UNIVERSITÀ DELLA CALABRIA

Dipartimento di Economia, Statistica e Finanza
Ponte Pietro Bucci, Cubo 0/C
87036 Arcavacata di Rende (Cosenza) - Italy
http://www.unical.it/desf/

Working Paper n. 12 - 2016

ON THE SOURCES OF HETEROGENEITY IN BANKING EFFICIENCY LITERATURE

Francesco Aiello
Dipartimento di Economia,
Statistica e Finanza
Università della Calabria
Ponte Pietro Bucci, Cubo 1/C
Tel.: +39 0984 492440
Fax: +39 0984 492421
e-mail: f.aiello@unical.it

Graziella Bonanno
Dipartimento di Ingegneria Informatica
Automatica e Gestionale "Antonio Ruberti"
Università degli Studi di Roma
"La Sapienza"
Via Ariosto, 25
00185 Roma
e-mail: bonanno@diag.uniroma1.it

Novembre 2016

On the Sources of Heterogeneity in Banking Efficiency Literature·

Francesco Aiello[a], Graziella Bonanno[b]
francesco.aiello@unical.it - bonanno@diag.uniroma1.it
[a] Department of Economics, Statistics and Finance, University of Calabria
I-87036, Arcavacata di Rende (CS), Italy
[b] Department of Computer, Control and Management Engineering "Antonio Ruberti"
Sapienza University, I- 00185, Rome, Italy

Abstract This study reviews the empirical literature on banking efficiency by conducting a meta-regression analysis. The meta-dataset consists of 1,661 observations retrieved from 120 papers published over the period 2000–2014. While the role of study design and method-specific characteristics of primary studies is evaluated, the focus concerns regulation in banking. The results are fourfold. First, parametric methods always yield lower levels of banking efficiency than nonparametric studies. Second, banking efficiency is higher in studies using the value-added approach rather than the intermediation method. Third, efficiency scores also depend on the journal's ranking and on the number of observations and variables used in the primary papers. Finally, regulation matters: primary papers focusing on countries with a liberalized banking industry provide higher values for efficiency scores.

JEL classification: C13, C14, C80, D24, G21, G28, L25, L43, K20
Keywords: Banking, Frontier Models, Efficiency, Meta-analysis, Regulation, Study design

1. Introduction

Efficiency in banking has been a long-standing topic of discussion in economics and has received considerable attention over the last 25 years. Two main forces have brought about the great interest in this subject. First, even though theory clearly explains whether a decision unit is efficient or not (Farrell 1957), controversy has surrounded the empirics of much of the research. This is because the efficiency frontier is unknown and there is no consensus on the

· The authors would like to thank Antonio Alvarez, Sergio Destefanis, Kristiaan Kerstens, Camilla Mastromarco, Luis Orea, Paolo Coccorese, Damiano Silipo, Elizabeth Tipton, Angelo Zago for their valuable comments on an earlier version of this paper. They also benefit from the comments of conference and seminar participants in Bologna, Helsinki (EWEPA 2013 Conference), London (LSE), Rome (La Sapienza), Milan (SIE 2016 Conference), Nanterre (Paris) and Salerno. A particular acknowledgment is for the three anonymous referees of the journal and for Chris Doucouliagos. They provide very fruitful suggestions throughout the reviewing process of the paper. The usual disclaimer applies. Data and routines for replication are freely downloadable also from ResearchGate.

Aiello F., Bonanno G., 2017, "On the Sources of Heterogeneity in Banking Efficiency Literature", *Journal of Economic Surveys*, (forthcoming)

superiority of one estimation method over another, as argued by Berger and Humphrey (1997), Coelli and Perelman (1999) and Fethi and Pasourias (2010). The sensitivity of results to model specifications has been addressed in several individual studies which compare the results that different methods (i.e. parametric vs. nonparametric) yield from a fixed sample of banks (Beccalli et al. 2006; Casu and Girardone 2004; Ferrier and Lovell 1990; Goddard et al. 2014; Huang and Wang 2002; Kumar and Arora 2010; Mobarek and Kalonov 2014; Resti 1997; Weil 2004; Yildirim and Philippatos 2007). Furthermore, the reviews provided by Berger (2007), Berger and Humphrey (1997), Fethi and Pasiouras (2010) and Paradi and Zhu (2013) offer valuable arguments in terms of why results differ. However, no study has yet quantified the impact of methodological choices on the variability of efficiency scores.

Second, the structure of many banking industries has changed rapidly since the 1990s due to extensive deregulation and consolidation processes. Such reforms have considerably liberalized the banking industry around the world. This has been accompanied by an increase in prudential regulation, particularly in relation to the adequacy of minimum capital requirements. There have also been important reforms concerning the relaxing of geographic constraints – so inducing a territorial diversity in bank organization – and ownership structure, with the result that the current market configuration in many countries includes large private commercial banks and small and medium-sized cooperatives. Based on theory, predictions about the impact of regulatory and supervisory policies on bank performance are conflicting and range from the "public interest view" to the "private interest view" (see e.g. Barth et al. 2004, 2006, 2007, 2010). Some authors have emphasized the role of capital standards in preventing bank failure and in safeguarding customers and the whole economy from negative externalities (e.g. Hovakimian and Kane 2000; Gorton and Winton 1995; Rochet 1992). However, if regulation restricts bank activities, it affects banks' business conduct and therefore the efficiency with which they operate. This occurs as banks react to a higher regulatory burden by engaging in riskier activities and investing in ways that circumvent regulation (Jalilian et al. 2007). Whatever the case, the motivation for deregulation and reforms has been the driver for higher efficiency. This introduces the second issue that we try to address in this paper. On the one hand, efficiency in banking has become a concern in many policy-oriented papers as they aim to evaluate the effectiveness of any country-specific restructuring process (Barth et al. 2004, 2006, 2008, 2013; Chortareas et al. 2012). On the other hand, there is still high variability in cross-country banking industries, as revealed for instance by the world index of credit market regulation (Gwartney et al. 2014). This index varies between zero and 10 and in 2012 was, on average, equal to 8.46, ranging from 2.67 (Zimbabwe) to 10 (i.e. Hong Kong, Norway, Singapore and the USA). In brief, it is reasonable to assume that this observed heterogeneity in market conditions translates into heterogeneity in banking efficiency.

This said, the purpose of this paper is to measure the impact of methodological choices and country-specific factors on efficiency score variability. To this end, we perform a meta-regression analysis (henceforth MRA), which is a statistical method that reveals more about a phenomenon which has been studied in a large set of empirical works. By investigating the relationship between the dependent variable (i.e. the efficiency scores of primary studies) and some features of each paper, MRA provides a systematic synthesis of a substantial number of studies and quantifies the role that specific aspects of original papers play in explaining the heterogeneity in results (Glass 1976; Glass et al. 1981; Stanley 2001; Stanley and Jarrell 1989). As Glass (1976: 3) states, MRA "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". Compared to standard qualitative literature surveys, MRA does not suffer from potential bias in selecting the studies to be reviewed because it can cover all the literature without restrictions accruing from the reviewer's judgments. As will become

evident later, this study employs a very large sample of papers, thus ensuring ample coverage of the banking efficiency literature.

Given the increased interest in MRA in economics and the fact that the literature on banking industry efficiency lends itself well to being summarized through this approach, it is noteworthy that no exhaustive work has yet explored the heterogeneity in results.[1] In attempting to fill this gap, this paper uses different MRA specifications and refers to a meta-dataset which comprises 1,661 observations from 120 papers published between 2000 and 2014 (available in April 2014). At this stage of the discussion, it is important to note how we address a specific issue, known as publication bias, which is result of two facts. On one side, journals tend to publish papers with robust evidence. On the other side, authors propose and publish results that satisfy their expectations. This is a relevant issue in empirical economics, suggesting to be cautious in interpreting the role of publication bias in any MRA paper. To control this issue, many scholars weight their observations by using appropriate measures for the variability of estimates (Bumann et al. 2013; Cipollina and Salvatici 2007; Doucouliagos and Stanley 2009; Feld et al. 2013; Gallet and Doucouliagos 2014; Stanley 2008). Following this literature and after controlling for publication bias, we proceed by using a random effects model estimated with the REML technique because it controls for within- and between-study heterogeneity. However, we also run a fixed effect unrestricted WLS regression.

Due to its main research focus, i.e. measuring the impact of potential sources of heterogeneity on banking efficiency, this article contributes to the debate in two ways. One of these concerns the role of methodological choices in banking empirics and the other investigates the impact of two sector-specific effects, that is regulation and how researchers specify the banking frontier. The paper's contributions are threefold.

First, by applying MRA to such a wide set of observations, we are able to address the following relevant issues: whether parametric studies yield different results from nonparametric studies; whether the approach regarding the variables to be included in frontiers has an impact on the average level of efficiency; whether the impact differs when considering cost instead of profit or production efficiency. As these issues refine the identification of the problem to be studied, they address the so-called "*apples and oranges*" MRA problem, which arises when bringing together studies which are different from one another (Glass et al. 1981).

