA, which are equal to one if the study used data from that specific part of the world (the controlling group is composed of efficiency scores associated with a large sample of countries that cannot be assigned to specific geographical areas).

6.2 Econometric Results

In presenting the results, we start from a basic regression which includes just the dummies relating to the methodological choices made when performing an estimation of banks' efficiency. The underlying idea is to test the robustness of results (sign, magnitude and significance) when moving from basic to extended regressions. In table 3, Model 1 considers just the variables Parametric, Intermediation and Value added. Model 2 controls for the type of efficiency effect and, to this end, adds the variables Cost and Profit to Model 1. Model 3 is the expanded version of our meta-regression, introducing the interacting terms PA∗Y and PA∗INT and considering all the other moderator variables in order to better identify the origin of the heterogeneity in banking efficiency, as already defined. Model 4 and 5 limit the analysis to the sub-samples of studies belonging to the class of parametric and nonparametric, respectively.[7] Table 4 displays the results obtained from a sensitivity analysis which was carried out to test whether the evidence is robust to the exclusion of 1%, 5% and 10% tails of the efficiency and sample size distributions.[8]

Before the results are presented, it is worthwhile commenting on some diagnostics. The main evidence regards $\hat{\beta}_0$, the parameter used as a test for publication bias: $\hat{\beta}_0$ is significant in Model 1 and 2 and not in Models 3, 4 and 5 of table 3. Findings in table 3 indicate that there is no evidence of publication bias when covariates enter into regressions to explain the heterogeneity in efficiency. The same applies after excluding the tails of the key variable of our study, that is to say the efficiency distribution (table 4). Furthermore, we present some statistics at the bottom of each table that we retrieved from the Stata-command "metareg" developed by Harbord and Higgins (2008). As can be seen, the proportion of the residual variance that is attributable to between-study heterogeneity is very high. In Model 3, it is 98.58%. Again, in the same regression, the proportion of between variance explained by the covariates is 56%, the measure of within-study sampling variability. Finally, the joint-significance of moderators is high in each model.

In order to ensure clarity in the presentation of results, the discussion is divided into two sub-sections. The first devotes attention to the role of estimating methods and approaches in the choice of variables, while the second sub-section looks at the effects exerted by the other variables included in the meta-regression.

6.2.1 The roles of the estimating method and variable approaches

The first finding to be discussed regards the role of using parametric or nonparametric methods. This issue is important because the majority of parametric studies in our sample use SFA and, similarly, almost all nonparametric studies are based on DEA, which is expected to determine higher efficiency indexes than stochastic models do (Ekanayake and Jayasuriya, 1987). According to our estimates, parametric techniques generate significantly lower

[7] Splitting the sample should allow better evaluation of the role of specific methodological choices. For instance, this is the case of the dummy Cobb-Douglas: in model 4 the "zeros" only refer to functional forms other than Cobb-Douglas and not to point-observations from nonparametric studies, as in Model 3. The same applies for the dummy VRS. Even though assumptions on return to scale are possible whatever the method, many parametric studies do not report which return to scale they use and there is no way to understand the assumption. While the procedure followed in Models 4 and 5 is more appropriate compared with Model 3, it is interesting to point out that the results do not change moving from Model 3 to Model 4 or to Model 5 (see table 3).

[8] In performing a sensitivity analysis, we restrict the sample to 1%-99%, 5%-95% and 10%-90% intervals of the distribution of efficiency scores (Model 1, 2 and 3 of table 4) and sample size (Model 4, 5 and 6 of table 4).

efficiency scores than nonparametric models do: the coefficient associated with the dummy *Parametric* is negative and highly significant in Models 1 and 2, indicating that, other things being fixed, the efficiency scores are lower for parametric than for nonparametric techniques. This is in line with the movement of the erratic component as depicted in the hypothetical case of bank A in figure 1: in reviewing the banking literature, we find that the random noise is high and positive and, thus, that the efficiency scores from parametric procedures are systematically lower than those obtained from nonparametric ones (cfr. figure 1). This finding is confirmed after controlling for the approach used in selecting the variables, as can be seen from Model 3 (see the results displayed in table 5 below). It is also worth pointing out that the parametric effect in the other MA applications is found to be neutral with respect to the counterpart, as documented by the inconclusive evidence provided by Thiam et al. (2001) for agriculture in developing countries, Coelli and Nguyen (2009) for hospitals, Brons et al. (2005) for transport and Kolawole (2009) for Nigerian agriculture. Conversely, some similarity with our evidence is found in Bravo-Ureta et al (2007) with regard the agricultural efficiency in developed and developing economies and in Odeck and Bråthen (2009) for efficiency in seaports.

We also show that the approach (value added, intermediation or hybrid) followed in choosing inputs and outputs of the frontier is relevant in the evaluation of banking efficiency. Estimations of Models 1 and 2 indicate that the dummy variable *Intermediation* is always positive, suggesting that studies based on the intermediation approach provide, all being equal, efficiency scores which are higher that those generated by the hybrid approach. The same applies for the value added approach. The order between the effect exerted by the intermediation and the value added approaches depends upon the model we refer to. When considering Model 1, both value added and intermediation approaches over-perform compared with the hybrid and share the same effect ($\hat{\beta}_3 = 0.1; \hat{\beta}_4 = 0.11$). In moving to Model 2, we find that, on average, the value added approach yields the highest level of efficiency, followed by the intermediation and the hybrid approaches ($\hat{\beta}_4 = 0.11$ and $\hat{\beta}_3 = 0.078$). The main conclusions to be drawn are that the hybrid approach generates low levels of efficiency, followed by the intermediation approach. The highest average level of banking efficiency is yielded by papers based on the value added approach.

The discussion presented so far concerns the effects on the efficiency due to a particular methodological choice rather than another, excluding the possible effects relating to choices that combine the different methods. For instance, it is fruitful to test whether efficiency scores differ when combining the parametric and variable approaches (intermediation, value added or hybrid). Similarly, it appears important to understand whether efficiency differs when using parametric or nonparametric methods, provided that the variables of the frontier are chosen according to one of the three approaches. These issues may be addressed by augmenting the meta-regression with the interacting terms PA*INT and PA*Y. Compared with the basic model 1 of table 3, the regression to be estimated now becomes:

$$\begin{aligned} E_i^* = \beta_0 + \beta_1 S_i^* + \beta_2 PA + \beta_3 INT + \beta_4 Y + \textstyle\sum_j \beta_j X_j^* + \\ + \beta_7 (PA * INT) + \beta_8 (PA * Y) + u_i + \varepsilon_i \end{aligned} \qquad [4]$$

By focusing on the dummies PA and INT, the equation [4] allows us to identify six groups, three of which are in the class of parametric methods and three in the class of nonparametric studies. The controlling group is composed of the nonparametric estimations obtained when referring to the hybrid approach, with an expected value of efficiency given by PA=INT=Y=0. The power of eq. [4] lies in the possibility to compare results within and between each class of estimating method. To this end, we calculate the differentials in the efficiency levels for each group compared with the base group. They are:

1. Parametric and Intermediation
$$\Delta Eff\left(PA=1; INT=1; Y=0\right)=\beta_2+\beta_3+\beta_7$$
2. Parametric and Value added
$$\Delta Eff\left(PA=1; INT=0; Y=1\right)=\beta_2+\beta_4+\beta_8$$
3. Parametric and Hybrid
$$\Delta Eff\left(PA=1; INT=0; Y=0\right)=\beta_2$$
4. Nonparametric and Intermediation
$$\Delta Eff\left(PA=0; INT=1; Y=0\right)=\beta_3$$
5. Nonparametric and Value added
$$\Delta Eff\left(PA=0; INT=0; Y=1\right)=\beta_4$$

Some of these are immediately clear. Indeed, it is clear that, compared with hybrid studies, the decision to use the intermediation (value added) approach within the class of nonparametric studies generates a difference in results that is equal to β_3 (β_4). The other cases of interest are the following:

1. The effect of using the intermediation approach instead of the hybrid approach within the parametric studies is $\beta_3+\beta_7$:
$$\begin{aligned}\Delta Eff\left(PA=1; INT=1\,\&\,Y=0\right)-\Delta Eff\left(PA=1; INT=0\,\&\,Y=0\right)&=\beta_2+\beta_3+\beta_7-\beta_2\\&=\beta_3+\beta_7\end{aligned}$$
2. The effect of using the intermediation approach instead of the value added approach within the parametric studies is $\beta_3+\beta_7-\beta_4-\beta_8$:
$$\begin{aligned}\Delta Eff\left(PA=1; INT=1\,\&\,Y=0\right)-\Delta Eff\left(PA=1; INT=0\,\&\,Y=1\right)&=\beta_2+\beta_3+\beta_7-\beta_2-\beta_4-\beta_8\\&=\beta_3+\beta_7-\beta_4-\beta_8\end{aligned}$$
3. The effect of using the value added approach instead of the hybrid approach within the parametric studies is $\beta_4+\beta_8$:
$$\begin{aligned}\Delta Eff\left(PA=1; INT=0\,\&\,Y=1\right)-\Delta Eff\left(PA=1; INT=0\,\&\,Y=0\right)&=\beta_2+\beta_4+\beta_8-\beta_2\\&=\beta_4+\beta_8\end{aligned}$$
4. The effect of using the intermediation approach instead of the value added approach within the nonparametric studies is $\beta_3-\beta_4$:
$$\Delta Eff\left(PA=0; INT=1\,\&\,Y=0\right)-\Delta Eff\left(PA=0; INT=0\,\&\,Y=1\right)=\beta_3-\beta_4$$
5. The effect of using parametric instead of nonparametric method within the intermediation approach is $\beta_2+\beta_7$:
$$\Delta Eff\left(PA=1; INT=1\,\&\,Y=0\right)-\Delta Eff\left(PA=0; INT=1\,\&\,Y=0\right)=\beta_2+\beta_7$$
6. The effect of using parametric instead of nonparametric method within the value added approach is $\beta_2+\beta_8$:
$$\Delta Eff\left(PA=1; INT=0\,\&\,Y=1\right)-\Delta Eff\left(PA=0; INT=0\,\&\,Y=1\right)=\beta_2+\beta_8$$

By using results of Model 3 displayed in table 3, in table 5 we report the differences in efficiency obtained when using one variable approach over another, within the class of parametric or nonparametric studies (panel A). The findings confirm the role played by the approach to be followed when selecting the variables of the frontier. The intermediation and the value added approaches yield higher efficiency scores than the hybrid approach does. This holds true in both parametric and nonparametric estimates, although the difference is significant in the latter group. Indeed, when comparing the average level of efficiency resulting from the intermediation and the hybrid approaches, we find a difference of 0.138 in parametric studies and of 0.35 in nonparametric methods. Similarly, while the difference between the value added and the hybrid approaches is 0.2 in parametric studies, it becomes 0.48 in the nonparametric group. The conclusion we can draw is that use of the hybrid approach generates a lower level of efficiency scores than the intermediation and the value added approaches, whatever the method chosen to estimate the frontier. There are also some differences between the intermediation and the value added approaches: on average, the first generates lower levels of efficiency than the second, in both the parametric and nonparametric classes. The difference is low (-0.069) in parametric studies and increases to -0.13 for nonparametric methods (table 5, panel A).

