Determinants of bank efficiency: evidence from the Latin American banking industry

Ignacio Jiménez-Hernandez
Economía Internacional y de España, Universidad de Granada, Granada, Spain
Gabriel Palazzo
CEDES-CONICET-University of Buenos Aires, Argentina, Buenos Aires, Argentina, and
Francisco Javier Sáez-Fernández
Economía Internacional y de España, Universidad de Granada, Granada, Spain

Received 11 May 2018
Revised 16 September 2019
Accepted 23 September 2019

Abstract

Purpose – The purpose of this paper is to analyze a variety of factors that can explain the differences in commercial bank efficiency among 17 countries in Latin America (LatAm).

Design/methodology/approach – In a first stage, data envelopment analysis (DEA) and conditional efficiency analysis techniques are used to assess the relative efficiency level of 409 banks for the 2014-2016 period. The conditional efficiency approach considers environmental variables (that are beyond the manager's control), which could influence the shape and the level of the boundary of the attainable set. In the second stage, the resulting conditional efficiency scores are correlated with internal variables (those that are under the manager's control), which might affect the distribution of the inefficiencies. For this purpose, an econometric approach developed by Simar and Wilson (2007) is used.

Findings – First stage scores reveal the heterogeneity of average efficiency within the region. Regarding the factors that may explain the differences in performance in the LatAm banking sector, the results allow us to state that certain internal variables such as bank size, the ratio of loans to total assets and the ratio of non-performing loans show the expected relationship to efficiency, in line with much of the previous literature.

Originality/value – This is the first time that conditional efficiency and Simar and Wilson (2007) approaches have been applied at the same time to analyse the LatAm banking industry.

Keywords Commercial banks, Data envelopment analysis, Conditional efficiency

Paper type Research paper

1. Introduction

The banking industry plays a crucial role in modern economies. Banking institutions are business entities dedicated to financial intermediation, involving the allocation of surplus liquidity among different economic agents. They use deposits and other liabilities from

This research was funded by the European Regional Development Fund (project ECO2016-7523-R) and Spanish Ministry of Economy and Competitiveness.

Applied Economic Analysis
Emerald Publishing Limited
2632-7627
DOI 10.1108/AEA-09-2019-0027

people or firms with a surplus of resources, redirecting them to economic agents who lack such resources, in the form of loans and other assets. These are fundamental functions from a micro- and macro-economic perspective.

In the last few decades, the structure of the banking industry and the relationships among its key players has substantially changed. The internationalisation of banking activity has been one of the most significant recent trends in the sector, and Latin America (LatAm) is one of the world regions that has undergone the greatest transformations in this new competitive scenario. As a consequence of this process and because of the implementation of the Washington Consensus policies in the 1990s, the region has witnessed extensive deregulation of its financial system and has become increasingly integrated with the international capital markets.

The financial reform has given rise to various policy developments, technological transformation, an increased level of deregulation, numerous privatisations of financial institutions, as well as the active involvement of foreign banks in the financial sector (Sáez-Fernández *et al.*, 2015). Moreover, during these years, some LatAm economies have achieved significant economic development and deeper regional integration. All of this has increased efficiency and productivity in the LatAm banking sector, helping banks to reach the most efficient production frontier – as has been suggested in previous literature – and has led to growing market concentration in the region. On this topic, Carvallo and Kasman (2017) provide a comprehensive analysis of the efficiency in the LatAm banking sector using a panel of banks from 19 countries over the 1999-2013 period, finding that efficiency levels have improved in the region, particularly with regard to cost efficiency. However, important differences in performance (i.e. degree of development and level of efficiency) may persist, which is one of the reasons for the continuing relevance of this research topic (Saona, 2016; Tabak *et al.*, 2013; Yeyati and Micco, 2007).

Specialised literature highlights bank efficiency as an essential issue. Economic growth, financial stability and allocation of resources could improve when bank efficiency increases (Berger and Humphrey, 1997). Therefore, in the last few decades, numerous studies have appeared that assess efficiency in the banking sector; many of these focus on the LatAm region. In some of these studies, the analysis is limited to estimating banks' efficiency levels using different methodological approaches, namely, parametric and non-parametric (Miller and Noulas, 1996; Lang and Welzel, 1996). Other works, however, go further and explore the factors that explain observed efficiency differences; such analyses usually distinguish between the environmental factors and internal factors that can influence performance. Dietsch and Lozano-Vivas (2000), Tecles and Tabak (2010) and Lozano-Vivas *et al.* (2002) are good examples of this research line. However, as Simar and Wilson (2007) (SW hereafter) observed, these models include a critical assumption regarding the "separability" condition.

The present study is part of the second branch of the literature. To analyze LatAm bank efficiency, in a first stage, we use data envelopment analysis (DEA) to construct a non-parametric frontier for all banks in our sample, regardless of their home country. In this respect, this first stage is not suitable for comparing diverse banking systems because it does not consider cross-country differences in regulatory, economic and demographic determinants, which are beyond the control of bank managers. Given this weakness, to properly apply the well-known SW econometric approach to the resulting efficiency scores, we first examine those variables that might violate the separability condition and apply conditional measures of efficiency accounting for those variables.

This paper contributes to the present literature by introducing conditional measures of efficiency and the SW approach to analyse the LatAm banking sector. To that end, the separability condition proposed by SW has been considered to correctly select the factors used in the second stage of our analysis.

The remainder of this paper is organized as follows. Section II briefly reviews the existing literature. Section III outlines the methodology used for the measurement of banking efficiency and its determinants. Section IV describes the sources of data and the variables. Section V presents and discusses the empirical results, and Section VI provides the conclusion for this study.

2. Performance in banking: a brief literature review

In this section, we review the relevant literature on bank efficiency and highlight studies on LatAm countries. A banking institution's proximity to the best practice frontier is one way of considering how efficient a bank is. In recent decades, a large body of literature has emerged, which is aimed at studying performance in banking using different efficiency approaches.

The literature has also analysed performance in the banking industry from different perspectives, including technical efficiency (Miller and Noulas, 1996), scale and X-efficiency (Carbó *et al.*, 2002), allocative efficiency (Sathye, 2001), as well as cost and profit efficiency ((Prior, 2003; Ray and Das, 2010). In this line, Aiello and Bonanno (2018) performed a meta-regression analysis of the empirical literature on banking efficiency that includes 120 papers published over the 2000-2014 period, summarising the different results and perspectives regarding cost and profit efficiency.

The survey of the literature has pointed to a wide set of environmental variables that influence banking efficiency such as ownership of capital (Lin and Zhang, 2009), origin of investors (Havrylchyk, 2006), banking regulations (Barth *et al.*, 2013), size (Bonin *et al.*, 2005) or ownership structure (Beck *et al.*, 2013).

From a geographical point of view, some studies have examined banking performance on a global scale (Bhimjee *et al.*, 2016), while others have focused on emerging economies (Huang and Fu, 2013), transition economies (Weill, 2003; Yildirim and Philippatos, 2007), developed economies (Berger, 2007) or other particular economic areas.

As a result, some studies have specifically focused on the LatAm banking industry, estimating regional common frontiers as we have done in this study, (Vianna and Mollick, 2018; Kasman and Carvallo, 2013) or examining individual LatAm economies (Staub *et al.*, 2010). These studies on bank efficiency are particularly important because they depict LatAm as a region in which the macroeconomic and environmental variables are becoming increasingly similar to those in the international scenario. They focus on the relationship between efficiency and market power (Williams, 2012); the relative efficiency of large and small banks (Chortareas *et al.*, 2011); the influence of shareholders versus stakeholders on performance (Jiménez-Hernández *et al.*, 2019); the relationship between performance on the one hand, and public versus private ownership or foreign versus domestic ownership on the other hand (Figueira *et al.*, 2009) and the impact of liberalisation on performance (Leightner and Lovell, 1998).