Second, an important novelty of this paper is that regulation enters into an MRA specification as a potential source of banking efficiency heterogeneity. The empirical literature suggests that little attention has been paid to understanding the link between the regulatory environment and efficiency, as opposed to other measures of bank performance (Barth et al. 2008; Pasiouras et al. 2009). Furthermore, the evidence is mixed and depends upon the type of regulation. On the one hand, banking regulations that enhance market discipline empower the public supervisory power and increase capital requirements, costs and profit efficiency (Chortareas et al. 2012; Pasiouras et al. 2009). On the other hand, tighter restrictions are negatively associated with bank efficiency (Barth et al. 2013; Chortareas et al.

[1] Poot (2012) counts 626 papers which applied MRA in the field of economics between 1980 and 2010, with an exponential growth in the 2000s. Some examples of recent MRA use in economics are Abreu et al. (2005), Bumann et al. (2013), Card et al. (2010), Chetty et al. (2011), Disdier and Head (2008), Gallet and Doucouliagos (2014), Doucouliagos and Paldam (2009), Ègert and Halpern (2006), Feld et al. (2013), Feld and Heckemeyer (2011) and Havránek et al. (2012). However, few MRA papers deal with efficiency. Bravo-Ureta et al. (2007) examine the efficiency scores of 167 farm-level studies published over the last four decades. Thiam et al. (2001) review 34 articles on agricultural efficiency in developing countries. Brons et al. (2005) focus on 45 urban transport studies and Odeck and Bråthen (2012) analyse the efficiency of seaports using 40 published papers. Nguyen and Coelli (2009) focus on hospital efficiency, referring to 95 studies published over the period 1987–2008. Finally, Havránek and Iršová (2010) review 32 efficiency studies – with just 53 observations – on banking in the US published in 1977–1997.

2012). Departing from this, we try to understand whether the heterogeneity that we obtain by collecting data from different papers is related to the level of regulation revealed for the country analysed in each primary study. In other words, the aim here is to understand whether efficiency studies for countries with highly regulated banking industries are expected to yield results which differ from those obtained when focusing on more liberalized countries.

Last but not least, we consider two additional factors that are meant to be good predictors of heterogeneity in results in the banking efficiency literature. As MRA may suffer from the same weight being assigned to the results of different works regardless of the quality of the publications, a common practice is to use a dummy variable, distinguishing between journal papers and works published as working papers (Disdier and Head 2008). This paper addresses the quality of publication issue by controlling for a continuous variable based on the impact factor (IF) of each journal at the time of the publication of the primary paper. There is another potential source of heterogeneity which is sector specific. This concerns the choice of the variables to be included in the frontiers. The extreme options are the value-added and intermediation approaches (Berger and Humphrey 1992, 1997; Sealey and Lindley 1977). These basically differ in how they treat deposits. The value-added approach considers loans and deposits as outputs while labour and physical capital are inputs. Therefore, the bank is considered in the same way as other manufacturers of products and services. In contrast, the intermediation approach identifies loans as the output, while labour, capital and deposits are the inputs. In this case, the bank is seen as a company which collects and manages funds to provide loans to customers. Between these two extremes, there is a combination of the two, using deposits as outputs and inputs, as in Berger and Humprey (1992), Pasiouras et al. (2009) and Williams (2012). We label this the hybrid approach.

The paper is structured into five sections. Section 2 describes the criteria adopted to create the meta-dataset and highlights the heterogeneity in efficiency scores. Section 3 presents the MRA, while section 4 presents and discusses the results. Section 5 concludes.

2. The bank efficiency meta-dataset

A delicate phase of MRA is the creation of the database. The number of potential papers in the banking literature is impressive: for instance, when searching through Google for "banking efficiency", one obtains more than 45,000 results (as of 24 April 2014), which diminishes to 10,800 after controlling for "frontier" (Figure 1). Therefore, to collect a representative sample of works, we employed some criteria to identify relevant academic studies from the large pool of papers on bank efficiency. Both authors searched, read and coded the research literature. The search was conducted in two phases.

First, we referred to the EconBiz, Repec, ScienceDirect, IngentaConnect and Econlit archives. The key words used in the baseline search of titles, abstracts and key words were "bank", "efficiency" and "frontier". At the beginning, the search was not restricted and provided a sample of 1,322 published works and working papers encompassing 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 to perform the MRA (efficiency scores and standard deviations); (c) ran specific models to estimate the frontier (DEA, SFA, other); (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 papers with the same efficiency score results as reported in other papers by the same author(s) and papers that did not report efficiency estimates.

Second, 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 Google Scholar and the Social Science Research Network (SSRN); (c) verified that we had not overlooked efficiency studies by scanning the references of qualitative surveys dealing with issues strictly related to our research question that were published after 2000, i.e. Berger (2007), Fethi and Pasiouras (2010) and Paradi and Zhu (2013). The second round of the search yielded 29 additional studies. The compilation of the dataset was concluded on 24 April 2104 with a set of 120 papers and 1,661 observations (Figure 1).

A synthesis of the collected estimates is reported in Table 1, in which different sub-samples of scores have been considered according to the approach used in the estimations (parametric or nonparametric), the approach followed in selecting the variable for the frontiers (intermediation, value-added or hybrid), the structure of the data (panel or cross-sectional), 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).[2]

Overall, the sample of 1,661 observations yields an (un-weighted) 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.[3] The data also highlight that the overall mean of the 872 observations from parametric studies is always lower than that of the 789 observations from nonparametric papers: the difference in the mean is 0.0599 (0.7313–0.6714) and is statistically significant.

Differences between the efficiency of nonparametric and parametric studies remain positive and significant whichever type of efficiency we refer to (cost, profit or production). 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 the input or output. The hybrid approach is made up of 391 observations. The difference in means is only high when 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 regard to the structure of the 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 third from cross-sectional 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-sectional rather than 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 frontier). While Cobb–Douglas

[2] The list of the studies which make up the meta-dataset is provided in Table 1 of the online supplementary material. This table includes the authors' name, the year of publication, the type of publication, the journal, the number of estimates, the average efficiency and some measures of variability (standard deviation, maximum and minimum values). We only 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.

[3] The average of efficiency by frontier (cost, production, profit) is not intended to propose a ranking, but simply to summarize what emerges from papers which differ from each other in a number of ways. The outcome ought to be viewed just as the result of the empirics surrounding any paper (see footnotes 7–9). It is also important to note that the sub-sample of papers on profit efficiency includes different measure of profit, such as in Luo (2993) and Xiang et al. (2013), thereby necessitating some caution in interpreting the results associated with the different types of frontier.

specifications yield a higher level of efficiency when studying cost efficiency (0.8246 compared to 0.6731 from translog and 0.7746 from Fourier), the translog form applied to the profit frontier yields a higher value for efficiency (0.5964 compared to 0.5341 from Cobb–Douglas and 0.5795 from Fourier). Finally, an interesting pattern is observed for the hypothesis of returns to scale in nonparametric studies. Overall, the assumption of variable returns to scale (VRS) translates to an average level of efficiency which is higher (0.7452) than that (0.7035) associated with observations using the hypothesis of constant returns to scale (CRS). However, the results differ according to the frontier. For instance, when considering profit frontiers, we find that the average level of efficiency obtained in primary studies using CRS is 0.8320, that is to say a much higher value than that (0.6675) associated with studies based on VRS. In addition, heterogeneity in the banking efficiency literature is confirmed when looking at the distributions of the estimated scores by group. What clearly emerges is that these distributions follow different shapes and forms (these graphs are available upon request).

A lesson learnt from this discussion is that the study design of primary papers plays an important role in determining differences in the means and distributions of banking efficiency scores.