Another finding provided by the estimations of Model 3 regards the evaluation of choosing a parametric instead of a nonparametric method, assuming that the approach taken to select the variables is fixed (table 5, panel B). What clearly emerges is similar to what is found in Models 1 and 2. While Models 1 and 2 refer to an overall effect of parametric *versus* nonparametric methods, the use of Model 3 disaggregates the evidence by intermediation, value added and hybrid approaches. According to our computations, parametric studies yield, on average, an efficiency level of -0.21 less than nonparametric studies when using the intermediation approach. The difference becomes -0.27 when the value added approach is taken into account. No difference exists within the hybrid approach: indeed the coefficient β_2 in Model 3 is not significant.

Table 3 Meta-regression of banking efficiency scores. REML estimations.

		Model 1		Model 2		Model 3		Model 4		Model 5	
Constant	β_0	0.65155	***	0.64924	***	0.19390		-0.21194		-0.10914	
1/S	β_1	0.00004	***	0.00004	***	0.00006	***	0.00006	***	0.00232	***
Parametric (PA)	β_2	-0.08358	***	-0.12730	***	-0.06639					
Intermediation (INT)	β_3	0.10105	***	0.07894	***	0.35355	***	0.14684	***	0.43016	***
Value added (Y)	β_4	0.10884	***	0.11079	***	0.48407	***	0.35842	***	0.65248	***
Cost (CE)	β_5			0.10219	***	0.14219	***	0.23202	***	0.14281	***
Profit (PE)	β_6			-0.01173		0.05335	**	0.13296	***	0.08724	**
PA*INT	β_7					-0.27648	***				
PA*Y	β_8					-0.21536	**				
Panel	β_9					0.01396		0.00519		0.05899	**
Published	β_{10}					-0.16518	***	-0.23780	***		
ln(IF)	β_{11}					-0.21458	***	0.07809	**	-0.15004	**
ln(IF)*PA	β_{12}					0.29915	***				
ln(Dimension)	β_{13}					0.44544	***	0.20789	***	0.31999	***
ln(Dimension)*PA	β_{14}					-0.13725	**				
ln(Sample Size)	β_{15}					-0.04448	***	0.01720	**	-0.02348	***
ln(Sample Size)*PA	β_{16}					0.05499	***				
D2000-2004	β_{17}					-0.04350	**	-0.03360		-0.08575	**
D2005-2009	β_{18}					-0.16622	***	-0.24943	***	0.05302	***
Cobb Douglas	β_{19}					0.19499	***	0.17644	***		
VRS	β_{20}					0.07466	**			0.08352	***
USA	β_{21}					-0.05863		0.45090	***	-0.06719	
EU	β_{22}					-0.01627		0.41255	***	-0.00240	
Eastern Europe	β_{23}					-0.02432		0.41720	***	-0.23040	
Latin America	β_{24}					-0.02359		0.32491	**	0.24339	
Africa	β_{25}					0.01035				-0.10024	
Asia	β_{26}					-0.07840		0.37175	***	-0.11843	
Oceania	β_{27}					0.03286		0.38922	***	0.04167	
Observations		1165		1165		1048		597		451	
tau^2 (between-study variance)		0.02412		0.02247		0.01233		0.01375		0.00168	
% residual variation due to heterogeneity		98.64%		98.55%		98.58%		99.18%		0.00%	
Adj R-squared		11.69%		17.73%		56.00%		57.26%		90.02%	
F- Fisher		24.67		27.49		30.06		28.03		36.10	

Table 4 Meta-regression of banking efficiency scores. A sensitivity analysis. REML estimations.

		Efficiency distribution			Sample Size distribution		
		Model 1 1%-99%	**Model 2 5%-95%**	**Model 3 10%-90%**	**Model 4 1%-99%**	**Model 5 5%-95%**	**Model 6 10%-90%**
Constant	β_0	0.29508	0.35634	0.29122	0.49631	0.45583 **	0.29953 *
1/se	β_1	0.00071 ***	0.00045 ***	0.00033 ***	0.00006 ***	0.00006 ***	0.00006 ***
Parametric (PA)	β_2	-0.15553 ***	-0.09152	0.02870	-0.21494	-0.11104	-0.22407
Intermediation (INT)	β_3	0.30813 ***	0.22007 ***	0.19858 ***	0.30984 ***	0.31800 ***	0.34949 ***
Value added (Y)	β_4	0.43171 ***	0.35009 ***	0.33547 ***	0.44110 ***	0.48299 ***	0.48927 ***
Cost (CE)	β_5	0.13491 ***	0.15140 ***	0.13868 ***	0.14304 ***	0.16456 ***	0.15265 ***
Profit (PE)	β_6	0.06371 **	0.04469 **	0.02356	0.05780 **	0.09109 ***	0.08678 ***
PA*INT	β_7	-0.20838 ***	-0.09773 *	-0.07728	-0.23466 ***	-0.21724 ***	-0.22874 ***
PA*Y	β_8	-0.15306 **	-0.10352	-0.15728 **	-0.15950 **	-0.19329 **	-0.19136 **
Panel	β_9	0.00438	-0.00424	-0.00687	0.02537	0.03634 *	-0.00222
Published	β_{10}	-0.16989 ***	-0.11914 ***	-0.08491 **	-0.19070 ***	-0.21185 ***	-0.17891 ***
ln(IF)	β_{11}	-0.23384 ***	-0.17843 ***	-0.15417 ***	-0.21285 ***	-0.24631 ***	-0.25951 ***
ln(IF)*PA	β_{12}	0.33208 ***	0.23491 ***	0.26098 ***	0.29308 ***	0.35049 ***	0.32060 ***
ln(Dimension)	β_{13}	0.43318 ***	0.33530 ***	0.29377 ***	0.42223 ***	0.44517 ***	0.44538 ***
ln(Dimension)*PA	β_{14}	-0.14257 **	-0.14649 **	-0.16121 **	-0.11644 *	-0.15468 **	-0.05377
ln(Sample Size)	β_{15}	-0.04624 ***	-0.02930 ***	-0.01777 **	-0.06459 ***	-0.05017 ***	-0.05334 ***
ln(Sample Size)*PA	β_{16}	0.06245 ***	0.04750 ***	0.03536 ***	0.06525 ***	0.05508 ***	0.05095 ***
D2000-2004	β_{17}	-0.04250 **	-0.02557	0.00300	-0.03551 *	-0.05125 **	-0.05218 **
D2005-2009	β_{18}	-0.18270 ***	-0.13317 ***	-0.09463 ***	-0.17783 ***	-0.19310 ***	-0.18553 ***
Cobb Douglas	β_{19}	0.18524 ***	0.15680 ***	0.11836 ***	0.19022 ***	0.21029 ***	0.15929 ***
VRS	β_{20}	0.08621 ***	0.06411 **	0.07654 ***	0.05481 **	0.07775 **	0.09121 ***
USA	β_{21}	-0.06310	-0.09661	-0.08522	-0.09928	-0.18857	-0.05965
EU	β_{22}	-0.04524	-0.06988	-0.07292	-0.10117	-0.20640	-0.07598 **
East Europe	β_{23}	-0.03456	-0.06045	-0.01945	-0.10797	-0.19194	-0.04108
Latin America	β_{24}	-0.07836	-0.10401	-0.11816	-0.07533		0.19179
Africa	β_{25}	0.03885	0.04911	0.08141	-0.05859	-0.14639	
Asia	β_{26}	-0.10820	-0.10781	-0.07943	-0.16002	-0.23245	-0.09874 **
Oceania	β_{27}	-0.01086	-0.00868	0.07488	-0.06345	-0.16047	0.00402
Observations		1027	936	847	1018	941	847
tau^2 (between-study variance)		0.00874	0.00618	0.00360	0.01196	0.01169	0.01037
% residual variation due to heterogeneity		79.30%	62.01%	36.04%	98.61%	98.70%	97.96%
Adj R-squared		64.21%	59.18%	61.35%	57.90%	57.63%	61.24%
F- Fisher		35.58	22.94	17.29	31.15	29.89	29.56

Table 5 Differences in average banking efficiency, by estimating method and variable approaches

Panel A *Variable Approach Effects*			
	INT *vs* Y	INT *vs* HY	Y *vs* HY
Parametric studies (PA)	-0.0694	0.1383	0.2077
Nonparametric studies (NON PA)	-0.1305	0.3536	0.4841

Panel B *Estimating Method Effects*	
	PA *vs* NON PA
Intermediation (INT)	-0.2153
Value added (Y)	-0.2764
Hybrid (HY)	0

