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# Efficiency and ownership structure in the banking industry

DOCTORAL DISSERTATION

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# Contents

# List of tables

# List of figures

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# Resumen

Tradicionalmente el negocio bancario ha sido definido como un intermediario financiero entre agentes económicos (entidades o personas) que desean ahorrar o invertir sus fondos y aquellas unidades que quieren tomar fondos prestados. Esta habilidad para acumular depósitos y ofrecer préstamos y créditos atribuye al sector bancario un papel fundamental dentro de la política crediticia llevada a cabo por la autoridad monetaria de aquellas economías donde operan, poniendo de manifiesto su relevancia desde los puntos de vista microeconómicos y macroeconómicos. Diferentes tipos de entidades operan en este sector. Cada entidad tiene unos objetivos particulares y desarrolla su actividad en torno a determinados productos, aunque todos operan bajo un mismo marco normativo. A finales de los ochenta y durante la década de los noventa, se implementaron en la región de América Latina y el Caribe (ALC) una serie de reformas, que han sido objeto de debate por parte de las autoridades políticas y los investigadores académicos a fin de comprender y predecir las causas y consecuencias de las mismas. En este sentido, la apertura comercial, los procesos de desregulación financiera y privatizaciones en la región de ALC, la liberalización de los movimientos internacionales de capital o las reformas fiscales, así como una mayor presencia de inversión directa extranjera en ALC han transformado completamente el entorno legal y operativo de las entidades bancarias.

En esta tesis se analizan, en primer lugar, los factores que pueden explicar las diferencias en los niveles de eficiencia técnica de la banca comercial en la región de ALC.

Posteriormente, el análisis tiene como objetivo mostrar cómo las diferencias entre la actividad de la banca comercial, la más común en la industria, y otros intermediarios financieros bancarios, como las cooperativas de crédito o la banca de inversión, explican en parte la distribución de los niveles de ineficiencias presentes en los diferentes sistemas bancarios de la región. Los cálculos de eficiencia orientados a los niveles de créditos impagados (NPLs) en ALC nos permiten destacar las similitudes y diferencias en la gestión y la tecnología de los bancos comerciales y cooperativas de crédito. Por último, se analiza los niveles de eficiencia con orientación output teniendo en cuenta el nivel de riesgo en dos escenarios diferentes de la banca brasileña cuando se incluye la variable riesgo en la función de producción. La industria bancaria brasileña es la más grande de la región de ALC y ha experimentado una importante transformación estructural en las últimas décadas, lo que hace que el análisis de su sistema bancario sea particularmente interesante. En este sentido, también se ha realizado un análisis por grupos, según el tipo de intermediario financiero bancario, con el fin de conocer más a fondo las posibles causas que explican los niveles de ineficiencia previamente identificados.

Para abordar el tema de esta tesis, la eficiencia en el sistema bancario de América Latina y el Caribe (ALC), se han aplicado diversos programas del Análisis Envolvente de Datos (DEA). Este método desarrollado por Charnes et al. (1978), se basa en la programación matemática y se ha aplicado en muchos sectores económicos. Su flexibilidad lo hace especialmente adecuado para su aplicación en el sector bancario. El DEA no requiere la asunción de una forma específica para la función de producción, ni una distribución específica de los niveles de eficiencia estimados por el programa. Además, la forma de construir la frontera eficiente que envuelve todos los puntos de datos permite al investigador comparar observaciones menos eficientes con otras más eficientes.

El desarrollo de nuevas técnicas y modelos metodológicos en los análisis de la eficiencia técnica permite aportar nuevos conocimientos que pueden ayudar a explicar qué factores ejercen una influencia significativa en el buen funcionamiento del sector bancario, medido a través de sus niveles de eficiencia técnica. Una de las principales contribuciones de este estudio a la literatura sobre ALC es el uso de la eficiencia condicional y la técnica propuesta por Simar y Wilson (SW) (2007) para explicar qué factores ejercen una influencia significativa en el buen funcionamiento del sector, medido a través de sus niveles de eficiencia técnica. Por otro lado, el análisis de metafrontera a través del ratio de la metatecnología (O'Donnell et al., 2008) y la aplicación del test de Simar-Zelenyuk-Li(Li (1996), y Simar & Zelenyuk (2006)) específicamente diseñado para ser aplicado a resultados de eficiencia técnica obtenidos a través de la programación DEA, han permitido realizar un análisis por tipos de intermediarios financieros bancarios en los diferentes sistemas bancarios de la región, contribuyendo así al desarrollo de la literatura especializada. Finalmente, la variable riesgo ha sido analizada bajo dos escenarios metodológicos diferentes lo que permite introducir el concepto de coste de oportunidad en el estudio cuando se tiene en cuenta los bad-outputs.