In this regard, some papers assume that bank-specific variables such as ownership, risk, financial ratios and size affect the evolution of bank inefficiency components, whereas country-level environmental variables produce changes in the cost or profit functions (Fries and Taci, 2005). However, several papers assume that changes in inefficiency over time and across countries depend on country-varying environmental variables, which play no role in explaining the main cost and profit functions (Kasman and Yildirim, 2006; Pasiouras *et al.*, 2006; Lozano-Vivas and Pasiouras, 2010).

Different techniques have been applied to assess the relative technical efficiency of banks and how this is influenced by environmental and market factors. All these techniques try to solve the problem of the inherent dependency of non-parametric full frontier efficiency scores when regression analyses have been used. Using non-parametric full frontier scores in a second-stage regression without any correction might violate basic model assumptions, thus yielding inconsistent estimates. In this sense, the bootstrapping technique (Delis and Papanikolaou, 2009), the SW (2007) approach, the slacks-based measure (Tone, 2001) and second-stage Tobit regression (Grigorian and Manole, 2002) produce more consistent results.

In recent years, a growing number of studies have used the SW approach to analyse correlations between efficiency and environmental variables from a range of perspectives (profit efficiency and productivity, super-efficiency analysis, cost and revenue efficiency and technical efficiency) and for different countries or regions (Indonesia, Central and Eastern European Countries, Jamaica, Gulf Cooperation Countries, France, Germany, Italy, Spain, the UK, Malaysia, Vietnam, China, India, and frontier markets in Africa). However, no studies to date have focused on the LatAm region as a whole (Pancurova and Lyócsa, 2013; Stewart *et al.*, 2016).

As we have indicated above, environmental variables may influence the production process, thus generating differences in the performance of production units. Recently, several models have been developed to provide an appropriate way of accounting for the effect of such variables in non-parametric production models (Bădin *et al.*, 2014). The conditional approach introduced by Cazals *et al.* (2002) and extended by Daraio and Simar (2005, 2007) and Daraio *et al.* (2015) is one such method proposed in the recent literature to overcome the restrictive condition of separability between the input–output space and the space of the environmental variables implicitly assumed by the two-stage approach (Cordero *et al.*, 2016). If the separability condition holds, the factors have no influence on either the shape or the level of the boundary of the attainable set, and the potential effects of environmental factors on the production process are only through the distribution of the inefficiencies. Alternatively, if the separability condition does not hold, then the environmental factors may influence the level and the shape of the boundary of the attainable sets (Daraio *et al.*, 2015).

3. Methodology

Since the mid-20th century, efficiency studies have developed different methodologies to assess the efficiency of observed units (Koopmans, 1951; Debreu, 1951; Farrell, 1957) in a wide range of industries (e.g. the banking industry). These include non-parametric (DEA and Free Disposal Hull, FDH) and parametric approaches (Stochastic Frontier Approach, SFA; Distribution Free Approach, DFA; and Thick Frontier Approach, TFA).

Before implementing the two-stage analysis that we use in this study, we apply the common frontier approach with non-parametric DEA techniques to determine the Farrell efficiency scores. These results provide us with an average efficiency level for each country in the region under study. Typically, two-stage estimation techniques involve assessing technical efficiency by DEA or FDH estimators in the first stage, and then regressing the resulting scores on particular environmental or internal variables in the second stage. This approach is extensively used in the relevant literature. Moreover, the FDH method (Deprins *et al.*, 1984) is best suited to identifying clear cases of inefficiency. While DEA (Charnes *et al.*, 1978) assumes a convex technology and applies linear programming for enveloping the data to construct empirical production frontiers and evaluate relative efficiency, FDH is based on the principle of weak dominance and envelops the data with a non-convex staircase-hull

(Tauchmann, 2012). Under the FDH method, if there is an insufficient number of similar DMUs for an evaluation, some DMUs are categorised as efficient by default. Over the years, DEA has been applied in a large number of papers (a recent survey can be found in Emrouznejad and Yang (2018)).

As our sample includes a varied group of countries with different levels of competition in the market, it seems more appropriate to use technical efficiency instead of cost or profit efficiency for international comparisons. Furthermore, cost or profit definitions of efficiency need information on input and output prices, which are not available with the required degree of disaggregation. For both these reasons, only technical efficiency is estimated in this study. Note that we use total operating expenses as the labour input instead of number of employees because of the high proportion of missing data for the latter (Barth *et al.*, 2013).

Before analysing the impact of the environmental variables on our technical efficiency scores, we should discuss the separability condition described by Simar and Wilson (2011) for each of our factors. We assume that the variables that are beyond the control of the bank managers may influence the level and the shape of the boundary of the attainable sets. Thus, before applying the second stage of the SW (2007) approach, we analyse the conditional efficiency scores using these environmental (exogenous) variables.

Variables that are beyond the control of the bank managers:

- *Market structure (The Herfindahl-Hirschman Index, HHI, using share of total assets)*: Theoretically, market concentration will reduce the competition in this sector resulting in lower efficiency levels for the industry as a whole. We assume the separability condition does not hold; thus, this factor may influence the level and the shape of the boundary of the attainable set. For this reason, we include this variable in the first-stage conditional efficiency calculation.
- *GDP per capita (in constant 2010 US$)*: Higher GDP per capita levels may mean higher purchasing power levels, which translates into a higher number and better quality of banking services. They are also likely to be associated with better-quality banking regulations. We therefore expect this variable to be correlated with higher levels of banking industry efficiency.
- *Domestic credit as % GDP*: Theoretically, a well-developed financial system in an economy could imply higher efficiency levels.
- *Population density*: We assume that high population density levels make it relatively cheaper for banks to market their products and services due to agglomeration economies, or external economies of scale. Accordingly, countries with higher levels of population density might present higher levels of technical efficiency.
- *Inflation rate*: A high inflation rate might generate higher levels of uncertainty regarding economic agents' decisions and lower levels of technical efficiency.

In the second stage of our analysis, we have applied the SW (2007) approach to analyse the internal variables that could influence the DMUs' efficiency distribution.

Variables that are under the control of the bank managers:

- *Size (Total assets)*: Because of internal economies of scale, we expect a significant positive relationship between bank efficiency and the size variable when a constant returns to scale (CRS) model is applied. A positive sign when applying a variable returns to scale (VRS) model, would indicate that large banks are closer to their technological frontier (i.e. better managers).

- *Foreign or Domestic*: Previous literature on this topic reports conflicting results and conclusions. Domestic banks are usually more involved with their home clients than foreign banks are. However, foreign banks enjoy certain comparative advantages because of their access to a wide range of financial markets and better 'know how'. Previous literature finds that, depending on the country or region under study, foreign ownership is associated with lower or higher efficiency.
- *Public or private*: Theoretically, private banks are more focused on achieving high profit levels than on providing socially-beneficial services. Public banks try to ensure that their production process has positive effects on their region and local population. In general, previous literature finds that non-state-owned banks achieve higher technical efficiency than state-owned banks.
- *Loan to assets*: Theoretically, we would expect this variable to have different effects depending on whether the focus of analysis is on technical, cost, revenue or profit efficiency. Previous literature finds that the loans-to-assets ratio is negatively associated with cost efficiency but positively associated with revenue efficiency.
- *Risk (Loan loss reserves to total assets)*: It is possible that, in the short run, banks that are over-producing risky loans and use fewer resources in the credit evaluation process may erroneously appear to be more technically efficient than banks that are otherwise equal but use more resources in the credit evaluation process and grant less risky loans. For this reason, we expect higher efficiency levels in the long run for the latter type of banks (Huang, 2005). Previous literature points out that risk (measured by the Z-Score or even by the ratio of non-performing loans to total loans) adversely affects efficiency.