6.2.2 The role of the other moderator variables

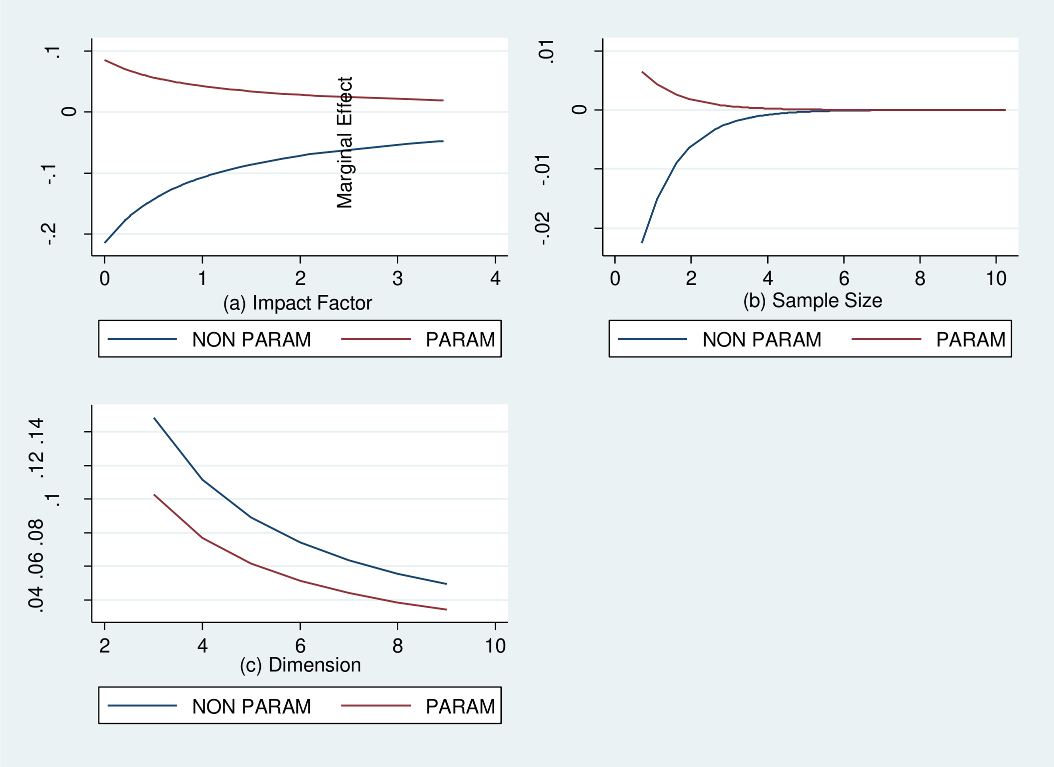
We proceed by discussing if estimation results differ by efficiency type. Other things being equal, performing a study of cost efficiency yields, on average, higher scores than when estimating a profit or a production frontier. This holds true whatever model we refer to. Furthermore, the size of this effect is also high: in Model 2, the parameter associated with the variable *Costs* is about 0.1 and becomes 0.14 when the complete regression is considered (Model 3). The coefficient of Costs increases to 0.23 and 0.14 in parametric and nonparametric studies respectively (Models 4 and 5 of table 3). Regressions also indicate that studies focusing on profits generate levels of efficiency that are higher than the production frontier, but lower than the average cost efficiency (i.e., in Model 3 $\hat{\beta}_5 = 0.14$ and $\hat{\beta}_6 = 0.05$).

With regard the effect exerted by publication type, results show that the variable *Published* is always negative (i.e., it is -0.165 in Model 3 of table 3) and significant, indicating that the average level of efficiency reported in journal papers is lower than that of studies published as working papers. Following this line of reasoning, further evidence emerges from the attempt to investigate whether the revealed efficiency scores depend upon the type of journals papers appear in. To this end, we use the journal IF and include the interaction *IF∗PA* in order to capture possible differences between parametric and nonparametric studies. As the effect of IF may be nonlinear, we take the logs and transform IF into (IF +1) in order to include all observations. According to Model 3, the parameter $\hat{\beta}_{11}$ is -0.21, implying that the level of banking efficiency within the group of nonparametric studies decreases as the IF of the journal increases. In other words, high IF ranked journals tend to publish nonparametric papers which report lower levels of banking efficiency. Results diverge as far as the parametric studies are concerned. Indeed, $\hat{\beta}_{12}$ is 0.29, implying that the relationship between IF and banks' efficiency becomes positive for parametric studies (the net effect is about 0.08). It is worthwhile noting that the sign of the relationship between efficiency and IF is robust to the sample of estimates referred to. As table 4 highlights, the effect of IF on the average level of banking efficiency does not change when 1%, 5% and 10% tails of efficiency and sample size distributions are removed. Furthermore, as IF is expressed in logs, the marginal effect of IF decreases as IF increases. For instance, when IF is 0.4 (a value close to the average of IF in both parametric and nonparametric subsamples), the marginal effect will be -0.53 in nonparametric studies. This means that publishing a banking efficiency paper in a journal with a higher IF, say 0.5, determines a decrease of about =0.1*-0.53 in the predicted efficiency. Similarly, with IF=0.4, the marginal effect is 0.21 in the parametric sample. However, in such a case, the 0.1 increase (from 0.4 to 0.5) in IF will determine an increase in efficiency of =0.1*0.21. The marginal effect of IF on efficiency is displayed in figure 8a.

The analysis of the relationship between banking efficiency and the number of observations used in estimating the frontier produces interesting findings. The continuous variable *Sample Size* enters our regressions in logs as we try to control for a potential non-linear effect. It is likely that the impact of sample size diminishes as the observations increase. We also introduce the interaction *Sample Size*PA* in order to verify whether the effect of Sample Size differs between parametric and nonparametric studies. In Model 3, the parameter $\hat{\beta}_{15}$ is negative (-0.044) and highly significant, indicating that nonparametric papers using a large sample of banks report lower levels of efficiency than studies with fewer observations. Interestingly, the coefficient $\hat{\beta}_{16} = 0.054$ is not only positive and significant but also larger in size than $\hat{\beta}_{15}$, implying that, in parametric studies, the effect exerted by the size of the sample is 0.008: the average level of efficiency increases with the number of observations when estimating banking efficiency using a parametric method. The Sample Size effect does not change when performing a sensitivity analysis of meta-regression results (table 4). All This also means that the pattern of marginal effect differs between the two approaches: as far as nonparametric studies are concerned, the marginal effect tends to zero from negative values, while in parametric studies it tends to zero from positive values (figure 8b). Nevertheless, the marginal impact in both cases rapidly tends to zero as sample size increases: it is 0.000284 and -0.00295, as calculated at the fifth percentiles of 37 and 15 of parametric and nonparametric of sub-samples, respectively. Again. with 108 and 63 point-observations (the first quartile of *Sample Size* distribution in parametric and nonparametric studies respectively), the marginal effect is effectively very weak: an increase in the number of observations would determine a very low change in mean efficiency (in figure 8b the curve of marginal effects rapidly tends to zero).

With regard the role of *Dimension*, we find that $\hat{\beta}_{13} = 0.45$ is positive: an increase in the number of inputs and/or outputs included in the nonparametric banking frontiers translates to an increase in the mean efficiency, so confirming the hypothesis of a positive link between the goodness of fit and the level of efficiency. The same applies for parametric studies ($\hat{\beta}_{14} = 0.14$ and the net effect becomes 0.31=0.45-0.14). A positive impact of *Dimension* on efficiency has been found by Coelli and Nguyen (2009), Kolawole (2009) and Thiam *et al.* (2001). Due to the use of logs, the marginal effect for nonparametric studies is 0.09 when *Dimension* is 5 (close to the overall mean of 5.5). For the parametric group, if DIM=5 the marginal effect will be 0.062. Figure 8c highlights the pattern of the marginal effect on mean banking efficiency when *Dimension* ranges between its minimum and maximum values: given the number of inputs and outputs, the marginal effect in nonparametric is always higher than in parametric studies.

Figure 8 Marginal effects of impact factor, sample size and dimension on banking efficiency



With regard the effect of the choice of the functional form, we find that, on average, the Cobb-Douglas generates higher levels of efficiency than the more flexible functional forms (translog and Fourier). Furthermore, the estimated coefficient of VRS is positive which means that models using VRS hypothesis yields higher efficiency scores than models based on CRS. These findings are confirmed in Models 4 and 5, which are, respectively, based on parametric or nonparametric sub-samples. Furthermore, we find that efficiency obtained from cross-sectional data is not different from that which uses panel data, as $\hat{\beta}_9$ is not significant in all the estimated models of tables 3 and 4. This evidence contrasts with the argument according to which panel data yield more accurate efficiency estimates given that there are repeated observations of each unit (see, among many others, Greene, 1993) and with the empirical results of Bravo-Ureta et al. (2007) and Thiam et al. (2001). With regard the time-effect, we find the average level of estimated efficiency over the years 2000-2004 and 2005-2009 is lower compared with the base years 2010-2014. This may be related to the market regulation which has occurred around the world over the last two decades and motivated by an expected increase in banking efficiency. Estimations related to 2005-2009 period may also be due the the effects on banking performances caused by the current crisis which originated in world financial markets. Finally, there is no geographical effect in the analysis we carried out when considering the full sample of data. Regressions control for this effect, but the coefficient associated with each dummy is not significant. One result which warrants more attention is that the geographical dummies only become significant in the regressions based on parametric studies.

7. Conclusions

This paper collected 1,661 observations of banking efficiency from 120 primary studies published from 2000 to 2014. It used a meta-analysis to evaluate the impacts of a number of related factors on the heterogeneities of efficiency in the primary studies. Our results show that methodological choices cause heterogeneities in banking efficiency. The sensitivity analyses also indicate that the main results are quite robust with respect to different models and subsamples.

First, the descriptive section of our metadata-set highlights the fact that efficiency scores are highly heterogeneous. To be precise, significant differences in means have been found when grouping efficiency on the basis of differing criteria. For instance, cost efficiency is significantly higher than profit and production efficiency. Furthermore, the unconditioned mean of efficiency scores from parametric studies is significantly lower than that from nonparametric studies. This holds true for any frontier type (cost, profit or production). Furthermore, selecting inputs and outputs according to the value added approach yields a higher level of efficiency than the intermediation and the hybrid approaches. Beside differences in means, data also emphasize the existence of substantial differences in the form and shape of efficiency distributions.

Second, it emerges from the meta analysis that some methodological choices can significantly affect banking efficiency. Meta regression results indicate that the studies using parametric methods provide, on average, lower efficiency scores than papers based on nonparametric models. This evidence is confirmed after distinguishing between the primary works based on intermediation and those which use the value added approach or a combination of both. Furthermore, heterogeneity in this area of research significantly depends on how authors select the inputs and outputs of the banking frontier. Other things being equal, papers following the value added approach generate higher levels of efficiency than studies using the intermediation method. Combining these two approaches (within the hybrid approach) yields low levels of efficiency. Importantly, the role of choices relating to the variable approaches is independent of the method (parametric or nonparametric) used to estimate the frontier.