Figure 1
The dataset assembling process

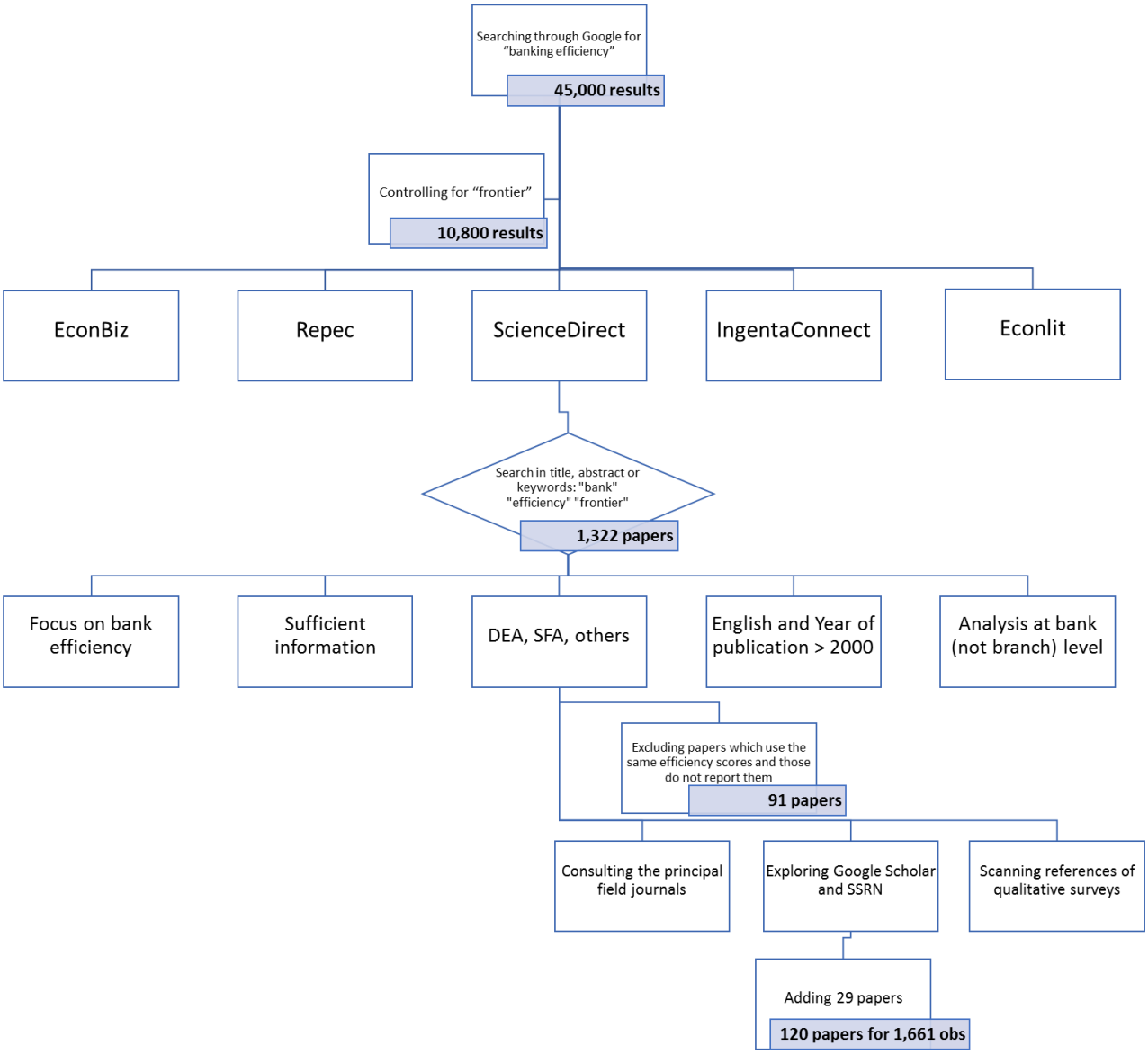


Table 1 Average, standard deviation and number of observations in bank efficiency literature, by group (averages are un-weighted)

		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*
Estimation 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*

3. Meta-analysis of banking efficiency: methodological issues

The previous section highlights that heterogeneity is relevant when grouping observations by different criteria. Given this, providing a systematic explanation of the variability in efficiency becomes an important issue to be addressed on econometric grounds. This section focuses on the MRA carried out to explain the heterogeneity in banking efficiency scores.

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

The dependent variable of the MRA is the bank efficiency score retrieved from the primary literature. As we have seen above, in creating the meta-dataset we have collected all the information from each paper and many papers provide more than one estimate 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 within-study heterogeneity to control for. As for publication bias, the success of a paper depends greatly on the study results in that the probability of a paper being published increases the more conclusive its conclusions. A simple method for detecting publication bias is to regress the key variable of the meta-analysis – bank efficiency in our case – against its precision in primary estimations (Egger et al. 1997). If this regression yields significant results, there is evidence of publication bias in the meta-dataset which must be controlled for in the MRA.

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

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

where the dependent variable E_i is the i-*th* efficiency score. Eq. [1] is known as the funnel asymmetry test–precision effect test (FAT-PET) MRA (Stanley 2005, 2008). X_j comprises the explanatory variables that summarize various model characteristics of the primary studies, while REG_{ct} is an index of banking regulation in country c at time t. Furthermore, $\mathrm{S_i}$ is a measure of the variability of $\mathrm{E_i}$, which is the standard deviation of the efficiency scores as estimated in primary papers. It 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 heteroscedastic because the variance in individual estimates changes in the sample and the estimates are not independent within the same study. This issue is addressed by weighting the observation through a measure S of the variability of each observation:

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

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

The method used in estimating eq. [2] may be a fixed effects or random effects model. These methods 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:

$$E_i^* = \beta_0 + \beta_1 S_i^* + \sum_j \beta_j X_i^* + \chi REG_{ct}^* + u_i + e_i \quad [3]$$

where $e_i \sim N(0, \sigma^2_i)$ is the disturbance and $u_i \sim N(0, \tau^2)$ is the primary study fixed effect. The parameter τ^2 is the between-study variance, which must be estimated from the data as in Harbord and Higgins (2008).[4] To provide some robustness of the results to clustering, we adopt a two-step procedure as in Gallet and Doucouliagos (2014). An REML regression is run in the first step, while in the second step we run a WLS regression in which the weights also include the value of τ^2 retrieved from the first step. This ensures that the REML estimates will be robust to clustering at the study level.[5] Finally, a standard WLS regression is run just as a check.

The right-hand side of eq. [3] includes the matrix X_i, which is related to the observed characteristics used to explain the variability in bank efficiency that we have identified on the basis of a systematic comparison of original papers.

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 pointed out (cf. Introduction), scholars use deposits as inputs or outputs in the 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*). Thus, when the focus of the analysis is on the method for estimating the frontier and on the variable approaches, eq. [3] has to include the interacting terms *PAxINT* and *PAxY* and thus becomes:

[4] 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 term "multilevel" refers to the structure of the meta-dataset, which combines observations at the single estimate level and observations at the study level (Harbord and Higgins 2008; Thompson and Sharp 1999). The choice of using REML is also driven by the structure of our data. As our dataset contains high variability in primary studies, the fixed effects estimator is expected not to perform well because it does not allow for between-study variability. Conversely, REML fits our case well. The evidence we find supports the use of the random effects model as the between-study variance is high and significant (cf. Table 2). This holds despite the potential caveat of REML, the results of which are reliable if the random effects variance is properly estimated (Oczkowski and Doucouliagos 2014). Importantly, Stanley and Doucouliagos (2015) compare REML and WLS and their analysis is not conclusive, depending on additional extra heterogeneity and publication bias effects.

[5] To address the clustering issue with greater effectiveness, we have also taken into consideration the developments proposed by Jackson et al. (2011) and Hedges et al. (2010). Jackson et al. (2011) claim "the absence of information about the within-study correlation structure does not entirely prohibit a multivariate approach but this does present very real statistical issues and a consensus about the best approach or approaches has yet to be reached" (p. 2495). The model proposed by Hedges et al. (2010) requires knowing the dependence structure within each study. Their routine (the "robumeta" Stata command) runs after assigning a value to the parameter of dependence. This means that on the one hand, we search for a technique yielding robust standard errors and on the other hand, the advances in econometrics assume that the within-study variability is known. In other words, in Hedges et al. (2010) the standard errors are correct if and only if the assumed value of the dependence is valid and there is no way to test this assumption. It is also worth pointing out that the "robumeta" command is not yet for use in research as noted in a message that emerges when launching a regression ("*this routine needs to be verified, do not use for research purposes*"). Based on these arguments, we left the within-study issue within the REML framework for future research as it is still an open question in the econometrics of meta-analysis.

$$E_i^* = \beta_0 + \beta_1 S_i^* + \beta_2 PA^* + \beta_3 INT^* + \beta_4 Y^* + \beta_7 (PAxINT)^* + \beta_8 (PAxY)^* + \\ + \sum_j \beta_j X_j^* + \chi REG_{ct}^* + u_i + e_i \quad [4]$$

Furthermore, to control for efficiency type we include two dummies, *Cost (CE*) and *Profit (PE*), each taking the value of 1 if the efficiency score refers to cost or profit efficiencies respectively (the controlling group is the efficiency obtained from the production frontiers).