SW is a commonly used procedure to perform second-stage analysis when the dependent variable is constructed using DEA. Simar and Wilson (2007) point out that efficiency scores generated by the DEA method are, by construction, serially correlated. They highlight that virtually no previous studies had corrected for this statistical problem until they drew attention to the issue.

3.1 Data envelopment analysis input-oriented technical efficiency model

To implement the method, let us first assume that we observe a sample of $k = 1, \ldots, K$ banks that make use of a set of N inputs, represented by $x = (x_1, \ldots, x_N)$, to produce a set of M outputs, namely, $y = (y_1, \ldots, y_M)$. It is also assumed that inputs and outputs are all non-negative. The technology used by the banking industry to transform inputs into outputs is formally defined as follows:

$$T = \left[(x, y) \in R_+^{(N+M)} | x \geq 0; y \geq 0; x \text{ can produce } y\right] \quad (1)$$

Furthermore, we assume that the technology satisfies the axioms initially proposed by Shephard (1970), including the possibility of inaction, no free lunch, free disposability of inputs, strong disposability of outputs and convexity. Based on this characterisation of the technology, Farrell's input-oriented technical efficiency (Farrell, 1957) can be defined as follows:

$$Technical efficiency = Min\, \varphi | (\varphi x, y) \in T \quad (2)$$

Under the assumption of variable returns to scale (Banker *et al.*, 1984), the technical efficiency of DMU k' can be assessed from the following program:

$$Min_{\varphi^{k'}} \quad \varphi^{k'}$$

Subject to:

$$\begin{aligned}
&\sum_{k=1}^{K} \lambda_k x_{kn} \leq \varphi_k x_{k\acute{n}} \quad n = 1, \ldots, N \quad \text{(i)}\\
&\sum_{k=1}^{K} \lambda_k y_{km} \geq y_{k'm} \quad m = 1, \ldots, M \quad \text{(ii)}\\
&\sum_{k=1}^{K} \lambda_k = 1 \qquad k = 1, \ldots, K \quad \text{(iii)}\\
&\lambda_k \geq 0 \qquad \text{(iv)}
\end{aligned} \tag{3}$$

where φ^k is the input-oriented technical efficiency of $DMU_{k'}$, y_{km} is the amount of the mth output (m = 1,. . .,M) produced by DMU_k, x_{kn} is the amount of the nth input (n = 1,. . .,N) consumed by DMU_k and λ_k is the weight assigned to DMU_k (k = 1, 2, . . ., K). Furthermore, variable returns to scale are assumed through restriction (iii); therefore, each bank is compared to another observed bank – or the linear combination of the activity of two or more observed banks in the sample – of a similar size.

Input-oriented technical efficiency has been selected because of supply and demand reasons. Demand side limitations in each country banking sector will not allow getting the maximum output reachable. It seems more appropriated to analyse how much input quantities can be proportionally reduced without changing the output quantities produced. Without this limitation, output-oriented technical efficiency might be actually as important. In general, in bank efficiency analysis, DEA model have been applied by assuming either input-oriented technical efficiency or output-oriented technical efficiency orientations (Aiello and Bonanno, 2018; Kaffash and Marra, 2017).

3.3 Conditional efficiency

The statistical model in SW (2007) is defined by Assumptions A1–A8 listed in their paper. These assumptions extend the standard non-parametric production model, where DEA efficiency estimators are consistent, to include environmental variables. SW notes that Assumptions A1–A2 imply a separability condition, which may or may not be supported by the data; hence, the condition should be analysed.

The environmental factors influence neither the shape nor the level of the boundary of the attainable set, and the potential effect of Z (external factors) on the production process is only through the distribution of the inefficiencies. If the separability condition holds, it is meaningful to measure the efficiency of a particular production plan (x, y) by its distance to the boundary of the technology.

We implemented the second SW (2007) algorithm to obtain bias-corrected technical efficiency scores in the input-oriented DEA model. Computations are based on the distance function, i.e. the reciprocal of the efficiency score, with a range of one to infinity.

The size of the confidence interval for the bias-corrected DEA score in our case is 0.05, and the number of bootstrap replications used in the second loop of the SW (2007) algorithm is (1000).

To assess the first-stage conditional efficiency scores, we have run the R-project package *'rDEA' version 1.2-5,* which allows us to estimate bias-corrected efficiency scores in input-oriented DEA models with environmental (exogenous) variables.

In the presence of environmental variables (Z), SW (2007) propose a semi-parametric bootstrap procedure for obtaining bias-corrected distance function estimates δ, which are the reciprocal of θ. For the input-oriented case, the algorithm is based on the separability of inputs and environmental variables (Simar and Wilson, 2011).

3.4 Simar and Wilson approach

SW (2007) proposed a procedure that allows the use of environmental variables as determinants of efficiency scores and corrections for the problem of serial correlation using bootstrapping and truncated regression. The bootstrap method is based on the idea of resampling the original data to assign statistical properties to the quantities of interest. It should be borne in mind that:

- the efficiency scores are not observed but estimated;
- they are relative rather than absolute scores;
- the two-stage DEA procedure depends on other explanatory variables that are not considered in the first stage; and
- the efficiency score is restricted to the zero-one interval, which should be considered in the second-stage estimation.

This last feature of the efficiency score is why this procedure also requires truncated regression. SW overcomes these difficulties by generating artificial bootstrap samples from this process, and constructing standard errors and confidence intervals for the parameters of interest through bootstrapping. We follow this procedure by applying the first algorithm proposed by SW (2007). In our case study, the procedure entails the following steps after having computed bank efficiency scores:

(1) Use maximum likelihood techniques to estimate the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}_{\varepsilon}$ in the truncated regression where bank efficiency scores are the dependent variable and z is a set of covariates related to the dependent variable. Formally:

$$EEff_{ci} = \boldsymbol{\beta}' z_{ci} + \xi_{ci} \quad \text{with, } \boldsymbol{\epsilon}_{ci} = \boldsymbol{\varepsilon}_{ci} + \xi_{ci} \text{ and } \xi_{ci} \equiv \widehat{EEff_{ci}} - EEff_{ci}$$

(2) Loop over the following three steps L times (in our case, 1000) to obtain a set of bootstrapped estimates of the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}_{\varepsilon}$, namely, $B = \left[\widehat{\beta^b}, \widehat{\sigma^b_\varepsilon}\right]_{b=1}^{1000}$

- For each bank's efficiency scores, draw$\boldsymbol{\varepsilon}_{ci}$ from a normal distribution: $N = [0, \widehat{\sigma_\varepsilon}]$, right truncated at $B = \left(1 - \hat{\boldsymbol{\beta}}' z_{ci}\right)$.
- Compute $\widehat{EEff^b_{ci}} = \boldsymbol{\beta}' z_{ci} + \boldsymbol{\epsilon}^b_{ci}$ again
- Estimate $\widehat{\beta^b}$ and $\widehat{\sigma^b_\varepsilon}$ by truncated regression and maximum likelihood using the artificially generated bank efficiency scores computed in step 2.

(3) The last step comprises using values in B and the original estimates to build a confidence interval for the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}_{\varepsilon}$.