Third, the analysis indicates that the estimated values of banking efficiency depend on other specific factors of primary papers. We find that the average efficiency of published papers is lower than that in unpublished studies, implying that the peer-review process negatively affects the estimates reported in primary papers. With regards to this, there is also a robust nonlinear relationship between efficiency and the journal impact factor. This link is negative in parametric studies, which suggests that efficiency decreases as impact factor increases. The opposite holds for nonparametric studies. These results are more pronounced when the journal impact factor is low. The sign of the effect determined by the sample size differs according to the estimating method: it is negative in nonparametric studies and positive in parametric papers. However, the marginal effect quickly converges to zero in both cases, suggesting that changes in the number of observations have no effect on the average efficiency level for large samples of banks, whatever the method. The number of inputs and outputs included in frontier models of primary studies also affects the results with more inputs and outputs leading to high banking efficiency. In this case too, the marginal effect decreases as dimension increases. A significant role is also exerted by the modeling choices regarding the returns to scale and the functional forms. On one hand, studies assuming variable returns to scale yield higher efficiency levels than studies based on constant returns to scale. On the other hand, the efficiency estimated in frontiers modeled as a Cobb-Douglas is higher than that obtained from more flexible functional forms. Interestingly, our meta-analysis does not corroborate the view that the specific characteristics of each national banking industry affect the average level of efficiency. However this aspect deserves further attention because it only holds when using the entire sample, whereas some differences across countries exist when MA regression is restricted to the parametric papers. Finally, the use of panel data does not produce different efficiency scores compared with the use of cross sectional data.

In conclusion, this study organizes the flood of estimates stemming from the recent literature on efficiency in banking. While many individual papers present conflicting arguments concerning the advantages of the various methodologies, we provide clear-cut quantitative effects on banks' efficiency caused by alternative methodological choices. Therefore, MA results hopefully give some insights for researchers who are interested in estimating efficiency in banking and testing the sensitivity of their findings to the choice of study design.

Appendix A

Table A1. Papers included in the metadata base

N.	Authors	Year of publication	Type of publication	Journal	Number of estimations	Average Efficiency	St. Dev.	Min	Max
1	Abrahim-MdNor-Ubaidillah	2012	published	International Journal of Business and Society	2	0.640	0.094	0.573	0.707
2	Aiello-Bonanno	2013	published	Economics and Business Letters	2	0.903	0.002	0.902	0.905
3	Akhigbe-McNulty	2003	published	Journal of Banking and Finance	8	0.760	0.078	0.641	0.855
4	Akhigbe-Stevenson	2010	published	The Quarterly Review of Economics and Finance	1	0.621	.	0.621	0.621
5	Al Sharkas-Hassan-Lawrence	2008	published	Journal of Business Finance & Accounting	4	0.730	0.164	0.525	0.894
6	Altunbas-Liu-Molyneux-Seth	2000	published	Journal of Banking and Finance	2	0.943	0.005	0.939	0.946
7	Altunbas-Gardener-Molyneux- Moore	2001	published	European Economic Review	1	0.794	.	0.794	0.794
8	Andreis-Capraru	2012	published	Procedia - Social and Behavioral Sciences	3	0.711	0.004	0.707	0.714
9	Ataullah-Cockerill-Le	2004	published	Applied Economics	92	0.705	0.165	0.286	0.934
10	Avkairan	2009	published	Omega	6	0.781	0.046	0.718	0.841
11	Bader-Mohamad-Ariff-Hassan	2008	published	Islamic Economic Studies	72	0.868	0.056	0.739	0.969
12	Barra-Destefanis-Lubrano Lavadera	2011	WP	Centre for Studies in Economics and Finance - University of Naples	54	0.797	0.086	0.633	0.945
13	Barth-Lin-Ma-Seade-Song	2013	published	Journal of Banking and Finance	1	0.760	.	0.760	0.760
14	Battaglia-Farina-Fiordelisi-Ricci	2010	published	Applied Financial Economics	4	0.776	0.075	0.685	0.868
15	Beccalli-Casu-Girardone	2006	published	Journal of Business Finance & Accounting	6	0.825	0.026	0.795	0.866
16	Behr	2010	published	European Journal of Operational Research	4	0.797	0.084	0.724	0.891
17	Behr-Tente	2008	WP	Deutsche Bundesbank – Banking and Financial Studies	4	0.599	0.075	0.531	0.673
18	Berger-Hasan-Zhou	2009	published	Journal of Banking and Finance	2	0.687	0.298	0.476	0.897
19	Berger-Bonaccorsi di Patti	2006	published	Journal of Banking and Finance	8	0.362	0.212	0.136	0.587
20	Bokpin	2013	published	Corporate Governance	2	0.465	0.369	0.204	0.725
21	Bonin-Hasan-Wachtel	2005	published	Journal of Banking and Finance	3	0.663	0.189	0.445	0.786
22	Bos-Heid-Koetter-Kolari-Kool	2009	published	European Journal of Operational Research	10	0.762	0.110	0.610	0.912
23	Bos-Kolari	2005	published	Journal of Business	8	0.782	0.136	0.607	0.976
24	Canhoto-Dermine	2003	published	Journal of Banking and Finance	14	0.746	0.096	0.590	0.930
25	Carbo-Gardener-Williams	2002	published	The Manchester School	1	0.782	.	0.782	0.782
26	Casu-Girardone	2004	published	The Service Industries Journal	6	0.753	0.102	0.637	0.874
27	Casu-Girardone	2010	published	Omega	1	0.765	.	0.765	0.765

28	Casu-Molyneux	2003	published	Applied Economics	15	0.629	0.033	0.567	0.690
29	Cavallo-Rossi	2002	published	The European Journal of Finance	4	0.825	0.033	0.788	0.869
30	Chen C.	2009	WP	International Monetary Fund	3	0.761	0.032	0.725	0.781
31	Chen K.H.-Yang	2011	published	Journal of Productivity Analysis	2	0.700	0.083	0.641	0.759
32	Chen T.	2002	published	The Journal of Operational Research Society	3	0.878	0.083	0.782	0.932
33	Chiu-Chen Y.-C.	2009	published	Economic Modelling	2	0.825	0.162	0.710	0.939
34	Chortareas-Garza Garcia-Girardone	2011	published	Review of Development Economics	9	0.657	0.144	0.458	0.836
35	Christopoulos-Tsionas	2001	published	The Manchester School	4	0.843	0.039	0.792	0.884
36	Cuesta-Orea	2002	published	Journal of Banking and Finance	2	0.885	0.035	0.860	0.910
37	Daley-Matthews-Zhang	2013	published	Applied Financial Economics	16	0.768	0.204	0.356	0.961
38	Delis-Tsionas	2009	published	Journal of Banking and Finance	2	0.874	0.006	0.869	0.878
39	Dietsch-LozanoVivas	2000	published	Journal of Banking and Finance	12	0.768	0.204	0.356	0.961
40	Drake-Hall	2003	published	Journal of Banking and Finance	2	0.794	0.098	0.724	0.863
41	Esho	2001	published	Journal of Banking and Finance	18	0.734	0.213	0.153	0.915
42	Fang-Hasan-Marton	2011	WP	Bank of Finland	4	0.612	0.090	0.530	0.700
43	Fiordelisi-Marques Ibanez-Molyneux	2011	published	Journal of Banking and Finance	3	0.537	0.093	0.445	0.631
44	Fiordelisi-Ricci	2011	published	The European Journal of Finance	6	0.794	0.129	0.659	0.915
45	Fontani-Vitali	2007	WP	Department of Economics - LUISS Rome	8	0.837	0.092	0.706	0.977
46	Fries-Taci	2005	published	Journal of Banking and Finance	2	0.658	0.071	0.608	0.708
47	Fuentes-Vergera	2007	WP	Central Bank of Chile	4	0.788	0.192	0.520	0.950
48	Giordano-Lopes	2006	WP	Department of Economics, Mathematics and Statistics - University of Foggia	2	0.941	0.021	0.926	0.955
49	Giordano-Lopes	2012	book chapter		2	0.889	0.020	0.875	0.903
50	Girardone-Molyneux-Gardener	2004	published	Applied Economics	2	0.858	0.001	0.857	0.859
51	Glass-McKillop-Quinn-Wilson	2014	published	The European Journal of Finance	1	0.955	.	0.955	0.955
52	Goddard-Molyneux-Williams	2014	published	Journal of Banking and Finance	6	0.793	0.111	0.578	0.870
53	Gordo	2013	published	Philippine Management Review	10	0.804	0.307	0.032	1.000
54	Guzman-Reverte	2008	published	Applied Economics	15	0.943	0.023	0.906	0.973
55	Hahn	2007	published	Empirica	28	0.438	0.153	0.156	0.742
56	Halkos-Salamouris	2004	published	Management Accounting Research	6	0.930	0.017	0.910	0.950
57	Halkos-Tzeremes	2013	published	Journal of Banking and Finance	6	0.980	0.013	0.959	0.991