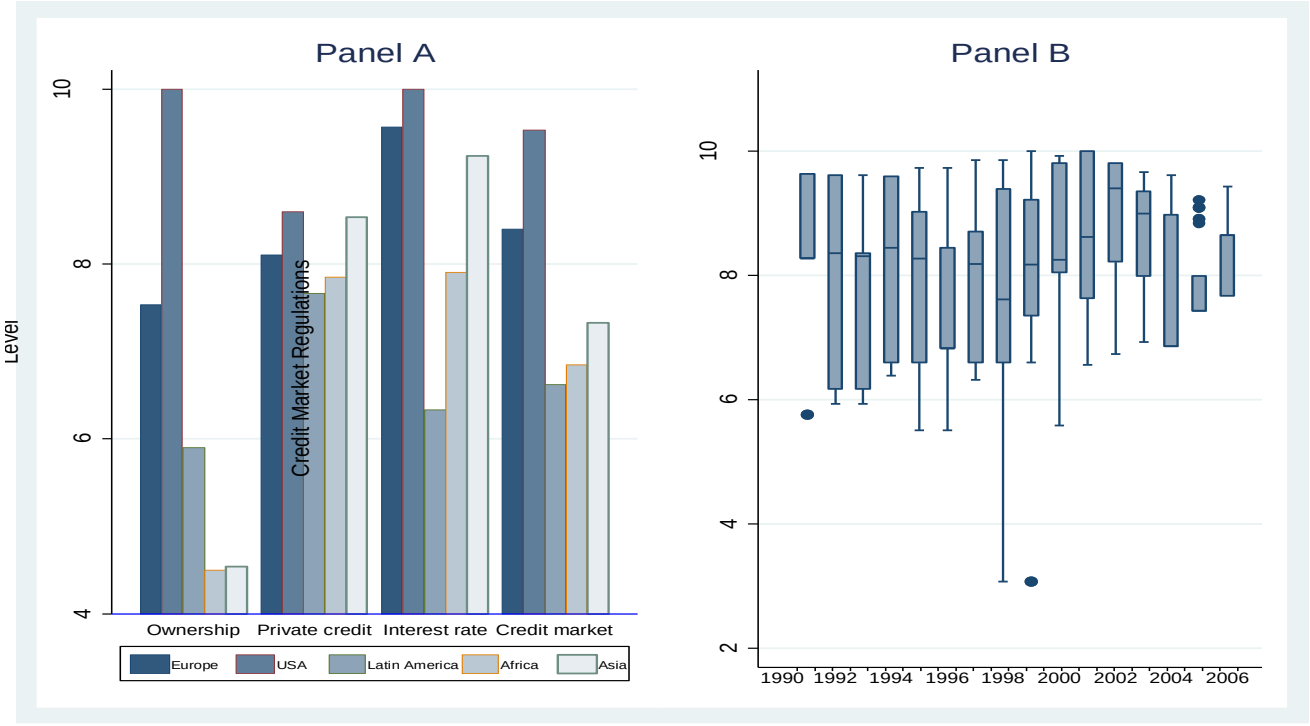
The literature on meta-regression gives some guidance regarding the other variables to be used in the analysis. A distinction to be made is between the efficiency obtained in papers using cross-sectional data and that derived from studies based on panel data. The dummy variable *Panel* is equal to unity if the original works used panel data and zero otherwise. Furthermore, to separate the estimates reported in published works from others, we use the dummy *Published*, which takes the value of 1 for published papers and zero otherwise. To provide better control for any potential quality effect of primary papers, 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 an impact factor and when the efficiency score comes from book chapters, working papers and unpublished papers. We also consider the variable *Sample Size*, i.e. the number of observations used in primary papers when estimating the efficiency score. This is a typical variable in the MRA literature on efficiency (see footnote 1), which in our case can be used to verify if efficiency differs between parametric and nonparametric studies. Finally, 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 equal to unity if the Cobb–Douglas functional form is used in modelling the frontier (the reference category comprises translog and Fourier specifications), while *VRS* is a dummy variable equal to 1 if the primary study assumes VRS and zero otherwise. Finally, MRA includes the dummy D_{All}, which distinguishes between the efficiency observations for a specific sample of banks (D_{All}=0) and observations referring to the banking industry as a whole (D_{All}=1). The underlying idea is as follows: the coefficient of D_{All} is expected to be negative because when using a homogeneous sample of banks (for instance, listed banks, commercial banks, cooperatives, small or large banks), the estimated efficiency score is expected to be higher than that obtained from heterogeneous samples (i.e. all banks of a specific country): all else being equal, similar banks exhibit similar behaviour and thus are more clustered around a frontier than different banks with divergent goals. In addition, to control for geographical differences, we consider the dummy variables Africa, Asia, East Europe, the EU, Latin America, Oceania and the USA, which are equal to 1 if the study used data from that specific part of the world (in estimating the MRA, the USA is the controlling group).[6] A final element which should be considered is time, so that estimations must control for any change likely to occur over

[6] Here, it is worth mentioning that the numerous different ways of performing an efficiency study (see Table A1 in the Appendix) make conclusive expectations of the impact of each regressor difficult. Indeed, despite the high degree of specialization in the use of various methods, the effect of some methodological choices is still not certain. For example, efficiency in parametric studies may be higher or lower than that obtained in nonparametric papers, depending on the nature of disturbances from the frontier (Nguyen and Coelli 2009). The use of panel data would generate higher efficiency levels than those from cross-sectional data. 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 sizes and the assumption of CRS (Berger and Humphrey 1997; Coelli 1995; Fethi and Pasourias 2010; Nguyen and Coelli 2009). However, while theory predicts the likely impact of any choice, the actual measure of how sensitive the results are to the study design is an issue to be addressed empirically.

time. For instance, the level of financial development is expected gradually to lead to improvements in how banks work all else being equal. We control for the time effect by using a set of dummies and the continuous variable REG_{ct}, which is country specific and time variant.

Figure 2 Banking regulation over the world in 1990–2012



Source: Computation of data from Gwartney et al. (2014)
Legend: Panel A displays the average values of each component by geographical area, where higher values mean less regulation. In panel B, which reports the cross-country variability by year, the circles represent the observations beyond the interquartile range.

As far as the dummies are concerned, the time effect is gauged by the variables $Y_{2000\text{-}2004}$ and $Y_{2005\text{-}2009}$, which are equal to 1 if the paper was published in the corresponding years and zero otherwise (the controlling group is composed of the studies published in the years 2010–2014).

The variable REG_{ct} is defined at the country level. It is the index of credit market regulation as calculated in Gwartney et al. (2014). It is time variant and combines three components. The first is related to the ownership of banks: countries with larger shares of privately held deposits receive higher ratings. The second component takes into account the extent of government borrowing relative to private sector borrowing. In this case, greater government borrowing indicates more central planning and results in lower ratings. Finally, REG_{ct} incorporates credit market controls and regulations, taking account of the fact that countries with interest rates determined by the market, stable monetary policy and reasonable real deposits and lending rate spreads receive higher ratings. In brief, higher values of Reg_{ct} signal higher levels of economic freedom in banking. Figure 2 reports the Reg_{ct} index of the countries analysed in the primary papers. It highlights between-country differences in regulation averaged over the years 2000–2012 (Panel A) and high country heterogeneity year by year (Panel B). It emerges that the USA is the country with the most liberalized banking industry in our study, followed by Europe. This holds true whatever the

market profile (ownership, private credit, interest rate) and for the credit market as a whole (Panel A). Freedom is also high in Asia as far as the private credit and interest rate components are concerned. It is expected that this country's differences in regulation affect the variability of the results that we have observed in the banking literature.

4. Fitted models and analysis

4.1. Fitted models

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 bank efficiency. The underlying idea is to test the robustness of the results (sign, magnitude and significance) when moving from basic to extended regressions. In Table 2, model 1 considers just the variables *Parametric*, *Intermediation* and *Value-added*. Model 2 adds the variables *Cost* and *Profit* to Model 1 and is meant just to control the results for efficiency type.[7] To identify the origin of the heterogeneity in banking efficiency with greater clarity, model 3 includes the interaction terms *PAxY* and *PAxINT*, the bank regulation index and the other explanatory variables as already defined.[8] As the role of regulation may differ from country to country, model 4 adds the interactions between the bank regulation index and the geographical dummies. The last column displays the results obtained when estimating model 4 using the WLS method instead of REML (model 5).

Table 3 reports the evidence we find for specific sub-samples of observations belonging to the classes of parametric and nonparametric studies (columns 1 and 2 respectively) and to studies using the intermediation approach (column 3) and the value-added approach (column 4). Evidence from the sample of hybrid studies is not shown as it is poor because the group comprises few observations.[9] Finally, we carried out a sensitivity

[7] The dummies associated with CE and PE enter into the regression not to provide a ranking across efficiency types, but simply to check if the main results hold when controlling for the frontiers to which the single observation refers. Furthermore, the MRA collects observations from very different papers and thus there is no expectation on CE and PE compared to TE. We can use an example to explain the issue. When estimating a cost frontier with input-oriented technology for a given sample of banks, say sample A, we know that a bank is inefficient because its technical and/or allocative efficiency is low. Therefore, for this sample of banks, the cost efficiency, say CE_A, is at best equal to the technical efficiency TE_A. This ranking TE≥CE is predicted by theory (Kumbhakar and Lovell 2000: 54) and then holds for any other sample of banks, as in Kumar (2013). However, any empirical outcome is admitted when comparing efficiency scores retrieved from different samples of banks, even when the analytical framework remains the same (which in our example is a cost frontier with input-oriented technology). In this respect, let us consider another sample of banks, say B. It is true that $TE_B \geq CE_B$, but if in sample B the overall level of efficiency is very high, CE_A may be higher than TE_B. In brief, the result that cost efficiency is higher than technical efficiency might be misleading when referring to a specific setting (i.e. a cost frontier with input orientation and a given sample of banks), but is admitted in the empirics of MRA.

[8] Model 3 of Table 2 refers to eq. [4] and might be augmented by including all implicit interactions. For instance, by taking into account the efficiency type (cost, profit and technical efficiency), it could be augmented with 10 additional interacting terms (6 doubles and 4 triples). This expanded specification has the caveat that many "interactions" are full of zeros (the sample has fewer observations when we increase the number of interactions), thereby implying that many coefficients are not estimated. As this exercise is poor in econometric terms (results available upon request), we overcome the shortcomings of including all implicit interactions by performing another check, the results of which are displayed in Table 3.