4. Data, variables and sample

Our empirical analysis is based on data from Moody's Analytics BankFocus, a database that includes information on about 44,000 banks worldwide, including commercial and investment banks. The information is sourced by Bureau van Dijk and Moody's Investors Service, from a mixture of annual reports, information providers and regulatory sources. The resulting data set provides accounting and financial statistics that are highly suitable for cross-country comparisons and also offer good coverage of the selected banking markets in our case study.

After removing banks with missing data for some of our variables of interest, and detecting and removing outliers using partial frontier approaches[1], our final data set includes information on 409 commercial banks, referring to the years 2014, 2015 and 2016 from 17 LatAm countries. We have only selected banks in civil law countries in the region, and we have excluded Aruba, Curacao, Haiti, Suriname and Venezuela because of tax haven and political instability concerns. Because we observe these banks over a three-year period and that a few of them have no available data for a particular year, our final data set includes a total of 1124 observations.

Regarding the representativeness of our final sample, Table I presents some figures at the country level, as well as the representativeness for the whole sample of economies.

The appropriate definition and measurement of banking inputs and outputs has been the subject of discussion in the literature. To characterise the banking production function, empirical studies implement one of two approaches: the production or the intermediation approach. The production approach regards banks as producers of deposit and loan account services using only traditional inputs (e.g. capital and labour). However, the intermediation approach regards banks as intermediaries between savers and investors, collecting deposits and funds on one side and providing them as different types of loans and other assets. We have followed the intermediation approach (Sealey and Lindley, 1977) to characterise the banking production function, and the asset approach for the input-output selection. These two approaches are the most commonly used in analyses of performance in the banking industry in previous literature (Berger *et al.*, 1997). The asset, user cost and value-added methods differ as to whether various bank liabilities and assets should be considered inputs or outputs. Under the asset approach, banks are considered as financial intermediaries only

	Observations	(%)	Total assets	(%)
Argentina	130	82	505991996	99
Bolivia	41	95	59743451	100
Brazil	232	56	6167967183	97
Chile	46	84	941932031	99
Colombia	51	75	646913669	86
Costa Rica	42	95	123712273	100
Dominican republic	54	52	93345503	99
Ecuador	51	86	101996472	90
El Salvador	33	65	48261960	94
Guatemala	50	88	107401963	100
Honduras	7	88	14533144	100
Mexico	97	69	1286086286	98
Nicaragua	15	100	18735607	100
Panama	144	76	343300856	84
Paraguay	46	100	53763934	100
Peru	54	86	318555576	99
Uruguay	31	72	104380714	99

Source: Authors' elaboration from Moody's Analytics BankFocus

Table I. Representativeness of the banks in the sample (% for the 2014-2016 period) between liability holders and those who receive bank funds. Loans and other assets are considered bank outputs, and deposits and other liabilities are inputs in the intermediation process (Berger and Humphrey, 1992). Recent studies show the sensitivity of bank efficiency scores to different output definitions (Tortosa-Ausina, 2002).

Accordingly, and in line with previous papers, the inputs included in our characterisation of the technology are operating expenses as a proxy for labour, non-earning assets as a proxy for physical capital, plus equity and customer deposits as two financial inputs. The outputs, however, are gross loans and financial assets (Bhatia *et al.*, 2018). Some descriptive statistics are presented in Table II. The high standard deviations seen in Table II highlight the large size differences among the banks operating in the region.

5. Results and discussion

In this section, we present and discuss the results obtained in the two stages of our analysis. In the first stage, the input-oriented technical efficiency has been computed for each one of the observations in the sample using program (3). In this respect, it is worth noting that to obtain the performance scores, all the observations for all years – 2014, 2015 and 2016, as explained in Section 4 – have been pooled into a single sample. While this enables an increase in both the number of observations in the data set and in the discriminating power of our DEA-based models (Cooper *et al.*, 2007), it also requires assuming that no technical progress has occurred during this three-year period. In our opinion, this is a realistic assumption since 2014-2016 is a fairly short period and no important technical changes have occurred in LatAm economies or international financial markets during that time. Table III reports the banking industry radial efficiency means and conditional efficiency means, as well as the standard deviations for efficiency for each country under VRS[2]. Before applying the SW (2007) second-stage analysis, we estimate bias-corrected efficiency scores in an input-oriented DEA model with environmental (exogenous) variables, which we assume do not meet the separability condition described above. These efficiency scores allow us to use the SW (2007) approach for the rest of the variables, which we assume do meet the separability condition and enable the analysis of the effect these variables have on the conditional efficiency levels estimated in the first stage.

Technical VRS efficiency scores and conditional VRS efficiency scores have been weighted by the total assets of each bank. These results provide a clearer picture of how efficient the banking industry is in each country and reveal the degree of heterogeneity in average efficiency within the region. Estimates show that the average efficiency levels vary widely among LatAm countries, with values ranging between 0.953 for Chile and 0.294 for

Table II. Sample descriptive statistics (in constant 2016 $US million)

	Mean	SD
Inputs		
Equity	845	2981
Customer deposits	4014	13179
Non-earning assets	1573	7214
Operating expenses	448	2266
Outputs		
Gross loans	4576	18810
Financial Assets	1736	8873

Source: Authors' elaboration from Moody's Analytics BankFocus

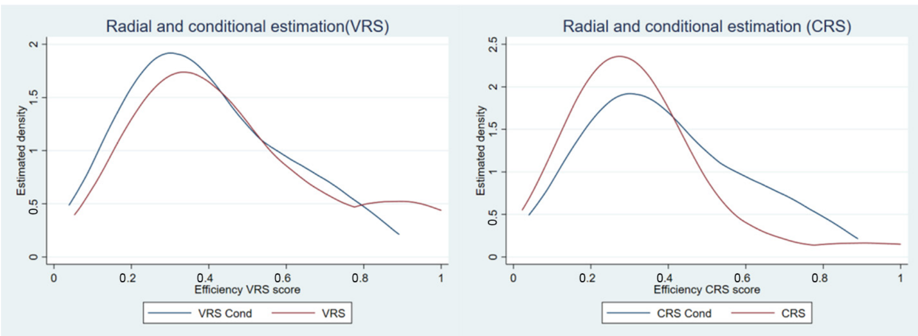
Table III. Estimates of technical efficiency

	Radial		Conditional		
	Mean	SD	Mean	SD	Rad – Cond
Brazil	0.9186	0.2906	0.6573	0.2052	0.26
Chile	0.9539	0.3014	0.7861	0.2489	0.17
Mexico	0.7456	0.2989	0.5939	0.2257	0.15
Panama	0.7022	0.229	0.5711	0.1588	0.13
Argentina	0.5915	0.2189	0.466	0.1543	0.13
Colombia	0.7614	0.2265	0.636	0.1929	0.13
Peru	0.6571	0.2018	0.5828	0.1836	0.07
Guatemala	0.5345	0.1425	0.4628	0.1218	0.07
Dominican republic	0.5284	0.2187	0.4717	0.1709	0.06
Uruguay	0.3721	0.2241	0.3188	0.1458	0.05
Costa Rica	0.5241	0.112	0.4724	0.1016	0.05
Ecuador	0.4797	0.1404	0.43	0.1154	0.05
Bolivia	0.4362	0.0874	0.3872	0.0726	0.05
Paraguay	0.3649	0.1032	0.3272	0.0935	0.04
El Salvador	0.3416	0.0815	0.314	0.0792	0.03
Honduras	0.4237	0.0838	0.3978	0.0846	0.03
Nicaragua	0.2944	0.0398	0.2703	0.0408	0.02
	0.5665		0.4791		

Nicaragua in the case of radial efficiency case; however, the corresponding values for conditional efficiency scores are 0.798 and 0.270, respectively. The weighted mean efficiency score for all countries analysed is 0.839.