58	Hao-Hunter-Yang	2001	published	Journal of Economics and Business	1	0.890	.	0.890	0.890
59	Hasan-Kamil-Mustafa-Baten	2012	published	PLOS one	7	0.946	0.035	0.883	0.985
60	Havránek-Irošvá	2011	published	Transition Studies Review	48	0.509	0.077	0.391	0.618
61	Havrylchyk	2006	published	Journal of Banking and Finance	12	0.753	0.125	0.529	0.935
62	Holod-Lewis	2011	published	Journal of Banking and Finance	69	0.564	0.113	0.356	0.779
63	Huang-Chiang-Chen	2011	published	The Manchester School	30	0.632	0.177	0.401	0.978
64	Huang-Fu	2013	published	Journal of Productivity Analysis	9	0.698	0.174	0.413	0.871
65	Huang-Wang	2002	published	The Manchester School	20	0.734	0.113	0.584	0.971
66	Huang-Wang	2003	published	The Manchester School	10	0.861	0.098	0.686	1.000
67	Huizinga-Nelissen-Vennet	2001	WP	Tinbergen Institute	2	0.778	0.192	0.642	0.914
68	Isik	2008	published	Journal of Multinational Financial Management	4	0.795	0.059	0.740	0.860
69	Isik-Hassan	2002	published	The Financial Review	2	0.866	0.041	0.837	0.895
70	Jiang-Yao-Zhang	2009	published	China Economic Review	3	0.722	0.019	0.700	0.734
71	Jimborean-Brack	2010	WP	MPRA	6	0.923	0.042	0.854	0.959
72	Kablan	2010	WP	International Monetary Fund	1	0.759	.	0.759	0.759
73	Kasman-Yildirim	2006	published	Applied Economics	92	0.716	0.085	0.533	0.865
74	Koetter	2006	published	Journal of Financial Serv Res	6	0.765	0.132	0.643	0.915
75	Koetter-Poghosyan	2009	published	Journal of Banking and Finance	4	0.828	0.075	0.722	0.896
76	Kohers-Huang-Kohers	2000	published	Journal of Financial Economics	6	0.631	0.136	0.449	0.781
77	Kosak-Zoric	2011	published	Economics of Transition	36	0.863	0.043	0.745	0.951
78	Koutsomanoli Filippaki-Margaritis-Staikouras	2009	published	Journal of Banking and Finance	1	0.594	.	0.594	0.594
79	Koutsomanoli Filippaki-Margaritis-Staikouras	2012	published	Journal of Productivity Analysis	2	1.025	0.512	0.663	1.387
80	Kraft-Hofler-Payne	2013	published	Applied Economics	9	0.674	0.104	0.562	0.872
81	Kumar S.	2013	published	Economic Change and Restructuring	9	0.882	0.082	0.745	0.960
82	Kumar M.-Arora	2010	published	Afro-Asian Journal Finance and Accounting	2	0.928	0.001	0.927	0.929
83	Kwan	2006	published	Journal of Banking and Finance	9	0.305	0.074	0.217	0.417
84	Kyj-Isik	2008	published	Journal of Economics and Business	14	0.543	0.121	0.320	0.741
85	Liadaki-Gaganis	2010	published	Omega	12	0.846	0.070	0.760	0.922
86	Lin-Tsao-Yang	2009	published	China and World Economy	8	0.279	0.159	0.090	0.477
87	Lozano Vivas-Kumbhakar-Fethi-Shaban	2011	published	Journal of Productivity Analysis	33	0.833	0.086	0.705	0.986
88	Luo	2003	published	Journal of Business Research	2	0.915	0.049	0.880	0.950
89	Mamatzakis-Staikouras-Filippaki	2008	published	International Review of Financial Analysis	46	0.387	0.055	0.306	0.474
90	Matthewes	2010	WP	Cardiff Business School	15	0.756	0.110	0.600	0.927

91	Maudos-Pastor-Péerez	2002	published	Applied Financial Economics	60	0.810	0.085	0.665	0.979
92	Maudos-Pastor-Pérez-Quesada	2002	published	Journal of International Financial Markets	6	0.609	0.254	0.217	0.839
93	Mghaieth-El Mehdi	2014	WP	Ipag Business School	2	0.823	0.002	0.821	0.825
94	Mobarek-Kalonov	2014	published	Applied Economics	162	0.679	0.097	0.470	0.950
95	Neal	2004	published	Australian Economic Papers	15	0.839	0.077	0.712	0.947
96	Papadopouls-Karagiannis	2009	published	South East European Journal of Economics and Business	9	0.781	0.007	0.768	0.788
97	Pasiouras-Tanna-Zopounidis	2009	published	International Review of Financial Analysis	2	0.824	0.078	0.768	0.879
98	Prior	2003	published	Journal of Banking and Finance	9	0.824	0.093	0.662	0.943
99	Ray-Das	2010	published	European Journal of Operational Research	14	0.721	0.213	0.425	0.970
100	Schure-Wagenvoort-Obrien	2004	published	Review of Financial Economics	1	0.770	.	0.770	0.770
101	Shanmugam-Das	2004	published	Applied Financial Economics	29	0.531	0.165	0.297	0.756
102	Shen-Liao-Weyamn Jones	2009	published	Journal of Chinese Economic and Business Study	64	0.581	0.255	0.102	0.990
103	Srairi	2010	published	Journal of Productivity Analysis	36	0.644	0.074	0.513	0.750
104	Staub-daSilvaeSouza-Tabak	2010	published	European Journal of Operational Research	3	0.583	0.119	0.447	0.669
105	Sturm-Williams	2010	WP	CESifo	8	0.840	0.022	0.800	0.870
106	Sun-Chang	2011	published	Journal of Banking and Finance	1	0.648	.	0.648	0.648
107	Tecles-Tabak	2010	published	European Journal of Operational Research	32	0.738	0.099	0.509	0.926
108	Thoraneennitiyan-Avkiran	2009	published	Socio-Economic Planning Sciences	36	0.847	0.099	0.700	0.983
109	Tortosa Ausina-Grifell Tatjé-Armero-Conesa	2008	published	European Journal of Operational Research	1	0.938	.	0.938	0.938
110	Turati	2008	book chapter		6	0.764	0.024	0.738	0.793
111	Vu-Turnell	2011	published	Economic Record	6	0.741	0.062	0.693	0.835
112	Weill	2003	published	Economics of Transition	3	0.660	0.042	0.620	0.704
113	Weill	2004	published	Journal of Productivity Analysis	15	0.660	0.134	0.402	0.842
114	Williams	2012	published	Journal of Financial Stability	4	0.628	0.250	0.387	0.903
115	Williams-Gardener	2003	published	Regional Studies	14	0.920	0.035	0.854	0.958
116	Xiang-Shamsuddin-Worthngton	2013	published	Journal of Economics and Finance	3	0.737	0.330	0.360	0.978
117	Yamori-Harimaya-Kondo	2003	published	Asia Pacific Financial Markets	6	0.858	0.055	0.799	0.925
118	Yildirim-Philippatos	2007	published	The European Journal of Finance	52	0.510	0.151	0.274	0.768
119	Yin-Yang-Mehran	2013	published	Global Finance Journal	10	0.679	0.105	0.527	0.810
120	Zhang-Wang-Qu	2012	published	China Economic Review	2	0.808	0.012	0.799	0.816

References

Ab-Rahim R., Md-Nor N.G., Ramlee S., Ubaidillah N.Z. (2012) "Determinants of Cost Efficiency in Malaysian Banking", *International Journal of Business and Society*, Vol. 13, N. 3, pp. 355-374

Abreu M., de Groot H.L.F., Florax R. J.G.M. (2005) "A Meta-Analysis of Beta-Convergence: the Legendary Two-Percent", *Discussion Papers,* Tinbergen Institute

Aiello F., Bonanno G. (2013) "Profit and Cost Efficiency in the Italian Banking Industry (2006-2011)", *Economics and Business Letters*, Vol.2, N. 4, pp. 190-205

Aigner D., Lovell C.K., Schmidt P. (1977) "Formulation and Estimation of Stochastic Frontier Production Function Models", *Journal of Econometrics*, Vol. 6, pp. 21-37

Akhigbe A., McNulty J.E. (2003) "The Profit Efficiency of Small U.S. Commercial Banks", *Journal of Banking and Finance*, Vol. 27, pp. 307-325

Akhigbe A., Stevenson B.A. (2010) "Profit Efficiency in U.S. BHCs: Effects of Increasing non-Traditional Revenue Sources", *The Quarterly Review of Economics and Finance*, Vol. 50, pp. 132-140

Al Sharkas A.A., Hassan M.K., Lawrence S. (2008) "The Impact of Mergers and Acquisitions on the Efficiency of the US Banking Industry: Further Evidence", *Journal of Business Finance and Accounting*, Vol. 35, pp. 50-70

Altunbaş Y., Gardener E. P. M., Molyneux P., Moore B. (2001) "Efficiency in European Banking", *European Economic Review*, Vol. 45, pp. 1931-1955

Altunbaş Y., Liu M.-H., Molyneux P., Seth R. (2000) "Efficiency and Risk in Japanese Banking", *Journal of Banking and Finance*, Vol. 24, pp. 1605-1628

Andrieş A.M., Căpraru B. (2012) "Impact of European Integration on Bank Efficiency", *Procedia - Social and Behavioral Sciences*, Vol. 58, pp. 587-595

Ataullah A., Cockerill T., Le H. (2004) "Financial Liberalization and Bank Efficiency: a Comparative Analysis of India and Pakistan", *Applied Economics*, Vol. 36, pp. 1915-1924

Avkiran N.K. (2009) "Removing the Impact of Environment with Units-Invariant Efficient Frontier Analysis: an Illustrative Case Study with Inter-temporal Panel Data", *Omega*, Vol. 37, pp. 535-544

Bader M.K.I., Mohamad S., Hassan T. (2008) "Cost, Revenue and Profit Efficiency of Islamic versus Conventional Banks: International Evidence using Data Envelopment Analysis", *Islamic Economic Studies*, Vol. 15, N. 2, pp.23-76

Barra C., Destefanis C., Lubrano Lavadera G. (2011) "Risk Regulation: the Efficiency of Italian Cooperative Banks", *Centre for Studies in Economics and Finance*, *University of Naples*, WP N. 290

Barth J.R., Lin C., Ma Y., Seade J., Song F.M. (2013) "Do Bank Regulation, Supervision and Monitoring Enhance or Impede Bank Efficiency?", *Journal of Banking and Finance*, Vol. 37, N. 8, pp. 2879-2892

Battaglia F., Farina V., Fiordelisi F., Ricci O. (2010) "The Efficiency of Cooperative Banks: the Impact of Environmental Economic Conditions", *Applied Financial Economics*, Vol. 20, N. 17, pp. 1363-1376

Battese G. E., Coelli T. J. (1995) "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data", *Empirical Economics*, Vol. 20, N. 2, pp. 325-332

Battese G. E., Coelli T. J., Rao D. S. P., O'Donnell C. J. (2005) *An Introduction to Efficiency and Productivity Analysis*, Springer, New York