Los resultados de la primera etapa del análisis muestran un alto grado de heterogeneidad en el nivel de eficiencia de los 17 sectores bancarios de ALC considerados. En línea con artículos anteriores centrados en esta región del mundo, Chile, Brasil, Colombia y México se muestran como las economías con mayores niveles de eficiencia técnica. Además de un primer análisis radial, se aplica una técnica conocida como análisis de eficiencia condicional la cual permite cuantificar la parte de la ineficiencia estimada en el análisis radial que puede estar asociada a factores externos más que a la transformación de los factores de producción incluidos en el estudio. Los resultados de eficiencia condicional también indican grandes diferencias en el grado en que los factores externos afectan los niveles de eficiencia de cada industria. Para analizar el impacto de los factores internos, bajo el control de los gestores, sobre los niveles de eficiencia previamente obtenidos se aplica la técnica propuesta por Simar y Wilson (SW) (2007). Estos resultados están en línea con los resultados obtenidos en la literatura previa. De la segunda etapa del análisis se concluye que, teniendo en cuenta las características estructurales de ALC, probablemente en aquellas economías donde las cooperativas de crédito estén aprovechando sus ventajas como entidades-miembros para reducir significativamente la información asimétrica en comparación con las entidades más orientadas a la maximización de beneficios, el fomento de las primeras por parte de las autoridades responsables podría tener un impacto positivo en los niveles de eficiencia de los sectores bancarios. Los resultados obtenidos en el análisis realizado sobre el sector bancario brasileño indican que los bancos analizados podrían aumentar significativamente su producción de good-outputs sin tener que aumentar el uso de sus inputs o aumentar sus niveles de riesgo. Estos resultados confirman que, además de los altos niveles de ineficiencia observados en la industria bancaria brasileña, existe un coste en términos de producción cuando tomamos en cuenta la variable riesgo. Este coste se deriva de desviar recursos para controlar el riesgo en lugar de utilizarlos en la producción de good-outputs. Al organizar los resultados por grupos, se observan diferencias significativas entre los diferentes tipos de entidades bancarias que componen la muestra. Los mejores niveles de eficiencia en la gestión de los bancos de inversión en comparación con los bancos comerciales puede indicar que tanto unas buenas prácticas en el control del riesgo por parte de los bancos de inversión como el nivel de cualificación de sus gerentes les estén ayudando a gestionar más eficientemente su negocio.

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# 1. Introduction

Traditionally, the banking business has been defined as a financial intermediary between economic agents (savers and borrowers) who have surplus capital and those who have a deficit. This ability to accumulate deposits and offer loans and credits gives banks a decisive role in the monetary policy of the economies in which they operate, underscoring the micro- and macroeconomic importance of these companies. Another important function of the banking system is the creation of means of payment.

A large number of different entities operate in the banking sector, each of which pursues its individual interests. Every bank has a particular objective and develops its activity based on given products, although they all face certain shared conditions under which they must conduct their activity within the sector. The different types of banks operating in the sector can be classified according to the type of activity they carry out or the ownership type. Depending on the type of operations, we can classify them as commercial banks, credit unions (cooperative banks), investment banks, corporate banks, retail banks, savings banks or mortgage banks. Based on the criterion of ownership type, a common classification is to divide them into public, private or mixed banks.

In the late seventies and early eighties, authors such as Leland and Pyle (1977) and Diamond (1984) explained the role of financial intermediation played by banks as a way of reducing market inefficiencies in environments with asymmetric information. In recent decades, the development of financial markets and the emergence of new competitors have led these specialised intermediaries to make better use of financial resources; they have thus achieved higher levels of efficiency than they would if driven by savers and private investors.

The high volume of transactions performed by these companies specialising in financial intermediation means that they can allocate more resources to the efficient management of their portfolios. This allows them to offer and conduct more profitable and efficient transactions between demanders and suppliers of funds, as well as achieving economies of scale and scope while managing various transactions with a low unit volume.