[9] It is interesting that splitting the sample should allow better evaluation of the role of specific methodological choices. For instance, when running an MRA only for parametric studies (model 1 of Table 3) the "zeros" of the dummy Cobb–Douglas only refer to functional forms rather than Cobb–Douglas functions and not to point observations from nonparametric studies as in models 3, 4 and 5 of Table 2. The same applies for the dummy VRS for the sub-sample of nonparametric studies (model 2 of Table 3). Even though assumptions concerning returns to scale are possible whatever the method, many parametric studies do not report which type of returns to scale they are using and there is no way of understanding the underlying assumption. While the

analysis to test whether the evidence is robust to the exclusion of 1%, 5% and 10% tails of the efficiency and sample size distributions (see Table 2 of the online supplementary material).

Before the results are presented, it is worth commenting on some diagnostics. The main evidence regards $\hat{\beta}_0$, the parameter used as a test for publication bias. A test of $\beta_0 = 0$ (FAT) is a test of the existence of asymmetry in the estimates and publication selection (Stanley 2005, 2008). $\hat{\beta}_0$ is significant in models 1, 2, but not in models 3 and 4, indicating that in our MRA there is no evidence of publication bias when covariates enter into REML regressions. The same applies after excluding the tails of the efficiency distribution in the sensitivity analysis (see the on line supplementary material). 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 4, it is 98.58%. Again, in the same regression, the proportion of between variance explained by the covariates is 57.53%, the measure of within-study sampling variability. Finally, the joint significance of the explanatory variables is high in each model.

Here it is also important to say that the WLS and REML estimations differ in size, but not in terms of the signs of the parameters. Finally, another advantage of REML is the fitted value of efficiency. As we learnt from Table 1, the observed efficiency is on average 0.69. Importantly, the average of fitted efficiency is 0.7 in the most parsimonious REML regressions (models 1 and 2) and 0.65 when WLS is used to replicate these regressions.[10]

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

procedure followed in models 1 and 2 of Table 3 is more appropriate compared to that of models 3, 4 and 5 of Table 2, it is fruitful to point out that the results do not change moving from Table 2 to Table 3.

[10] These are the conditional expected values of the efficiency, E[*Eff* | ***X***_*mean*], which come from averaging each explanatory variables included in an equation. The results are 0.697 and 0.696 for REML models 1 and 2. These expected values are 0.654 and 0.661 when WLS replaces REML. No comparison is admitted for models 3 and 4 because the statistically significant parameters differ between the REML and WLS regressions, thereby affecting the computation.

Table 2 Meta-regression of banking efficiency scores

Variable		Model 1		Model 2		Model 3		Model 4		Model 5	
Publication bias	β_0	0.6519	***	0.6498	***	-0.0745		-2.0151	*	-3.7993	**
S*	β_1	0.000043	***	0.000038	***	0.000056	***	0.000056	***	0.8386	***
Parametric (PA*)	β_2	-0.0845	*	-0.1278	***	-0.0583		-0.0127		-0.8125	**
Intermediation (INT*)	β_3	0.1018	**	0.0800	*	0.3631	***	0.3959	***	0.0887	
Value added (Y*)	β_4	0.1089	***	0.1108	***	0.4947	***	0.5268	***	0.0864	
Cost (CE*)	β_5			0.1012	***	0.1457	***	0.1524	***	0.1094	*
Profit (PE*)	β_6			-0.0126		0.0541		0.0581		0.0959	*
(PAxINT)*	β_7					-0.2164	***	-0.2161	***	-0.3166	**
(PA xY)*	β_8					-0.2655	**	-0.2741	**	-0.1055	
Panel*	β_9					0.0116		0.0020		-0.1115	***
Published*	β_{10}					-0.1743	***	-0.1818	***	-0.0512	
ln(IF)*	β_{11}					-0.2100	***	-0.2354	***	-0.1285	
[ln(IF) xPA]*	β_{12}					0.2988	***	0.3226	***	0.2159	*
ln(Dimension)*	β_{13}					0.4582	***	0.4593	***	0.1583	
[ln(Dimension)xPA]*	β_{14}					-0.1557		-0.1679	*	0.6261	***
ln(Sample Size)*	β_{15}					-0.0433	***	-0.0405	***	0.0531	*
[ln(Sample Size)xPA]*	β_{16}					0.0557	***	0.0524	***	-0.0521	*
D2000-2004*	β_{17}					-0.0374		-0.0500	*	-0.2719	***
D2005-2009*	β_{18}					-0.1680	***	-0.1702	***	-0.1788	***
Cobb Douglas*	β_{19}					0.2016	***	0.1951	***	0.2774	***
VRS*	β_{20}					0.0739	*	0.0815	**	-0.0387	
D_{All}*	β_{21}					-0.0174		-0.0213	*	-0.1034	*
ln(Reg*)	β_{22}					0.0793	*	0.9293	**	-0.1101	
ln(Reg EU)*	β_{23}							-0.7437		0.6182	*
ln(Reg East Europe)*	β_{24}							-0.6572		-0.6391	
ln(Reg Latin Amer) *	β_{25}							-1.7874	***	-1.0899	
ln(Reg Africa)*	β_{26}							-1.7275	*	1.3423	
ln(Reg Asia)*	β_{27}							-0.9851	*	0.1072	
ln(Reg Oceania)*	β_{28}							1.1087		-4.7984	
EU*	β_{29}					0.0694		1.7572		-1.1130	*
East Europe*	β_{30}					0.0733		1.5762		1.6162	
Latin America*	β_{31}					0.0702		3.8972	***	2.5630	
Africa*	β_{32}					0.1077		3.6936	*	2.7014	
Asia*	β_{33}					0.0092		2.1910	*	0.0186	
Oceania*	β_{34}					0.1116		-2.4322		10.9462	
Observations		1165		1165		1043		1043		1043	
tau^2 (between-study variance)		0.0241		0.0225		0.0123		0.0120		-	
% residual variation due to heterogeneity		98.64%		98.55%		98.58%		98.58%		-	
Adj R-squared		11.82%		17.79%		56.28%		57.53%		-	
F- Fisher		24.98		27.61		29.32		25.18		-	
Chi –Squared										67968.75	

Legend: * p<0.2; ** p<0.1; *** p<0.05.

Note: Random effects models 1-4 are estimated through REML. Model 5 is a fixed effect unrestricted WLS regression. The statistical significance of REML results is robust to clustering at study-level as in Gallet and Doucouliagos (2014).

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

	Parametric Studies		Nonparametric Studies		Studies based on the Intermediation approach		Studies based on the value added approach	
Publication bias	0.3113	*	-0.2522		1.3595	***	1.0220	
S*	0.0001	***	0.0028	***	0.0001	***	0.0003	***
Parametric (PA*)					-1.2558	***	§	
Cost Efficiency (CE*)	§		0.5494	***	0.0595	*	0.2675	
Profit Efficiency (PE*)	-0.1698	***	0.4663	***	0.0015		0.0635	***
Intermediation (INT*)	-0.1624	**	0.4886	***				
Production (Y*)	0.0946		0.6387	***				
(CE xINT)*	0.2243	***	-0.4006	***				
(CE xY)*	0.2444	**	§					
(PE xINT)*	0.3528	***	-0.3799	***				
(PE xY)*	0.2536	**	-0.2315	*				
(PA xCE)*					0.1431	*	§	
(PA xPE)*					0.1662	*	0.0295	
Controlling variables (study design and regulation)	YES		YES		YES		YES	
Time-Fixed Effect	YES		YES		YES		YES	
Country-Fixed Effect	YES		YES		YES		YES	
Observations	593		450		652		292	

Legend: * p<0.2; ** p<0.1; *** p<0.05. §=dropped for collinearity.
Note: The statistical significance of the REML results is robust to clustering at the study level, as in Gallet and Doucouliagos (2014).

5.2 The roles of the method of estimation and model specification in variable choice

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 stochastic frontier analysis (SFA) and similarly, almost all nonparametric studies are based on data envelopment analysis (DEA), which is expected to determine higher efficiency indices than stochastic models (Ekanayake and Jayasuriya 1987). According to our estimates, parametric techniques generate significantly lower efficiency scores than nonparametric models: the coefficient associated with the dummy *Parametric* is negative and significant in models 1 and 2, indicating that all else being equal, the efficiency scores are lower for parametric than for nonparametric techniques. This is in line with a high and positive movement of the random component, as depicted by Nguyen and Coelli (2009). It is also worth pointing out that the parametric effect in the other MRA 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, Nguyen and Coelli (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 to 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 the inputs and outputs of the frontier is relevant to the evaluation of banking efficiency. The 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 else being equal, efficiency scores which are higher than 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 to which we refer. When considering model 1, both the value-added and intermediation approaches outperform the hybrid approach and share the same effect ($\hat{\beta}_3 = 0.10; \hat{\beta}_4 = 0.11$). In moving to model 2, we find that the value-added approach on average yields the highest level of efficiency, followed by the intermediation and hybrid approaches ($\hat{\beta}_4 = 0.11$; $\hat{\beta}_3 = 0.08$). The main conclusions to be drawn are that the hybrid approach generates low levels of efficiency, followed by the intermediation approach. Papers based on the value-added approach yield the highest average level of banking efficiency.