Beccalli E., Casu B., Girandone C., (2006) "Efficiency and Stock Performance in European Banking", *Journal of Business Finance & Accounting*, Vol. 33, N. 1-2, pp. 245-262
Behr A. (2010) "Quantile Regression for Robust Bank Efficiency Score Estimation", *European Journal of Operational Research*, Vol. 200, pp. 568-581
Behr A., Tente, S., (2008) "Stochastic Frontier Analysis by Means of Maximum Likelihood and Method of Moments", *Deutsche Bundesbank – Banking and Financial Studies*, Discussion Paper N. 19
van den Bergh J., Button K.J. (1997) "Meta-Analysis of Environmental Issues in Regional Urban and Transport Economics", *Urban Studies*, Vol. 34, N. 5-6, pp. 927-944
Berger A.N. (2007) "International Comparisons of Banking Efficiency", *Financial Markets, Institutions and Instruments*, Vol. 16, N. 3, pp. 119-144
Berger A.N., Hasan I., Zhou M. (2009) "Bank Ownership and Efficiency in China: What will Happen in the World's Largest Nation?", *Journal of Banking and Finance*, Vol. 33, pp. 113-130
Berger A.N., Humphrey D.B. (1997) "Efficiency of Financial Institutions: International Survey and Directions for Future Research", *European Journal of Operation Research*, Vol. 98, pp. 175-212
Berger A.N., Bonaccorsi di Patti E. (2006) "Capital structure and firm performance: A new approach to testing agency theory and an application to the banking industry", *Journal of Banking and Finance*, Vol. 30, N. 4, pp. 1065-1102
Bokpin G.A. (2013) "Ownership Structure, Corporate Governance and Bank Efficiency: an Empirical Analysis of Panel Data from the Banking Industry in Ghana", *Corporate Governance*, Vol. 13, N. 3, pp. 274-287
Bonin J.P., Hasan I., Wachtel P. (2005) "Bank Performance, Efficiency and Ownership in Transition, *Journal of Banking and Finance*, Vol. 29, N. 1, pp. 31-53
Bos J.W.B., Koetter M., Kolari J.W., Kool C.J.M. (2009) "Effects of heterogeneity on bank efficiency scores", *European Journal of Operational Research*, Vol. 195, N. 1, pp. 251-261
Bos J.W.B., Kolari J.W. (2005) "Large Bank Efficiency in Europe and the United States: are there Economic Motivations for Geographic Expansion in Financial Services?", *The Journal of Business*, Vol. 78, N. 4, pp. 1555-1592
Bravo-Ureta B.E., Solìs D., Moreira Lopez V.H. , Maripani J. F., Thiam A., Rivas E. T., (2007), "Technical efficiency in farming: a meta-regression analysis", *Journal of Productivity Analysis*, Vol. 27, pp. 57-72
Brons M., Nijkamp P., Pels E. Rietveld P., (2005) "Efficiency of Urban Public Transit: A Meta Analysis", *Transportation*, Vol. 32, pp. 1-21
Bumann S., Hemres N., Lensink R. (2013) "Financial Liberalization and Economic Growth: a Meta-Analysis*", Journal of International Money and Finance*, Vol. 33, pp. 255-281
Canhoto A., Dermine J. (2003) "A Note on Banking Efficiency in Portugal, New vs Old Banks", *Journal of Banking and Finance*, Vol. 27, pp. 2087-2098
Carbo S., Gardener E.P.M., Williams J. (2002) "Efficiency in Banking: Empirical Evidence from the Savings Banks Sector", *Manchester School*, Vol. 70, N. 2, pp 204-228
Card D., Krueger A.B. (1995) "Time-Series Minimum-Wage Studies: a Meta-Analysis", *The American Economic Review*, Vol. 85, N. 2, pp. 238-243
Card D.E., Kluve J., Weber A.M. (2010) "Active Labor Market Policy Evaluations: a Meta-Analysis", *The Economic Journal*, Vol. 120, N. 548, pp. F452-F477
Casu B., Girardone C. (2004) "Large Banks' Efficiency in the Single European Market", *The Service Industries Journal*, Vol. 24, N. 6, pp. 129-142

Casu B., Girardone C. (2010) "Integration and Efficiency Convergence in EU Banking Markets", *Omega*, Vol. 38, pp. 260-267

Casu B., Molyneux P. (2003) "A Comparative Study of Efficiency in European Banking", *Applied Economics*, Vol. 35, N. 17, pp. 1865-1876

Cavallo L., Rossi S. (2002) "Do Environmental Variables Affect the Performance and Technical Efficiency of the European Banking System? A Stochastic Frontier Approach", *European Journal of Finance*, Vol. 8, pp. 123-146

Chen C. (2009) "Bank Efficiency in Sub-Saharan African Middle-Income Countries", *International Monetary Fund*, WP 09/14

Chen K.-H., Yang H.-Y. (2011) "A Cross-Country Comparison of productivity growth using the Generalised Metafrontier Malmquist Productivity Index: with Application to Banking Industries in Taiwan and China", *Journal of Productivity Analysis*, Vol. 35, N. 3, pp. 197-212

Chen T. (2002) "A Comparison of Chance-Constrained DEA and Stochastic Frontier Analysis: Bank Efficiency in Taiwan", *The Journal of Operational Research Society*, Vol. 53, pp. 492-500

Chetty R., Guren A., Manoli D., Weber A. (2011) "Does Indivisible Labor Explain the Difference Between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities", *The National Bureau of Economic Research*, WP N. 16729

Chiu Y.-H., Chen Y.-C. (2009) "The Analysis of Taiwanese Bank Efficiency: Incorporating both External Environment Risk and Internal Risk", *Economic Modelling*, Vol. 26, pp. 456-463

Chortareas G.E., Garza-Garcia J.G., Girardone C. (2011) "Banking Sector Performance in Latin America: Market Power versus Efficiency", *Review of Development Economics*, Vol. 15, N. 2, pp. 307-325

Christopoulos D.K., Tsionas E.G. (2001) "Banking Economic Efficiency in the Deregulation Period: Results from Heteroschedastic Stochastic Frontier Models", *The Manchester School*, Vol. 69, N. 6, pp. 656-676

Cipollina M., Salvatici L. (2010) "Reciprocal Trade Agreements in Gravity Models: a Meta-Analysis", *Review of International Economics*, Vol. 18, N. 1, pp. 63-80

Coelli T.J. (1995) "Recent Developments in Frontier Modelling and Efficiency Measurement", *Australian Journal of Agricultural and Resource Economics*, Vol. 39, N. 3, pp 219-245

Coelli T., Perelman S. (1999) "A Comparison of Parametric and Nonparametric Distance Functions: with Application to European Railways", *European Journal of Operational Research*, Vol. 117, N. 2, pp. 326-339

Cuesta R.A., Orea L. (2002) "Mergers and Technical Efficiency in Spanish Savings Banks: a Stochastic Distance Function Approach", *Journal of Banking and Finance*, Vol. 26, pp. 2231-2247

Daley J., Matthews K., Zhang T. (2013) "Post-Crisis Cost Efficiency of Jamaican Banks", *Applied Financial Economics*, Vol. 23, N. 20, pp. 1599-1607

Delis M.D., Tsionas E.G. (2009) "The Joint Estimation of Bank-Level Market Power and Efficiency", *Journal of Banking and Finance*, Vol. 33, pp. 1842-1850

Dietsch M., Lozano-Vivas A. (2000) "How the Environment Determines Banking Efficiency: a Comparison between French and Spanish Industries", *Journal of Banking and Finance*, Vol. 24, pp. 985-1004

Disdier A. C., Head K. (2008) "The Puzzling Persistence of the Distance Effect on Bilateral Trade", *The Review of Economics and Statistics*, *MIT Press*, Vol. 90, N. 1, pp. 37-48

Doucouliagos H., Paldam M. (2009) "The Aid Effectiveness Literature: the Sad Results of 40 Years of Research", *Journal of Economic Surveys*, Vol. 23, N. 3, pp. 433-461

Doucouliagos H., Stanley T.D. (2009) "Publication Selection Bias in Minimum-Wage Research? A Meta-Regression Analysis", *British Journal of Industrial Relations*, Vol. 47, N. 2, pp. 406-428

Drake L., Hall M.J.B. (2003) "Efficiency in Japanese Banking: an Empirical Analysis", *Journal of Banking and Finance*, Vol. 27, pp. 891-917

Égert B., Halpern L. (2006) "Equilibrium Exchange Rates in Central and Eastern Europe: a Meta-Regression Analysis", *Journal of Banking and Finance*, Vol. 30, pp. 1359-1374

Egger M., Davey S.G., Schneider M., Minder C. (1997) "Bias in Meta-Analysis Detected by a Simple, Graphical Test", *British Medical Journal*, Vol. 315, N. 7109, pp. 629-634

Ekanayake S.A.B., Jayasuriya S.K. (1987) "Measurement of Firm Specific Technical Efficiency: a Comparison of Methods", *Journal of Agricultural Economics*, Vol.38, pp. 115-122

Esho N. (2001) "The Determinants of Cost Efficiency in Cooperative Financial Institutions: Australian Evidence", *Journal of Banking and Finance*, Vol. 25, pp. 941-964

Espey M., Espey J., Shaw W.D. (1997) "Price Elasticity of Residential Demand for Water: a Meta-Analysis", *Water Resources Research*, Vol. 33, N. 6, pp. 1369-1374

Fang Y., Hasan I., Marton K. (2011) "Bank Efficiency in Transition Economies: Recent Evidence from South-Eastern Europe", *Bank of Finland Research,* WP N. 5

Farrel M. J. (1957) "The Measurement of Productive Efficiency", *Journal of Royal Statistical Society*, Vol. 120, N. 3, pp. 253-290

Feld L.P., Heckemeyer J.H. (2011) "FDI and Taxation: a Meta-Study", *Journal of Economic Surveys*, Vol. 25, N. 2, pp. 233-272

Feld L.P., Heckemeyer J.H., Overesch M. (2011) "Capital Structure Choice and Company Taxation: a Meta-Study", *Journal of Banking and Finance*, Vol. 37, pp. 2850-2866

Fethi M.D., Pasourias F. (2010) "Assessing Bank Efficiency and Performance with Operational Research and Artificial Intelligence Techniques: a Survey", *European Journal of Operational Research*, Vol. 204, pp. 189-198

Fiordelisi F., Marques-Ibanez D., Molyneux P. (2011) "Efficiency and Risk in European Banking", *Journal of Banking and Finance*, Vol. 35, N. 5, pp. 1315-1326