It is also interesting to take a closer look at the efficiency score distribution across the different countries in LatAm but without any kind of weight to examine the whole distribution of efficiency scores across banks and countries. In this regard, Table VI in the appendix provides descriptive statistics for all countries in our sample, while Figure 1 shows the kernel density estimation for radial and efficiency conditional scores under VRS and CRS.

The main differences between radial and conditional efficiency scores can be seen in Brazil, Chile, Mexico, Panama, Argentina and Colombia under both VRS and CRS. It is worth noting that, under VRS, the conditional efficiency scores are lower than the radial estimates in those countries, while the opposite is true for CRS estimations. These



Source: Authors' own elaboration

Figure 1. Univariate kernel density estimation (VRS and CRS) – All countries

differences in the efficiency measures point to how environmental variables affect the efficiency level in these industries and might indicate the importance of considering how the assumption of constant or variable returns to scale can affect the results. GDP and market size emerge as the main variables that can explain these changes in the differences between radial and conditional efficiency when we use CRS or VRS estimations. Figures A1 and A2 in the appendix show the univariate kernel density estimation for the major countries of our sample[3].

In our second-stage analysis, we applied the first SW algorithm, which is designed to enable inferences about the results. We performed 1,000 repetitions using the software Stata 12 and the package developed by Tauchmann. This algorithm should improve the robustness of the second-stage analysis and ensure consistent results.

Table IV shows our results when we use VRS for the conditional efficiency score. We use VRS conditional efficiency scores as a dependent variable in our baseline regression models to exclude the differences explained by economies of scale. However, we replicate our analysis with CRS efficiency scores, thus obtaining qualitatively and quantitatively similar results[4]. All our regressions include time fixed effects.

Table IV sheds light on the relationships between different covariates and our efficiency score estimated in the first stage. Size is positively related to our efficiency score under both VRS and CRS. This indicates that large banks are closer to the technological frontier, which can be explained by better managerial performance. This coefficient is semi-elasticity and holds for different specifications of the regression model. Regarding the variable loans to assets, the coefficient is positive and highly significant in all the models, while the coefficient for risk is negative. The results hold when we reduce the sample to nine countries with more complete data (Table V). In this reduced sample, we do find better performance in domestic banks, but the difference is not very significant. Regarding ownership, we do not find any difference between the performance of private and public banks.

6. Summary and conclusions

In recent decades, an abundant literature has been published on banking efficiency. Related studies have applied different approaches and methodological tools to different countries or regions all over the world, enabling a more accurate understanding of efficiency levels observed in the sector, as well as the factors that can determine inefficiencies. Latin America has been no exception to this trend and in recent years many studies have attempted to measure the efficiency of its regional banking and identify possible determinants of LatAm bank performance.

Following this trend, the present study performs a two-stage analysis to assess efficiency in the LatAm banking industry. In the first stage, we estimate the technical efficiency levels of banks in 17 LatAm countries using a conventional DEA technique and the conditional efficiency technique. Before applying the SW (2007) second-stage analysis, we estimate bias-corrected efficiency scores in an input-oriented DEA model with environmental (exogenous) variables, which we assume to not meet the separability condition described above. In the second stage, we identify internal factors that can influence the estimated levels of conditional efficiency, applying the SW (2007) model. As far as we are aware, this is the first time that this combination of the conditional efficiency and SW approach has been applied to the banking sector in LatAm. This model allows us to overcome certain problems associated with conventional regression, incorporating bootstrapping techniques and offering much more reliable and robust results than those obtained with more traditional econometric methods.

Table IV. Results of SW: Determinants of LatAm banks' efficiency (VRS)

Variables	VRS	VRS	VRS	VRS	VRS	VRS
ln(size)	0.0395*** (0.00337)	0.0384*** (0.00316)	0.0370*** (0.00340)	0.0418*** (0.00384)	0.0438*** (0.00383)	0.0441*** (0.00372)
Loan to assets		0.101*** (0.0280)	0.138*** (0.0306)	0.130*** (0.0321)	0.105*** (0.0337)	0.104*** (0.0336)
Risk			−0.895*** (0.311)	−0.934*** (0.306)	−0.562* (0.310)	−0.558* (0.322)
Private				−0.00440 (0.0254)		0.00806 (0.0251)
Foreign					−0.00749 (0.0120)	−0.00851 (0.0125)
Constant	−0.233*** (0.0502)	−0.267*** (0.0496)	−0.250*** (0.0532)	−0.301*** (0.0638)	−0.326*** (0.0580)	−0.335*** (0.0625)
Observations	1,124	1,124	1,093	993	879	879
Wald Chi2	386.3	410.4	401.1	396.8	388	389.7
Sigma	0.171	0.170	0.170	0.169	0.168	0.168

Table V. Results of SW: Determinants of LatAm banks' efficiency (VRS): reduced sample

Variables	VRS	VRS	VRS	VRS	VRS	VRS
ln(size)	0.0241*** (0.00452)	0.0199*** (0.00398)	0.0187*** (0.00387)	0.0225*** (0.00408)	0.0231*** (0.00429)	0.0231*** (0.00450)
Loan to assets		0.406*** (0.0328)	0.448*** (0.0354)	0.432*** (0.0387)	0.400*** (0.0392)	0.400*** (0.0395)
Risk			−1.169*** (0.315)	−1.099*** (0.330)	−0.867** (0.347)	−0.867*** (0.329)
Private				−0.0143 (0.0281)		0.000141 (0.0291)
Foreign					−0.0270* (0.0151)	−0.0270* (0.0153)
Constant	0.157** (0.0667)	0.0171 (0.0610)	0.0297 (0.0591)	−0.000117 (0.0684)	0.00380 (0.0640)	0.00366 (0.0739)
Observations	687	687	673	620	571	571
Wald Chi2	107.6	251.5	267.9	251.2	244.8	247.3
Sigma	0.190	0.169	0.166	0.165	0.166	0.166

First stage scores reveal the heterogeneity of average efficiency within the region, ranging between 0.953 for Chile and 0.294 for Nicaragua in the case of radial efficiency, and between 0.798 and 0.270 in the case of conditional efficiency scores. These results support previous efficiency scores reported in the literature. They show how bank industries in countries such as Chile, Brazil, Colombia and Mexico are operating at high levels of technical efficiency relative to the region. Regarding the conditional efficiency scores, these results show how variables that are beyond managerial control have a greater effect on some countries' banking industries than on others. In this regard, banks in Brazil, Chile, Mexico and Panama are the most affected by external variables.

Although the choice of determinants comes from previous banking industry studies, there is no general consensus as to the main drivers of efficiency in the banking sector. Regarding the factors that may explain the differences in performance in the LatAm banking sector, our results allow us to state that certain internal variables such as bank size, the ratio of loans to total assets and the ratio of non-performing loans show the expected relationship to efficiency, in line with much of the previous literature. In sum, everything seems to indicate that increasing the size of the banks makes them more efficient, which become more specialised in loans and credits also boosts efficiency and that inadequate credit risk management involves a higher relative consumption of inputs. However, although domestic banks seem to have an advantage in terms of efficiency, the results are not definitive. This weak result could indicate that national and foreign banks do not present significant differences in performance; in a sense, this finding would be in line with the results of Sáez-Fernández *et al.* (2015), who conclude that the entry of foreign banks in LatAm, primarily in the 1990s, prompted the modernisation of the national banks, indicating that efficiency levels in the two types of entities are now fairly similar.