The discussion presented so far concerns the effects of the choice of a particular method rather than another on efficiency, excluding the possible effects related 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 using the evidence related to the dummies *PA*, *INT* and *Y* and the interaction terms *PAxINT* and *PAxY*. The results are derived by using the evidence of model 4 in Table 2 and are displayed in Table 4 (Appendix B shows how the analytical calculations have been made). The findings confirm the role played by the approach being followed when selecting the variables of the frontier (panel A). The intermediation and value-added approaches yield higher efficiency scores than the hybrid approach. This holds true for 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 0.18 in parametric studies and of 0.40 in nonparametric methods. Similarly, while the difference between the value-added and hybrid approaches is 0.25 in parametric

studies, it becomes 0.53 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 value-added approaches, whatever the method chosen to estimate the frontier. There are also some differences between the intermediation and 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 equal to -0.19 in parametric studies and -0.13 for nonparametric methods (Table 4, panel A).

Another finding provided by the estimations of model 4 concerns the evaluation of choosing a parametric rather than a nonparametric method, assuming that the approach adopted to select the variables is the same (Table 4, panel B). What clearly emerges is similar to the findings in models 1 and 2 of table 2. While models 1 and 2 refer to an overall effect of parametric versus nonparametric methods, the use of model 4 disaggregates the evidence by variable approach: intermediation, value-added and hybrid. According to our computations, parametric studies yield, on average, an efficiency level of -0.22 less than nonparametric studies when using the intermediation approach. The difference becomes -0.27 when the value-added approach is taken into account. There is no difference within the hybrid approach: indeed the coefficient β_2 in model 4 is not significant.

Table 4 Differences in average banking efficiency by estimation method and variable approach

Panel A

Variable Approach Effects

	INT *vs* Y	INT *vs* HY	Y *vs* HY
Parametric studies (PA)	-0.19	0.18	0.25
Nonparametric studies (NON PA)	-0.13	0.40	0.53

Panel B

Estimation Method Effects

	PA *vs* NON PA
Intermediation (INT)	-0.221
Value added (Y)	-0.27
Hybrid (HY)	0

Source: own computations (Appendix B)

4.3 The role of other explanatory variables

We proceed by discussing if estimation results differ by efficiency type. All else being equal, performing a study of cost efficiency yields higher scores on average than when estimating a profit or a production frontier and this holds true regardless of the model to which we refer. In model 2, the parameter associated with the variable *Costs* is around 0.10 and becomes 0.15 when the complete regression is considered (model 4). The 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 $\hat{\beta}_5 = 0.15$ and $\hat{\beta}_6 = 0.05$). This outcome deserves attention as it differs from what one might expect. Theory states that technical efficiency is higher than cost and profit efficiency with input-oriented technology (Kumbhakar and Lovell 2000: 54), which is an assumption made in a few papers in our meta-dataset (on this, see footnote 7). Thus, to verify if the results are robust to the sample composition, we perform a test by running the MRA for specific sub-samples of observations. This procedure overcomes the shortcomings related to the MRA with all implicit interacting

terms (cf. footnotes 8 and 9). What emerges from Table 3 is that cost efficiency is still higher than technical efficiency (the controlling group) nonparametric studies (column 2 of Table 3). The same applies when considering the sub-sample of studies based on the intermediation approach (column 3). Finally, referring to the studies using the value-added approach, the evidence is unsatisfactory for cost efficiency in that is does not differ from technical efficiency (column 4, Table 3).

We find that efficiency obtained from cross-sectional data is no different from that for panel data, as $\hat{\beta}_9$ is not significant in any REML regression (Table 2). 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 to the effect exerted by publication type, the results show that the variable *Published* is always negative (i.e. it is -0.18 in model 4 of Table 2), indicating that the average level of efficiency reported in journal papers is lower than that in studies published as working papers. Following this line of reasoning, further evidence emerges from the attempt to investigate whether the efficiency scores depend upon the type of journals in which papers appear. To this end, we use the journal *IF* and include the interaction *IFxPA* 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) to include all observations. According to model 4, the parameter $\hat{\beta}_{11}$ is -0.23, 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 bank efficiency. The results diverge as far as the parametric studies are concerned. Indeed, $\hat{\beta}_{12}$ is 0.32, implying that the relationship between *IF* and bank efficiency becomes positive for parametric studies (the net effect is 0.09). It is worth noting that the sign of the relationship between efficiency and *IF* is robust to the sample of estimates referred to, as is displayed in Table 2 of the online supplementary material. Furthermore, as *IF* is expressed in log form, the marginal effect of *IF* decreases as *IF* increases.[11] For instance, when *IF* is 0.4 (a value close to the average *IF* in both parametric and nonparametric subsamples), the marginal effect will be -0.59 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 around -0.15 in the predicted efficiency.[12] Similarly, with *IF*=0.4, the marginal effect is 0.22 in the parametric sample. However, in such a case, the 0.1 increase (from 0.4 to 0.5, that is 25%) in *IF* will determine an increase in efficiency of 0.055=0.25*0.22. The marginal effect of *IF* on efficiency is displayed in Figure 3a. Interestingly, this graph highlights that the difference in the efficiency scores estimated with parametric and nonparametric method reduces when the primary papers are published in journals with high *IF*.

---

[11] As far as *IF* is concerned, the marginal effect is $\frac{\partial E}{\partial IF} = \frac{\hat{\beta}_{11}}{IF}$ for nonparametric studies and $\frac{\partial E}{\partial IF} = \frac{\hat{\beta}_{11} + \hat{\beta}_{12}}{IF}$ for parametric studies. The same applies for the other continuous variables of interest (dimension, sample size and regulation) entering into MRA in logarithm terms. The non-linearity implies that when the variable of interest increases, a positive beta will ensue the marginal effect approaching zero but not turning negative. The opposite happens when the beta is negative, allowing the marginal effect on efficiency to approach zero from below as the regressor increases. The main implication is that the marginal effect differs at any point of the sample, thereby providing useful information to researcher when performing an efficiency study.

[12] As our regressions are in linear-log form, the absolute change in efficiency (ΔE) is given by the slope (beta) times the relative change in the variable of interest. In the case here discussed, the relative change of *IF* amounts to 25% (Δ*IF* 0.1 is 25% of *IF*=0.4) and thus the efficiency loss is -0.15=0.25*-0.59. The same applies for analogous calculations throughout the paper.

With regard the role of *Dimension*, we find that $\hat{\beta}_{13} = 0.46$ is positive: an increase in the number of inputs and/or outputs included in the nonparametric banking frontiers translates into 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 to parametric studies ($\hat{\beta}_{14} = -0.17$ and then the net effect is 0.29=0.46-0.17). A positive impact of *Dimension* on efficiency was found by Nguyen and Coelli (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 5.5, which is the overall mean of our sample). For the parametric group, if *Dimension*=5, the marginal effect will be 0.06. Figure 3b 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 studies is always higher than in parametric studies.

The analysis of the relationship between bank efficiency and the number of observations used in estimating the frontier produces interesting findings. The continuous variable *Sample Size* enters our regressions in log form 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 term *Sample Size*x*PA* to verify whether the effect of sample size differs between parametric and nonparametric studies. In model 4, the parameter $\hat{\beta}_{15}$ is negative (-0.04), indicating that nonparametric papers using a large sample of banks report lower levels of efficiency than studies with fewer observations. Interestingly, the coefficient $\hat{\beta}_{16} = 0.05$ is not only positive and significant, but also larger than $\hat{\beta}_{15}$, implying that in parametric studies, the effect exerted by the size of the sample is 0.01: the average level of efficiency increases with the number of observations when estimating bank efficiency using a parametric method. The sample size effect does not change when performing a sensitivity analysis of meta-regression results (Table 2 of the online supplementary material). All this also means that the pattern of the 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 3c). Nevertheless, the marginal impact in both cases rapidly tends to zero as the sample size increases, indicating that the estimated value of efficiency scores does not vary for large samples above a certain threshold. With 108 and 63 point observations, which are the first quartiles of the *Sample Size* distribution in parametric and nonparametric studies, the marginal effect is effectively very weak, that is 0.000102 and 0.000643 respectively. In Figure 3c the curve of marginal effects rapidly tends to zero, implying that This implies that any increase in the number of observations would determine a very low change in mean efficiency.

Furthermore, we find that the coefficient of the dummy D_{All} is negative, thereby indicating that primary studies focusing on wide and divergent samples of banks are expected to yield lower levels of efficiency on average than those in papers using homogeneous groups of banks. This is in line with expectations as heterogeneous samples have a high dispersion of data and thus generate (*ceteris paribus*) lower efficiency than studies based on specific and homogenous groups of banks, which are highly clustered around a frontier. Looking at the effect of the choice of the functional form, we find that the Cobb–Douglas generates higher levels of efficiency on average than more flexible functional forms (translog and Fourier). Furthermore, the estimated coefficient of *VRS* is positive, which means that models using the VRS hypothesis yield higher efficiency scores than models based on CRS.