Fontani, A., Vitali, L. (2007) "L'efficienza di costo dei gruppi bancari italiani: un'analisi mediante frontiera stocastica", *Department of Economics and Business*, Luiss, Roma

Fries S., Taci A. (2009) "Cost Efficiency of Banks in Transition: Evidence from 289 Banks in 15 Post-Communist Countries", *Journal of Banking and Finance*, Vol. 29, pp. 55-81

Fuentes R., Vergara M. (2007) "Is Ownership Structure a Determinant of Bank Efficiency?", *Central Bank of Chile*, WP N. 456

Giordano L., Lopes A. (2006) *Preferenza al rischio e qualità degli impieghi come determinanti dell'efficienza del sistema bancario italiano*, in Giannola A. (a cura di) *Riforme istituzionali e mutamento strutturale. Mercati, imprese e istituzioni in un sistema dualistico*, Carocci Editore, Roma

Giordano L., Lopes A. (2012) *Le banche italiane tra consolidamento e recuperi di efficienza (1998-2008). Una promessa mantenuta?*, in Giannola A., Lopes A., Sarno D. (a cura di) *I problemi dello sviluppo economico e del suo finanziamento nelle aree deboli*, Carocci Editore, Roma

Girardone C., Molyneux P., Gardener E.P.M. (2004) "Analysing the Determinants of Bank Efficiency: the Case of Italian Banks", *Applied Economics*, Vol. 36, N. 3, pp. 215-227

Glass G.V. (1976) "Primary, Secondary, and Meta-Analysis of Research", *Educational Researcher*, Vol. 5, pp. 3-8

Glass G.V., McGaw B., Smith M.L. (1981) *Meta-Analysis in Social Research*, Sage Publications, Beverly Hills

Glass J.C., McKillop D.G., Quinn B., Wilson J. (2014) “Cooperative Bank Efficiency in Japan: a Parametric Distance Function Analysis”, *The European Journal of Finance*, Vol. 20, N. 3, pp. 291-317

Goddard J., Molyneux P., Williams J. (2014) “Dealing with Cross-Firm Heterogeneity in Bank Efficiency Estimates: some Evidence from Latin America”, *Journal of Banking and Finance*, Vol. 40, pp. 130-142

Gordo G.M. (2013) “Estimating Philippine Bank Efficiencies using Frontier Analysis”, *Philippine Management Review*, Vol. 20, pp. 17-36

Greene W.H. (1993) The econometric approach to efficiency analysis. In: Fried H.O., Lovell C.A.K., Schmidt S.S. (Eds.), *The Measurement of Productive Efficiency: Techniques and Applications*. Oxford University Press, Oxford, pp. 68-119

Guzmán I., Reverte C. (2008) “Productivity and Efficiency Change and Shareholder Value: Evidence from the Spanish Banking Sector, *Applied Economics*, Vol. 40, N. 15, pp. 2037-2044

Hahn F.R. (2007) “Environmental Determinants of Banking Efficiency in Austria”, *Empirica*, Vol. 34, pp. 231-245

Halkos G.E., Salamouris D.S. (2004) “Efficiency Measurement of the Greek Commercial Banks with the Use of Financial Ratios: a Data Envelopment Analysis Approach”, *Management Accounting Research*, Vol. 15, pp. 201-224

Halkos G.E., Tzeremes N.G. (2013) “Estimating the Degree of Operating Efficiency Gains from a Potential Bank Merger and Acquisition: a DEA Bootstrapped Approach”, *Journal of Banking and Finance*, Vol. 37, pp. 1658-1668

Hao J., Hunter W.C., Yang W.K. (2001) “Deregulation and Efficiency: the Case of Private Korean Banks”, *Journal of Economics and Business*, Vol. 53, pp. 237-254

Harbord R.M., Higgins J.P.T. (2008) “Meta-Regression in Stata”, *The Stata Journal*, Vol. 8, N. 4, pp. 493-519

Hasan M.Z., Kamil A.A., Mustafa A., Baten M.A. (2012) “A Cobb Douglas Stochastic Frontier Model on Measuring Domestic Bank Efficiency in Malaysia”, *PLoS ONE*, Vol. 7, N. 8

Havránek T., Irošvá Z. (2010) “Measuring Bank Efficiency: a Meta-Regression Analysis”, *Prague Economic Papers*, Vol.4, pp. 307-328

Havránek T., Irošvá Z. (2011) “Bank Efficiency in Transitional Countries: Sensitivity to Stochastic Frontier Design”, *Transition Studies Review*, Vol. 18, N. 2, pp. 230-270

Havránek T., Iršová Z., Janda K. (2012) “Demand for Gasoline is More Price-Inelastic than Commonly Thought”, *Energy Economics*, Vol. 34, N. 1, pp. 201-207

Havrylchyk O. (2006) “Efficiency of the Polish Banking Industry: Foreign versus Domestic Banks”, *Journal of Banking and Finance*, Vol. 30, pp. 1975-1996

Hedges L.V., Olkin I. (1985) *Statistical Methods for Meta-Analysis*, Academic Press, Orlando

Higgins J.P.T., Thompson S.G. (2004) “Controlling the Risk of Spurious Findings from Meta-Regression”, *Statistics in Medicine*, Vol. 23, pp. 1663-1682

Holod D., Lewis H.F. (2011) “Resolving the Deposit Dilemma: a New DEA Bank Efficiency Model”, *Journal of Banking and Finance*, Vol. 35, pp. 2801-2810

Huang T.H., Chiang L.C., Chen K.C. (2011) “An Empirical Study of Bank Efficiencies and Technology Gaps in European Banking”, *The Manchester School*, Vol. 79, N. 4, pp. 839-860

Huang M.Y., Fu T.T. (2013) "An Examination of the Cost Efficiency of Banks in Taiwan and China using the Metafrontier Cost Function", *Journal of Productivity Analysis*, Vol. 40, N. 3, pp. 387-406

Huang T.H., Wang MH. (2002) "Comparison of Economic Efficiency Estimation Methods: Parametric and Nonparametric Techniques", *The Manchester School*, Vol. 70, pp. 682-709

Huang T.H., Wang MH. (2003) "Estimation of Technical and Allocative Inefficiency using Fourier Flexible Cost Frontiers for Taiwan's Banking Industry", *The Manchester School*, Vol. 71, N. 3, pp. 341-362

Huizinga H.P., Nelissen J.H.M. Vennet R.V. (2001) "Efficiency Effect of Bank Mergers and Acquisitions in Europe", *Tinbergen Insitutite*, Discussion Paper, Vol. 88, N. 3

Isik I. (2008) "Productivity, Technology and Efficiency of *de novo* Banks: a Counter Evidence from Turkey", *Journal of Multinational Financial Management*, Vol. 18, pp. 427-442

Isik I., Hassan M.K. (2002) "Cost and Profit Efficiency of the Turkish Banking Industry: an Empirical Investigation", *The Financial Review*, Vol. 37, N. 2, pp. 257-279

Jarrell S.B., Stanley T.D. (1990) "A Meta-Analysis of the Union-Nonunion Wage Gap", *Industrial and Labor Relations Review*, Vol. 44, N. 1, pp. 54-67

Jeppesen T., List J.A., Folmer H. (2002) "Environmental Regulations and New Plant Location Decisions: Evidence from a Meta-Analysis", *Journal of Regional Science*, Vol. 42, N. 1, pp. 19-49

Jiang C., Yao S., Zhang Z. (2009) "The Effects of Governance Changes on Bank Efficiency in China: a Stochastic Distance Function Approach", *China Economic Review*, Vol. 20, pp. 717-731

Jimborean R., Brack E. (2010) "The Cost-Efficiency of French Banks", *MPRA*, WP N. 23471

Kablan S. (2010) "Banking Efficiency and Financial Development in Sub-Saharan Africa", *International Monetary Fund*, WP N. 10/136

Kasman A., Yilndirim C. (2006) "Cost and Profit Efficiencies in Transition Banking: the Case of New EU Members", *Applied Economics*, Vol. 38, pp. 1079-1090

Koetter M. (2006) "Measurement Matters. Alternative Input Price Proxies for Bank Efficiency Analyses", *Journal of Financial Services Research*, Vol. 30, N. 2, pp. 199-227

Koetter M., Poghosyan T. (2009) "The Identification of Technology Regimes in Banking: Implications for the Market Power-Fragility Nexus", *Journal of Banking and Finance*, Vol. 33, pp. 1413-1422

Kohers T., Huang M.H., Kohers N. (2000) "Market Perception of Efficiency in Bank Holding Company Mergers: the Roles of the DEA and SFA Models in Capturing Merger Potential", *Review of Financial Economics*, Vol. 9, pp. 101-120

Kolawole O. (2009) "A meta-analysis of technical efficiency in Nigerian agriculture", Paper presented at *the International Association of Agricultural Economists Conference*, *Beijing*, *China*, *August 16-22*

Kosak M., Zoric J. (2011) "Accounting for Heterogeneity in Cross-Country Bank Efficiency Comparisons. The Case of New EU Member States", *Economics of Transition*, Vol. 19, N. 3, pp. 473-494

Koutsomanoli-Filippaki A., Margaritis D., Staikouras C. (2009) "Efficiency and Productivity Growth in the Banking Industry of Central and Eastern Europe", *Journal of Banking and Finance*, Vol. 33, pp. 557-567

Koutsomanoli-Filippaki A., Margaritis D., Staikouras C. (2012) "Profit Efficiency in the European Union Banking Industry: a Directional Technology Distance Function Approach", *Journal of Productivity Analysis*, Vol. 37, pp. 277-293

Kraft E., Hofler R., Payne J. (2006) "Privatization, Foreign Bank Entry and Bank Efficiency in Croatia: a Fourier-flexible Function Stochastic Cost Frontier Analysis", *Applied Economics*, Vol. 38, N. 17, pp. 2075-2088

Kumar S. (2013) "Banking Reforms and the Evolution of Cost Efficiency in Indian Public Sector Banks", *Economic Change and Restructuring*, Vol. 46, pp. 143-182

Kumar M., Arora P. (2010) "Bank Efficiency Measurement using Alternative Techniques of Frontier Analysis: Evidence from India", *Afro-Asian Journal of Finance and Accounting*, Vol. 2, N. 1, pp. 40-69