Notes

1. By construction, non-parametric frontiers are defined by extreme values. The appearance of outliers may substantially influence efficiency scores. In this regard, recent studies have addressed non-parametric efficiency measurement using so-called partial frontier approaches; in particular, order-m (Cazals *et al.*, 2002) and order-α (Aragon *et al.*, 2005) efficiency. These approaches generalise FDH by allowing for superefficient observations to be located beyond the estimated production-possibility frontier (Tauchmann, 2012).
2. We also have run all the calculation for the seven main economies (in terms of GDP) in the region (Brazil, Mexico, Argentina, Colombia, Chile, Peru and Ecuador) as well as Uruguay and Paraguay (which have healthy banking industries) in order to ensure the robustness of the scores. See Table AI in the appendix.
3. The figures show interesting patterns within countries; particularly interesting are the asymmetric results between Argentina and Chile. However, more research is needed to analyze differences within countries.
4. Tables AIII and AIV in appendix.

References

Aiello, F. and Bonanno, G. (2018), "On the sources of heterogeneity in banking efficiency literature", *Journal of Economic Surveys*, Vol. 32 No. 1, pp. 194-225.

Aragon, Y., Daouia, A. and Thomas-Agnan, C. (2005), "Nonparametric frontier estimation: a conditional quantile-based approach", *Econometric Theory*, Vol. 21 No. 2, pp. 358-389.

Bădin, L., Daraio, C. and Simar, L. (2014), "Explaining inefficiency in nonparametric production models: the state of the art", *Annals of Operations Research*, Vol. 214 No. 1, pp. 5-30.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984), "Some models for estimating technical and scale inefficiencies in data envelopment analysis", *Management Science*, Vol. 30 No. 9, pp. 1078-1092.

Barth, J.R., Caprio, G., Jr and Levine, R. (2013), "Bank regulation and supervision in 180 countries from 1999 to 2011", *Journal of Financial Economic Policy*, Vol. 5 No. 2, pp. 111-219.

Barth, J.R., Lin, C., Ma, Y., Seade, J. and Song, F.M. (2013), "Do bank regulation, supervision and monitoring enhance or impede bank efficiency?", *Journal of Banking and Finance*, Vol. 37 No. 8, pp. 2879-2892.

Beck, T., Demirgüç-Kunt, A. and Merrouche, O. (2013), "Islamic vs. conventional banking: business model, efficiency and stability", *Journal of Banking and Finance*, Vol. 37 No. 2, pp. 433-447.

Berger, A.N. (2007), "International comparisons of banking efficiency", *Financial Markets, Institutions and Instruments*, Vol. 16 No. 3, pp. 119-144.

Berger, A.N. and Humphrey, D.B. (1992), "Measurement and efficiency issues in commercial banking", in *Output Measurement in the Service Sectors*, University of Chicago Press, Chicago, London, pp. 245-300.

Berger, A.N. and Humphrey, D.B. (1997), "Efficiency of financial institutions: international survey and directions for future research", *European Journal of Operational Research*, Vol. 98 No. 2, pp. 175-212.

Bhatia, V., Basu, S., Mitra, S.K. and Dash, P. (2018), "A review of bank efficiency and productivity", *OPSEARCH*, Vol. 55 Nos 3/4, pp. 557-600.

Bhimjee, D.C., Ramos, S.B. and Dias, J.G. (2016), "Banking industry performance in the wake of the global financial crisis", *International Review of Financial Analysis*, Vol. 48, pp. 376-387.

Bonin, J.P., Hasan, I. and Wachtel, P. (2005), "Bank performance, efficiency and ownership in transition countries", *Journal of Banking and Finance*, Vol. 29 No. 1, pp. 31-53.

Carbó, S., Gardener, E.P. and Williams, J. (2002), "Efficiency in banking: empirical evidence from the savings banks sector", *The Manchester School*, Vol. 70 No. 2, pp. 204-228.

Carvallo, O. and Kasman, A. (2017), "Convergence in bank performance: evidence from Latin american banking", *The North American Journal of Economics and Finance*, Vol. 39, pp. 127-142.

Cazals, C., Florens, J.P. and Simar, L. (2002), "Nonparametric frontier estimation: a robust approach", *Journal of Econometrics*, Vol. 106 No. 1, pp. 1-25.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978), "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444.

Chortareas, G.E., Garza-Garcia, J.G. and Girardone, C. (2011), "Banking sector performance in Latin America: market power versus efficiency", *Review of Development Economics*, Vol. 15 No. 2, pp. 307-325.

Cooper, W.W., Huang, Z., Li, S.X., Parker, B.R. and Pastor, J.T. (2007), "Efficiency aggregation with enhanced Russell measures in data envelopment analysis", *Socio-Economic Planning Sciences*, Vol. 41 No. 1, pp. 1-21.

Cordero, J.M., Polo, C., Santín, D. and Sicilia, G. (2016), "Monte-Carol comparison of conditional nonparametric methods and traditional approaches to include exogenous variables", *Pacific Economic Review*, Vol. 21 No. 4, pp. 483-497.

Daraio, C. and Simar, L. (2005), "Introducing environmental variables in nonparametric frontier models: a probabilistic approach", *Journal of Productivity Analysis*, Vol. 24 No. 1, pp. 93-121.

Daraio, C. and Simar, L. (2007), "Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach", *Journal of Productivity Analysis*, Vol. 28 Nos 1/2, pp. 13-32.

Daraio, C., Simar, L. and and Wilson, P.W. (2015), "Testing the 'separability' condition in two-stage nonparametric models of production (no. 2015/21)", LEM working paper series.

Debreu, G. (1951), "The coefficient of resource utilization", *Econometrica*, Vol. 19 No. 3, pp. 273-292.

Delis, M.D. and Papanikolaou, N.I. (2009), "Determinants of bank efficiency: evidence from a semi-parametric methodology", *Managerial Finance*, Vol. 35 No. 3, pp. 260-275.

Deprins D., Simar J., Tulkens, H. (Eds) (1984), *Measuring Labor-Efficiency in Post Offices in the Performance of Public Enterprises: Concepts and Measurement*, Tulkens H., North-Holland.

Dietsch, M. and Lozano-Vivas, A. (2000), "How the environment determines banking efficiency: a comparison between French and Spanish industries", *Journal of Banking and Finance*, Vol. 24 No. 6, pp. 985-1004.

Emrouznejad, A. and Yang, G.L. (2018), "A survey and analysis of the first 40 years of scholarly literature in DEA: 1978-2016", *Socio-Economic Planning Sciences*, Vol. 61, pp. 4-8.

Farrell, M.J. (1957), "The measurement of productive efficiency", *Journal of the Royal Statistical Society Series A-General*, Vol. 120 No. 3, pp. 253-290.

Figueira, C., Nellis, J. and Parker, D. (2009), "The effects of ownership on bank efficiency in Latin America", *Applied Economics*, Vol. 41 No. 18, pp. 2353-2368.

Fries, S. and Taci, A. (2005), "Cost efficiency of banks in transition: evidence from 289 banks in 15 post-communist countries", *Journal of Banking and Finance*, Vol. 29 No. 1, pp. 55-81.

Grigorian, D.A. and Manole, V. (2002), *Determinants of Commercial Bank Performance in Transition: An Application of Data Envelopment Analysis*, The World Bank.

Havrylchyk, O. (2006), "Efficiency of the polish banking industry: foreign versus domestic banks", *Journal of Banking and Finance*, Vol. 30 No. 7, pp. 1975-1996.

Huang, T.H. (2005), "A study on the productivities of it capital and computer labor: firm-level evidence from Taiwan's banking industry", *Journal of Productivity Analysis*, Vol. 24 No. 3, pp. 241-257.

Huang, M.Y. and 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 No. 3, pp. 387-406.