With regard to the time effect, we find that the average level of estimated efficiency over the years 2000–2004 and 2005–2009 is lower compared to the base years 2010–2014.

The estimations related to the period 2005–2009 may be due to the effects of the crisis originating in the world financial markets on banking performance. In terms of the geographical effect, we proceed in two ways. On the one hand, the country effect is meant to affect only the intercepts (model 3 of Table 2). On the other hand, it might affect the banking regulation slopes (model 4 of Table 2). Some country heterogeneity exists only when considering the expanded specification of the MRA (column 4 of Table 2). In such a case, the efficiency in papers addressing Latin America, Africa and Asia is higher than in papers from other geographical areas.

A valuable contribution of the paper is the use of banking regulation as a regressor. The positive coefficient (0.0793) of the variable *Reg* would indicate that the studies for countries with highly liberalized credit market yield higher efficiency scores on average than those focusing on more restricted national banking industries. This interpretation, however, has to be made with cautious as the coefficient of *Reg* is weakly significant (model 3 of Table 2). Beyond this average effect, we find that the regulation effect differs country-by-country (model 4 of Table 2). In detail, the regulation effect on efficiency is positive (0.9293) when considering studies focusing on the USA (the controlling group). It remains positive for Europe, Eastern Europe and Oceania. Interestingly, compared to the USA, the magnitude of the impact does not vary, as there is no difference in slope between the USA and these countries. For this geographical areas, MRA results indicate that if the economic freedom in banking increases from 4 to 5, then the absolute change of the estimated value of efficiency will be 0.2323=0.25*0.9293 (footnote 12). Regarding the studies evaluating the banking efficiency in the other countries of our sample, it emerges that slope coefficients of *Reg Latin America, Reg Africa* and *Reg Asia* are significant and negative. The regulation effect is also negative, as the differences in slope are higher in magnitude and opposite in sign to USA. The effect is -0.8581=0.9293+(-1.7874), -0.7982=0.9293+(-1.7275) and -0.058=0.9293+(-0.9851) for Latin American, African and Asian countries respectively (Table 2). Assuming a 25% increase in the index *Reg* in these countries, we obtain that the efficiency decreases of 0.21 in Latin America, 0.19 in Africa and of 0.01 in Asia.

Figure 4 provides further evidence, highlighting the marginal effects of regulation by geographical area. It allows to point out how, at the country level, the differences of the marginal effects are high when *Reg* is low and tend to disappear when *Reg* increases. Therefore, the additional information of figure 4 is that the role of *Reg* varies at each point of the sample, thereby widening the assessment of any change in regulation. While for Asian countries the marginal effect flows around zero, ranging from –0.0558 with *Reg*=1 to -0.0056 when *Reg*=10, it assumes very different values for the other countries. In the USA, the average value of *Reg* is 9.53, while it is 8.4 in the EU countries (cf. figure 2) with a marginal effect of 0.097 in the USA and of 0.11 in the EU. Assuming a 10% increase in the economic freedom in USA and EU banking, the efficiency gain will be 0.0097 in the USA and 0.011 in the EU. On the opposite side, *Reg* is, on average, 6.62 in Latin America with a marginal effect equal to -0.129 (=-0.8586/6.62). In such a case, a 10% increase in economic freedom is associated with an efficiency loss of 0.013 (Figure 4 and Table 2).

In brief, this MRA provides some insights into regulation around the world. In the USA and EU, market liberalization is associated with high values of efficiency scores from primary papers. Freedom in banking also plays a positive role in the efficiency studies focusing on Oceania and East Europe. The opposite holds in Latin America and Africa where countries have tighter regulations and economic freedom appear to be a threat for banking efficiency.

Figure 3 Marginal effects of impact factor, sample size and dimension

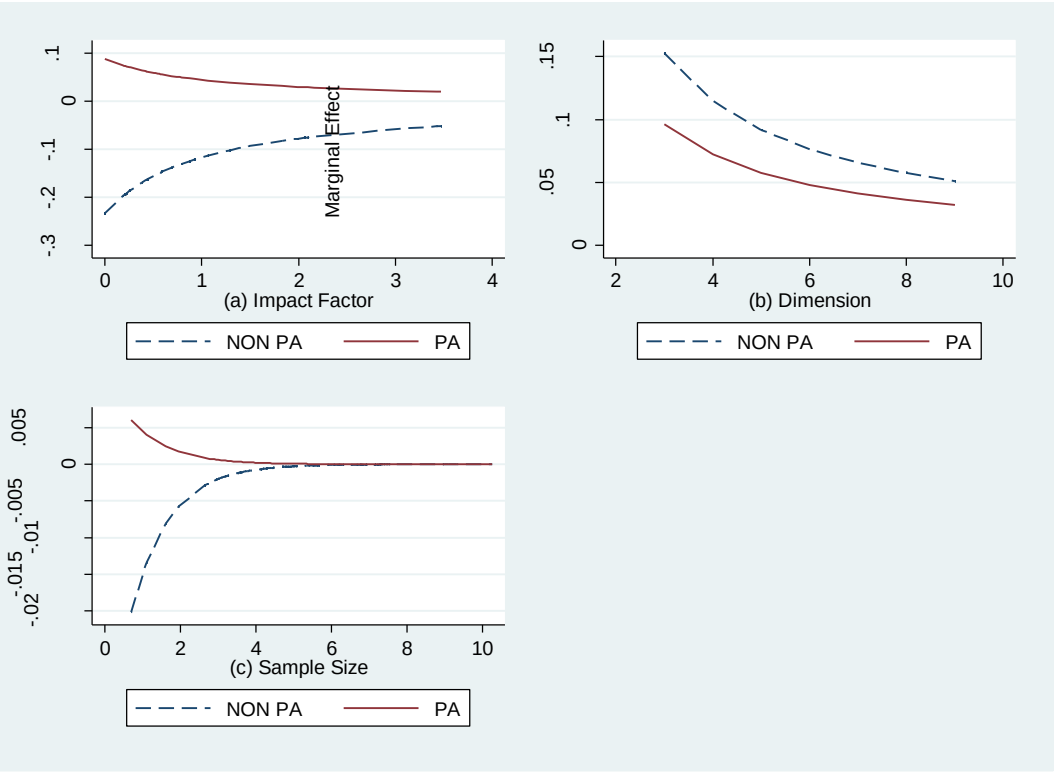
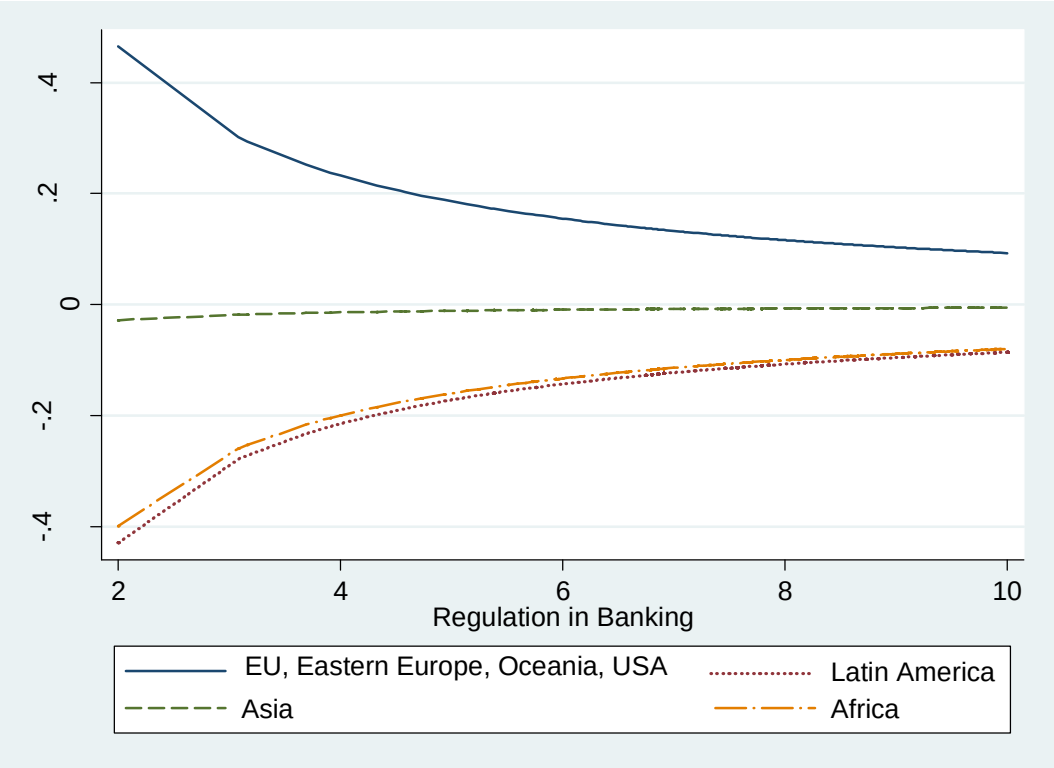


Figure 4 Marginal effects of regulation in banking



5. 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 heterogeneity of efficiency in 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 meta-dataset highlights the fact that efficiency scores are highly heterogeneous. To be precise, significant differences in means are found when grouping efficiency on the basis of different 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 based on the value-added approach yields a higher level of efficiency than the intermediation and the hybrid approaches. Besides differences in means, the 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 bank efficiency. The meta-regression results indicate that studies using parametric methods provide lower efficiency scores on average than papers based on nonparametric models. This evidence is confirmed after distinguishing between 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. All else 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 adopted is independent of the method (parametric or nonparametric) used to estimate the frontier.