Kwan S.H. (2006) "The X-Efficiency of Commercial Banks in Hong Kong", *Journal of Banking and Finance*, Vol. 30, pp. 1127-1147

Kyj L., Isik I. (2008) "Bank x-efficiency in Ukraine: An analysis of service characteristics and ownership", *Journal of Economics and Business*, Vol. 60, pp.369-393

Liadaki A., Gaganis C. (2010) "Efficiency and Stock Performance of EU Banks: is there a Relationship?", *Omega*, Vol. 38, pp. 254-259

Lin H.L., Tsao C.C., Yang C.H. (2009) "Bank Reforms, Competition and Efficiency in China's Banking System: are Small City Bank Entrants more Efficient?", *China & World Economy*, Vol. 17, N. 5, pp. 68-87

Lozano-Vivas A., Kumbhakar S.C., Fethi M.D., Shaban M. (2011) "Consolidation in the European banking industry: how effective is it?", *Journal of Productivity Analysis*, Vol. 36, pp. 247-261

Luo X. (2003) "Evaluating the Profitability and Marketability Efficiency of Large Banks. An Application of Data Envelopment Analysis", *Journal of Business Research*, Vol. 56, pp. 627-635

Mamatzakis E., Staikouras C., Koutsomanoli-Filippaki A. (2008) "Bank Efficiency in the New European Union Member States: is there Convergence?", *International Review of Financial Analysis*, Vol. 17, pp. 1156-1172

Matthewes K. (2010) "Banking Efficiency in Emerging Market Economies", *Cardiff Business School*, WP N. 12

Maudos J., Pastor J.M., Perez F. (2002) "Competition and Efficiency in the Spanish Banking Sector: the Importance of Specialization", *Applied Financial Economics*, Vol. 12, pp. 505-516

Maudos J., Pastor J.M., Perez F., Quesada J. (2002) "Cost and Profit Efficiency in European Banks", *Journal of International Financial Markets*, *Institutions and Money*, Vol. 12, pp. 33-58

Mghaieth A., El Mehdi I.K. (2014) "The determinants of cost/profit efficiency of Islamic banks before, during and after the crisis of 2007-2008 using SFA approach", *IPAG*, WP N. 107

Mobarek A., Kolonov A. (2014) "Comparative Performance Analysis between Conventional and Islamic Banks: Empirical Evidence from OIC Countries", *Applied Economics*, Vol. 46, N. 3, pp. 253-270

Neal P. (2004) "X-Efficiency and Productivity Change in Australian Banking", *Australian Economic Papers*, Vol. 43, N. 2, pp. 174-191

Nguyen K.H., Coelli T. (2009) "Quantifying the Effects of Modelling Choices on Hospital Efficiency Measures: a Meta-Regression Analysis", *Centre for Efficiency and Productivity Analysis*, WP N. 7

Odeck J., Bråthen S. (2012) "A Meta-Analysis of DEA and SFA Studies of the Technical Efficiency of Seaports: a Comparison of Fixed and Random-Effects Regression Models", *Transportation Research*, Vol. 46 (A), pp. 1574-1585

Pagano M. (1993) “Financial Markets and Growth: an Overview”, *European Economic Review*, Vol. 37, N. 2-3, pp. 613-622

Papadopoulos S., Karagiannis S. (2009) “New Evidence on Efficiency in Southern European Banking”, *South East European Journal of Economics and Business*, Vol. 4, N. 1, pp. 7-14

Pasiouras F., Tanna S., Zopounidis C. (2009) “The Impact of Banking Regulations on Banks' Cost and Profit Efficiency: Cross-Country Evidence”, *International Review of Financial Analysis*, Vol. 18, pp. 294-302

Poot J. (2012) “Learning from the Flood of Findings: Meta-Analysis in Economics”, *National Institute of Demographic and Economic Analysis*, *The University of Waikato*, *New Zealand*

Prior D. (2003) “Long and Short-Run Nonparametric Cost Frontier Efficiency: an Application to Spanish Savings Banks”, *Journal of Banking and Finance*, Vol. 27, pp. 655-671

Raghuram G. Rajan R.G., Zingales L. (1998) “Financial Dependence and Growth”, *The American Economic Review*, Vol. 88, N. 3, pp. 559-586

Ray S.C., Das A. (2010) “Distribution of Cost and Profit Efficiency: Evidence from Indian Banking”, *European Journal of Operational Research*, Vol. 201, pp. 297-307

Resti A. (1997) “Evaluating the Cost-Efficiency of the Italian Banking System: what can be Learned from the Joint Application of Parametric and nonparametric Techniques”, *Journal of Banking and Finance*, Vol. 21, pp. 221-250

Rosenthal R. (1984) *Meta-Analytic Procedures for Social Research*, Sage Publications, Beverly Hills

Schure P., Wagenvoortb R., O’Brien D. (2004) “The Efficiency and the Conduct of European Banks: Developments after 1992”, *Review of Financial Economics*, Vol. 13, pp. 371–396

Shanmugam K.R., Das A. (2004) “Efficiency of Indian Commercial Banks during the Reform Period”, *Applied Financial Economics*, Vol. 14, pp. 681-686

Shen Z., Liao H., Weyman-Jones T. (2009) “Cost Efficiency Analysis in Banking Industries of Ten Asian Countries and Regions”, *Journal of Chinese Economic and Business Studies*, Vol. 7, N. 2, pp. 199-218

Srairi S.A. (2010) “Cost and Profit Efficiency of Conventional and Islamic Banks in GCC Countries”, *Journal of Productivity Analysis*, Vol. 34, pp. 45-62

Stanley, T.D. (2001) “Wheat From Chaff: A Meta-Analysis as Quantitative Literature Review”, *Journal of Economic Perspectives*, Vol. 15, n° 3, pp. 131-150

Stanley, T.D. (2008) “Meta-Regression Methods for Detecting and Estimating Empirical Effects in the Presence of Publication Selection”, *Oxford Bulletin of Economics and Statistics*, Vol. 70, N. 1, pp. 103-127

Stanley T.D., Jarrell S.B. (1989) “Meta-Regression Analysis: A Quantitative Method of Literature Surveys”, *Journal of Economic Surveys*, Vol. 3, N. 2, pp. 161-170

Staub R.B., da Silva e Souza G., Tabak B.M. (2010) “Evolution of Bank Efficiency in Brazil: a DEA Approach”, *European Journal of Operational Research*, Vol. 202, pp. 204-213

Sturm J.-E., Williams B. (2010) “What Determines Differences in Foreign Bank Efficiency? Australian Evidence”, *Journal of International Financial Markets, Institutions and Money*, Vol. 20, pp. 284-309

Sun L., Chan T.-P. (2011) “A Comprehensive Analysis of the Effects of Risk Measures on Bank Efficiency: Evidence from Emerging Asian Countries”, *Journal of Banking and Finance*, Vol. 35, pp. 1727-1735

Tecles P.L., Tabak B.M. (2011) “Determinants of Bank Efficiency: the Case of Brazil”, *European Journal of Operational Research*, Vol. 207, pp. 1587-1598

Thiam A., Bravo-Ureta B.E., Rivas T.E. (2001) “Technical Efficiency in Developing Country Agriculture: a Meta-Analysis” *Agricultural Economics*, Vol. 25, pp. 235-243

Thompson S.G., Sharp S.J. (1999) “Explaining Heterogeneity in Meta-Analysis: a Comparison of Methods, *Statistics in Medicine*, Vol. 18, pp. 2693-2708

Thoraneenitiyan N., Avkiran N.K. (2009) “Measuring the Impact of Restructuring and Country-Specific Factors on the Efficiency of Post-Crisis East Asian Banking Systems: Integrating DEA with SFA”, *Socio-Economic Planning Sciences*, Vol. 43, pp. 240-252

Tortosa-Ausina E., Grifell-Tatje´ E., Armero C., Conesa D. (2008) “Sensitivity Analysis of Efficiency and Malmquist Productivity Indices: an Application to Spanish Savings Banks”, *European Journal of Operational Research*, Vol. 184, pp. 1062-1084

Turati G. (2008) La valutazione del grado di concorrenza nell’industria bancaria negli anni Novanta, in Cella G., Zago, A. (a cura di) Competitività ed efficienza dell’economia italiana: fattori sistemici e valutazioni quantitative, Il Mulino, Bologna

Vu H., Turnell S. (2011) “Cost and Profit Efficiency of Australian Banks, and the Impact of the Global Financial Crisis”, *Economic Record*, Vol. 87, N. 279, pp. 525-536

Weill L. (2003) “Banking Efficiency in Transition Economies. The Role of Foreign Ownership”, *Economics of Transition*, Vol. 11, N. 3, pp. 569-592

Weill L. (2004) “Measuring Cost Efficiency in European Banking: a Comparison of Frontier Techniques”, *Journal of Productivity Analysis*, Vol. 21, n° 2, pp. 133-152

Williams J. (2012) “Efficiency and Market Power in Latin American Banking”, *Journal of Financial Stability*, Vol. 8, pp. 263-276

Williams J., Gardener E. (2003) “The Efficiency of European Regional Banking”, *Regional Studies*, Vol. 37, N.4, pp. 321-330

Xiang D., Shamsuddin A., Worthington A.C. (2013) “The Differing Efficiency Experiences of Banks Leading up to the Global Financial Crisis: a Comparative Empirical Analysis from Australia, Canada and the UK”, *Journal of Economics and Finance*, pp. 1-20

Yamori N., Harimaya K., Kondo K. (2003) “Are Banks Affiliated with Bank Holding Companies more Efficient than Independent Banks? The Recent Experience Regarding Japanese Regional BHCs”, *Asia-Pacific Financial Markets*, Vol. 10, pp. 359-376

Yildirim H.S., Philippatos G.C. (2007) “Efficiency of Banks: Recent Evidence from the Transition Economies of Europe, 1993–2000”, *The European Journal of Finance*, Vol. 13, N. 2, pp. 123-143

Yin H., Yang J., Mehran J. (2013) “An Empirical Study of Bank Efficiency in China after WTO Accession”, *Global Finance Journal*, Vol. 24, pp. 153-170

Zhang J., Wang P., Qu B. (2012) “Bank Risk Taking, Efficiency and Law Enforcement: Evidence from Chinese City Commercial Banks”, *China Economic Review*, Vol. 23, pp. 284-295