Jiménez-Hernández, I., Picazo-Tadeo, A.J. and Sáez-Fernández, F.J. (2019), "Are Lac cooperative and commercial banks so different in their management of non-performing loans?", *Annals of Public and Cooperative Economics*, Vol. 90 No. 3, pp. 419-440.

Kaffash, S. and Marra, M. (2017), "Data envelopment analysis in financial services: a citations network analysis of banks, insurance companies and money market funds", *Annals of Operations Research*, Vol. 253 No. 1, pp. 307-344.

Kasman, A. and Carvallo, O. (2013), "Efficiency and risk in Latin american banking: explaining resilience", *Emerging Markets Finance and Trade*, Vol. 49 No. 2, pp. 105-130.

Kasman, A. and Yildirim, C. (2006), "Cost and profit efficiencies in transition banking: the case of new EU members", *Applied Economics*, Vol. 38 No. 9, pp. 1079-1090.

Koopmans, T.C. (1951), "Efficient allocation of resources", *Econometrica*, Vol. 19 No. 4, pp. 455-465.

Lang, G. and Welzel, P. (1996), "Efficiency and technical progress in banking empirical results for a panel of German cooperative banks", *Journal of Banking and Finance*, Vol. 20 No. 6, pp. 1003-1023.

Leightner, J.E. and Lovell, C.K. (1998), "The impact of financial liberalization on the performance of Thai banks", *Journal of Economics and Business*, Vol. 50 No. 2, pp. 115-131.

Lin, X. and Zhang, Y. (2009), "Bank ownership reform and bank performance in China", *Journal of Banking and Finance*, Vol. 33 No. 1, pp. 20-29.

Lozano-Vivas, A. and Pasiouras, F. (2010), "The impact of non-traditional activities on the estimation of bank efficiency: international evidence", *Journal of Banking and Finance*, Vol. 34 No. 7, pp. 1436-1449.

Lozano-Vivas, A., Pastor, J.T. and Pastor, J.M. (2002), "An efficiency comparison of European banking systems operating under different environmental conditions", *Journal of Productivity Analysis*, Vol. 18 No. 1, pp. 59-77.

Miller, S.M. and Noulas, A.G. (1996), "The technical efficiency of large bank production", *Journal of Banking and Finance*, Vol. 20 No. 3, pp. 495-509.

Pancurova, D. and Lyócsa, S. (2013), "Determinants of commercial banks' efficiency: evidence from 11 CEE countries", *Finance a Uver*, Vol. 63 No. 2, p. 152.

Pasiouras, F., Gaganis, C. and Zopounidis, C. (2006), "The impact of bank regulations, supervision, market structure, and bank characteristics on individual bank ratings: a cross-country analysis", *Review of Quantitative Finance and Accounting*, Vol. 27 No. 4, pp. 403-438.

Prior, D. (2003), "Long-and short-run non-parametric cost frontier efficiency: an application to Spanish savings banks", *Journal of Banking and Finance*, Vol. 27 No. 4, pp. 655-671.

Ray, S.C. and Das, A. (2010), "Distribution of cost and profit efficiency: evidence from Indian banking", *European Journal of Operational Research*, Vol. 201 No. 1, pp. 297-307.

Sáez-Fernández, F.J., Picazo-Tadeo, A.J. and Beltrán-Esteve, M. (2015), "Assessing the performance of the Latin american and Caribbean banking industry: Are domestic and foreign banks so different?", *Cogent Economics and Finance*, Vol. 3 No. 1, p. 1006976.

Saona, P. (2016), "Intra-and extra-bank determinants of Latin american banks' profitability", *International Review of Economics and Finance*, Vol. 45, pp. 197-214.

Sathye, M. (2001), "X-efficiency in Australian banking: an empirical investigation", *Journal of Banking and Finance*, Vol. 25 No. 3, pp. 613-630.

Sealey, C.W. and Lindley, J.T. (1977), "Inputs, outputs, and a theory of production and cost at depository financial institutions", *The Journal of Finance*, Vol. 32 No. 4, pp. 1251-1266.

Shephard, R.W. (1970), *Theory of Cost and Production Functions*, Princeton University Press. Princeton, NJ.

Simar, L. and Wilson, P.W. (2007), "Estimation and inference in two-stage, semi-parametric models of production processes", *Journal of Econometrics*, Vol. 136 No. 1, pp. 31-64.

Simar, L. and Wilson, P.W. (2011), "Two-stage DEA: caveat emptor", *Journal of Productivity Analysis*, Vol. 36 No. 2, p. 205.

Staub, R.B., e Souza, G.D.S. and Tabak, B.M. (2010), "Evolution of bank efficiency in Brazil: a DEA approach", *European Journal of Operational Research*, Vol. 202 No. 1, pp. 204-213.

Stewart, C., Matousek, R. and Nguyen, T.N. (2016), "Efficiency in the Vietnamese banking system: a DEA double bootstrap approach", *Research in International Business and Finance*, Vol. 36, pp. 96-111.

Tabak, B.M., Fazio, D.M. and Cajueiro, D.O. (2013), "Systemically important banks and financial stability: the case of Latin America", *Journal of Banking and Finance*, Vol. 37 No. 10, pp. 3855-3866.

Tauchmann, H. (2012), "Partial frontier efficiency analysis", *The Stata Journal: Promoting Communications on Statistics and Stata*, Vol. 12 No. 3, pp. 461-478.

Tecles, P.L. and Tabak, B.M. (2010), "Determinants of bank efficiency: the case of Brazil", *European Journal of Operational Research*, Vol. 207 No. 3, pp. 1587-1598.

Tone, K. (2001), "A slacks-based measure of efficiency in data envelopment analysis", *European Journal of Operational Research*, Vol. 130 No. 3, pp. 498-509.

Tortosa-Ausina, E. (2002), "Bank cost efficiency and output specification", *Journal of Productivity Analysis*, Vol. 18 No. 3, pp. 199-222.

Vianna, A.C. and Mollick, A.V. (2018), "Institutions: Key variable for economic development in Latin America", *Journal of Economics and Business*, Vol. 96, pp. 42-58.

Weill, L. (2003), "Banking efficiency in transition economies", *The Economics of Transition*, Vol. 11 No. 3, pp. 569-592.

Williams, J. (2012), "Efficiency and market power in Latin american banking", *Journal of Financial Stability*, Vol. 8 No. 4, pp. 263-276.

Yeyati, E.L. and Micco, A. (2007), "Concentration and foreign penetration in Latin american banking sectors: impact on competition and risk", *Journal of Banking and Finance*, Vol. 31 No. 6, pp. 1633-1647.

Yildirim, H.S. and Philippatos, G.C. (2007), "Restructuring, consolidation and competition in Latin American banking markets", *Journal of Banking and Finance*, Vol. 31 No. 3, pp. 629-639.