Third, the analysis indicates that the estimated values of bank efficiency depend on other specific factors in primary papers. We find that the average efficiency in published papers is lower than in unpublished studies, thereby signalling that the peer-review process is negatively associated with the estimates reported in primary papers. With regard 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 the 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 estimation 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 also, the marginal effect decreases as the dimension increases. A significant impact is also exerted by the modelling choices regarding returns to scale and functional forms. On the one hand, studies assuming VRS yield higher efficiency levels than studies based on CRS. On the other hand, the efficiency estimated in frontiers modelled as a Cobb–Douglas function is higher than that obtained from more flexible functional forms. Again, the use of panel data does not produce different efficiency scores compared to the use of cross sectional data. Interestingly, our MRA corroborates the view that the specific characteristics of each national banking industry affect

the average level of efficiency. In this respect, we find that estimated efficiency scores in primary papers increases with the level of banking liberalization.

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 bank efficiency caused by alternative methodological choices. Therefore, our MRA results will we hope provide 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. However, while our main results are robust to different samples of banking observations, the study has some limitations depending on data quality. Indeed, many authors of primary papers do not report any detail regarding their empirical setting. A lesson that we have learnt from this paper is that it is a good practice for primary papers to provide full explanations, not only so that readers are informed concerning each single study, but also because it would help the understanding of some key issues in the efficiency literature. For instance, it would be valuable for academics to know if heterogeneity in bank efficiency might be explained by orientation in technology (input- versus output-oriented models). Similarly, the data available for our MRA do not allow us to determine whether efficiency differs according to the bank type analysed in the primary papers (i.e. small versus large; commercial versus mutual cooperatives; listed versus non-listed). Researchers might address these issues in future work by performing a new MRA. However, this is feasible only if primary papers provide more detailed information than those used in this meta-study.

Appendix A

This appendix summarizes the methods applied to estimate the frontier. 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.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.

Table A1 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.

Appendix B

This appendix reports the methods used in calculating the differences in average banking efficiency, by estimating method and variable approaches. Compared with the basic model 1 of table 2, the regression to be estimated is augmented by the interacting terms PAxINT and PAxY and becomes (Equation [4] of Section 3):

$$E_i^* = \beta_0 + \beta_1 S_i^* + \beta_2 PA^* + \beta_3 INT^* + \beta_4 Y^* + \beta_7 \left(PAxINT\right)^* + \beta_8 \left(PAxY\right)^* + \\ + \sum_j \beta_j X_j^* + \chi REG_{ct}^* + u_i + e_i$$

By focusing on the dummies PA and INT, this equation 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 this equation 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 $\beta_3 + \beta_7$:
$$\Delta Eff\left(PA=1; INT=1 \,\&\, Y=0\right) - \Delta Eff\left(PA=1; INT=0 \,\&\, Y=0\right) = \beta_2 + \beta_3 + \beta_7 - \beta_2 \\ = \beta_3 + \beta_7$$
2. The effect of using the intermediation approach instead of the value added approach within the parametric studies is $\beta_3 + \beta_7 - \beta_4 - \beta_8$:
$$\Delta Eff\left(PA=1; INT=1 \,\&\, Y=0\right) - \Delta Eff\left(PA=1; INT=0 \,\&\, Y=1\right) = \beta_2 + \beta_3 + \beta_7 - \beta_2 - \beta_4 - \beta_8 \\ = \beta_3 + \beta_7 - \beta_4 - \beta_8$$
3. The effect of using the value added approach instead of the hybrid approach within the parametric studies is $\beta_4 + \beta_8$:
$$\Delta Eff\left(PA=1; INT=0 \,\&\, Y=1\right) - \Delta Eff\left(PA=1; INT=0 \,\&\, Y=0\right) = \beta_2 + \beta_4 + \beta_8 - \beta_2 \\ = \beta_4 + \beta_8$$
4. The effect of using the intermediation approach instead of the value added approach within the nonparametric studies is $\beta_3 - \beta_4$:

$\Delta Eff\,(PA=0; INT=1 \& Y=0) - \Delta Eff\,(PA=0; INT=0 \& Y=1) = \beta_3 - \beta_4$

5. The effect of using parametric instead of nonparametric method within the intermediation approach is $\beta_2 + \beta_7$:
   $\Delta Eff\,(PA=1; INT=1 \& Y=0) - \Delta Eff\,(PA=0; INT=1 \& Y=0) = \beta_2 + \beta_7$
6. The effect of using parametric instead of nonparametric method within the value added approach is $\beta_2 + \beta_8$:
   $\Delta Eff\,(PA=1; INT=0 \& Y=1) - \Delta Eff\,(PA=0; INT=0 \& Y=1) = \beta_2 + \beta_8$

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., Caprio G., Levine R. (2004) "Bank Regulation and Supervision: What Works Best?", *Journal of Financial Intermediation*, Vol. 13, N. 2, pp. 205-248.

Barth J.R., Caprio G., Levine R. (2006*) Rethinking Bank Regulation: Till Angels Govern*, Cambridge University Press, Cambridge

Barth J.R., Caprio G., Levine R. (2008) "Bank Regulations are Changing: for Better or Worse?", *Comparative Economic Studies*, Vol. 50, pp. 537-563

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, 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., Girardone 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

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. (1992) Measurement and Efficiency Issues in Commercial Banking, in Griliches Z. (ed.), Output Measurement in the Service Sectors, University of Chicago Press

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

Chortareas G.E., Girardone C., Ventouri A. (2012) "Bank Supervision, Regulation, and Efficiency: Evidence from the European Union", *Journal of Financial Stability*, Vol. 8, pp. 292-302

Christopoulos D.K., Tsionas E.G. (2001) "Banking Economic Efficiency in the Deregulation Period: Results from Heteroscedastic 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. (2013) "Capital Structure Choice and Company Taxation: a Meta-Study", *Journal of Banking and Finance*, Vol. 37, pp. 2850-2866

Ferrier G.D., Lovell C.K. (1990) "Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence", *Journal of Econometrics*, Vol. 46, N. 1-2, pp. 229-245

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 University, Rome

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

Gallet C.A., Doucouliagos H. (2014) "The Income Elasticity of Air Travel: a Meta Analysis, *Annals of Tourism Research*, Vol. 49, pp. 141-1559

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

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. (ed.) *I problemi dello sviluppo economico e del suo finanziamento nelle aree deboli*, Carocci Editore, Rome

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

Gorton G., Winton A. (1995) "Bank Capital Regulation in General Equilibrium", *NBER*, WP N. 5244

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

Gwartney J., Lawson R., Hall J. (2014) "Economic Freedom of the World: 2014 Annual Report", *FRASER Institute*

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., Tipton E., Johnson M.C. (2010) "Robust variance estimation in meta-regression with dependent effect size estimates", *Research Synthesis Methods*, Vol. 11n, 1, pp- 39-65

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

Hovakimian A., Kane E.J. (2000) "Effectiveness of Capital Regulation at U.S. Commercial Banks, 1985 to 1994", *The Journal of Finance*, Vol. 55, pp. 451-468

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 Institute*, 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

Jackson D, Riley R, White I.R.(2011) "Multivariate meta-analysis: potential and promise", *Statistics in Medicine*, Vol. 30, n° 20, pp. 2481-98

Jalilian H., Kirkpatrick C., Parker D. (2007) "The Impact of Regulation in Developing Countries: a Cross Sectional Analysis", *World Development*, Vol. 35, N. 1, pp. 87-103

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., Yildirim 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) "Meta-Analysis of Technical Efficiency in Nigerian Agriculture", *Contributed Paper for the International Association of Agricultural Economists*

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

Kumbhakar S.C., Lovell K.C.A. (2000) *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge

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

Oczkowski E., Doucouliagos H. (2014) "Wine Prices and Quality Ratings: a Meta-Regression analysis", *American Journal of Agriculture Economics*, Vol. 97, N. 1, pp. 103-121

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

Paradi J.C., Zhu H. (2013) "A Survey on Bank Branch Efficiency and Performance Research with Data Envelopment Analysis", *Omega*, Vol. 41, pp. 61-79

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

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

Rochet J.-C. (1992) "Capital Requirements and the Behaviour of Commercial Banks", *European Economic Review*, Vol. 36, pp. 1137-1178

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

Sealey C.W., Lindley J.T. (1977) "Input, Output and a Theory of Production and Cost at Depository Financial Institutions", The Journal of Finance, Vol. 32, pp. 1251-1266

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. (2005) "Beyond Publication Bias", *Journal of Economic Surveys*, Vol. 19, N. 3, pp. 309-345

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., Doucouliagos H. (2015) "Better than Random: Weighted Least Squares Meta-Regression Analysis", *Statistics in Medicine*, Vol. 34, n°. 13, pp. 2116-27

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