Corresponding author
Ignacio Jiménez-Hernandez can be contacted at: ignaciojimenez@correo.ugr.es

Appendix

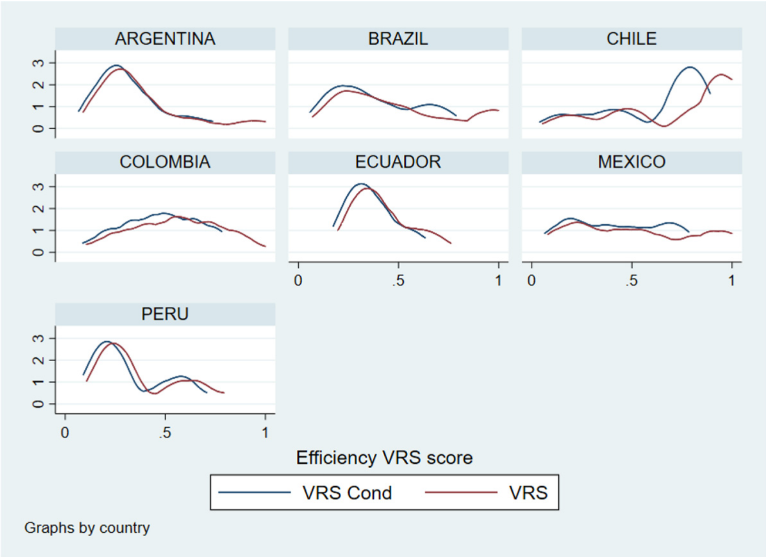


Figure A1. Univariate kernel density estimation (VRS) – Selected countries

Source: Authors' own elaboration

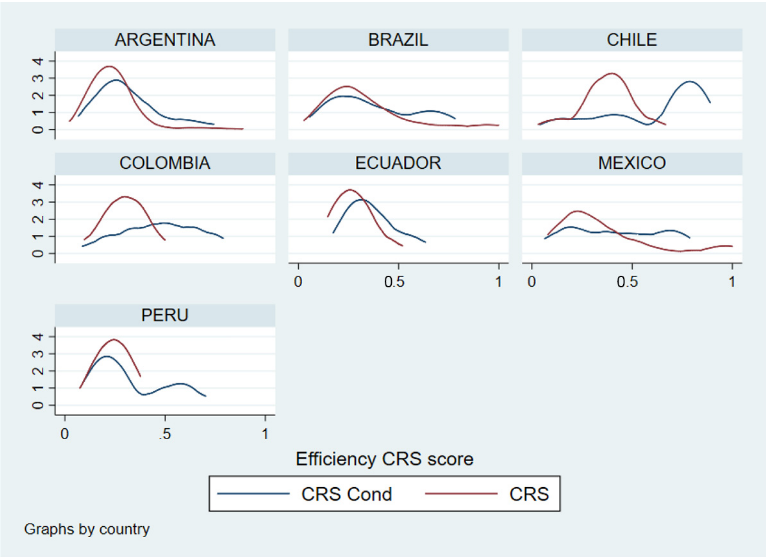


Figure A2. Univariate kernel density estimation (CRS) – Selected countries

Source: Authors' own elaboration

	Radial		Conditional		
	Mean	SD	Mean	SD	Rad – Cond
Brazil	0.926	0.28	0.7007	0.209	0.23
Chile	0.9689	0.247	0.8193	0.212	0.15
Mexico	0.7635	0.264	0.647	0.214	0.12
Colombia	0.7894	0.182	0.6864	0.16	0.10
Argentina	0.653	0.19	0.559	0.143	0.09
Peru	0.7171	0.151	0.6533	0.142	0.06
Ecuador	0.6124	0.163	0.5635	0.134	0.05
Uruguay	0.5095	0.192	0.4621	0.154	0.05
Paraguay	0.6497	0.178	0.6088	0.169	0.04
	0.7322		0.6333		

Table AI. Estimates of efficiency scores (9 countries)

	Simple average		Median		SD		P(90)		P(10)	
Row labels	VRS	VRS – Cond	VRS	VRS – Cond	VRS	VRS – Cond	VRS	VRS – Cond	VRS	VRS -cond
Argentina	0.38	0.32	0.32	0.29	0.22	0.15	0.67	0.54	0.18	0.16
Bolivia	0.44	0.39	0.43	0.39	0.09	0.07	0.52	0.52	0.35	0.35
Brazil	0.49	0.38	0.42	0.34	0.29	0.21	1.00	0.69	0.16	0.13
Chile	0.74	0.62	0.87	0.75	0.30	0.25	1.00	0.82	0.22	0.19
Colombia	0.55	0.47	0.53	0.47	0.23	0.19	0.83	0.71	0.25	0.21
Costa Rica	0.42	0.38	0.39	0.34	0.11	0.10	0.61	0.54	0.31	0.28
Dominican republic	0.42	0.36	0.36	0.32	0.22	0.17	0.80	0.68	0.24	0.22
Ecuador	0.42	0.37	0.37	0.33	0.14	0.12	0.65	0.54	0.27	0.25
El Salvador	0.30	0.27	0.33	0.30	0.08	0.08	0.40	0.35	0.18	0.16
Guatemala	0.38	0.33	0.36	0.31	0.14	0.12	0.52	0.46	0.19	0.15
Honduras	0.39	0.36	0.41	0.39	0.09	0.09	0.46	0.44	0.29	0.26
Mexico	0.52	0.42	0.52	0.43	0.30	0.23	1.00	0.73	0.16	0.13
Nicaragua	0.29	0.26	0.29	0.27	0.04	0.04	0.33	0.31	0.23	0.21
Panama	0.65	0.52	0.62	0.53	0.23	0.16	1.00	0.73	0.36	0.31
Paraguay	0.32	0.28	0.30	0.27	0.10	0.09	0.45	0.41	0.54	0.16
Peru	0.37	0.33	0.28	0.24	0.20	0.19	0.69	0.61	0.19	0.16
Uruguay	0.40	0.33	0.37	0.32	0.23	0.15	0.66	0.54	0.15	0.14

Table AII. Estimates of efficiency scores – descriptive statistics

Table AIII. Results of SW: Determinants of LatAm banks' efficiency (CRS)

Variables	CRS	CRS	CRS	CRS	CRS	CRS
ln(size)	0.0395*** (0.00322)	0.0384*** (0.00326)	0.0371*** (0.00336)	0.0418*** (0.00370)	0.0439*** (0.00375)	0.0441*** (0.00384)
Loan to assets		0.102*** (0.0267)	0.138*** (0.0301)	0.130*** (0.0330)	0.104*** (0.0333)	0.103*** (0.0348)
Risk			−0.884*** (0.301)	−0.921*** (0.311)	−0.555* (0.306)	−0.553* (0.320)
Private				−0.00654 (0.0258)		0.00585 (0.0265)
Foreign					−0.00767 (0.0130)	−0.00841 (0.0131)
Constant	−0.234*** (0.0489)	−0.268*** (0.0503)	−0.252*** (0.0516)	−0.301*** (0.0635)	−0.328*** (0.0583)	−0.334*** (0.0644)
Observations	1,124	1,124	1,093	993	879	879
Wald Chi2	401.1	411.3	431	404.1	391.6	412.6
Sigma	0.171	0.170	0.169	0.169	0.167	0.167

Table AIV. Results of SW: Determinants of LatAm banks' efficiency (CRS): reduced sample

Variables	CRS	CRS	CRS	CRS	CRS	CRS
ln(size)	0.0244*** (0.00454)	0.0203*** (0.00389)	0.0190*** (0.00391)	0.0228*** (0.00442)	0.0234*** (0.00443)	0.0234*** (0.00450)
Loan to assets		0.401*** (0.0327)	0.443*** (0.0356)	0.426*** (0.0387)	0.395*** (0.0396)	0.395*** (0.0396)
Risk			−1.165*** (0.309)	−1.095*** (0.325)	−0.860** (0.339)	−0.860** (0.343)
Private				−0.0132 (0.0285)		0.000750 (0.0293)
Foreign					−0.0259* (0.0153)	−0.0260 (0.0161)
Constant	0.152** (0.0672)	0.0138 (0.0596)	0.0265 (0.0594)	−0.00274 (0.0740)	0.00204 (0.0647)	0.00130 (0.0726)
Observations	687	687	673	620	571	571
Wald Chi2	96.80	268.4	273.4	253.7	234.1	234.3
Sigma	0.189	0.168	0.166	0.165	0.166	0.166