In terms of bank reputation, financial institutions specialised in financial intermediation with efficiency advantages can turn to a more efficient way of solving the problems of adverse selection and moral hazard present in the market (see Chemmanur and Fulghieri, 1994). Banks' reputation as entities specialised in risk management and diversification allow depositors to accept and trust the way their savings are invested. Savings with immediate liquidity and low risk are transformed by these institutions into loans or other financial assets that in many cases have low liquidity and higher risk. The high costs an individual saver would face in terms of inefficiencies if carrying out a risk assessment to assign his/her savings to a borrower of funds illustrates the importance of the specialisation of the banking business in this industry, and the relationship between a qualified risk department and optimal levels of efficiency.

When a bank allocates a large amount of resources to produce information about an investment project and, based on this inside information, invests in those assets through the creation of loans, credits or other financial assets, it will fully benefit from the resulting value. In turn, this will be reflected in the return on its portfolio of assets. On the other hand, when a bank achieves a highly diversified portfolio, whether through economies of scale or scope, the chances of non-compliance with its obligations to depositors are reduced to a minimum. As indicated above, the reputation of the entity will be positively affected, enabling it to seek out new financial resources to feed into its function of transformation and creation of new financial assets.

From a macroeconomic perspective, and in line with the above, if a direct relationship can be established between changes in monetary policy as a result of banks' activity and the changes observed in the levels of aggregate output of an economy as a result of these actions, it will reveal the importance of the efficient transformation of these institutions' available resources in the development of economic activity.

In the late eighties and nineties, a series of reforms were enacted in the LAC region, which have not only been the subject of debate by the political authorities of the various countries in the region, but have also attracted the attention of a great deal of academic research aimed at understanding and predicting the causes and consequences of these reforms for the region's economies. In this respect, trade openness, financial deregulation processes, privatisations in the LAC region, financial account opening, and fiscal reforms, as well as a greater presence of foreign companies in LAC industries, have completely changed the environment and the rules by which companies in these economies previously operated.

Although there is intense interest in understanding the impact of these reforms on the banking industry in the region, the lack of data, especially in some of the region's smaller, more opaque economies, has made it more difficult to reach conclusions as robust as those drawn in studies focusing on more developed and transparent regions of the world.

At the country level, studies reveal high levels of heterogeneity among the different economies that make up the region; in some cases, this makes it necessary to classify the region’s countries into groups that enable more representative results on the research subject. A possible explanation for these levels of heterogeneity can be found in the fact that, although similar changes have occurred throughout the region, the pace of adaptation and change prompted by the abovementioned reforms has differed between countries. As a starting point, the different legal systems in effect in the region (common law and civil law) provide researchers with one way of controlling for the different areas.

In order to determine how the LAC banking industry performs in terms of technical efficiency, some studies in the specialised literature have applied either an individual frontier for each country or a common frontier for all countries of the region. These studies have helped provide an understanding not only of the similarities or disparities in the region since the beginning of the reform process, but also the role that these industries play in the international landscape. Not only have these studies focused on computing average levels of technical efficiency for each economy in the region or the region as a whole, they have also centred on aggregate and individual factors that have affected and continue to influence the distribution of inefficiencies in the LAC banking sector. Such factors include the size of the banks, the ownership of capital, the type of bank, the origin of ownership ,the regulatory framework, market power and risk management, as well as the macroeconomic variables inherent in each economy, which, one way or another, ultimately affect the banking activity carried out by these entities (see Delis et al. , 2009). In the LAC banking industry, the origin of the ownership of these banks has been particularly relevant, as the inflow of foreign capital into the industry in the 1990s had a very significant effect on the entire sector.

However, the above mentioned literature include a critical assumption regarding the “separability” condition when they analyse the factors that may explain the differences in the levels of technical efficiency in the commercial banking industry in the LAC region. In this sense, we first examine those variables that might violate the separability condition and apply conditional measures of efficiency accounting for those variables. Furthermore, while several papers have studied different facets of the performance of cooperative banks, just a few have analysed the direct relationship between the relative performance of cooperatives and commercial banks and risk-taking. Our work contributes to this field of research by assessing the technical efficiency of cooperative banks and commercial banks in the management of NPLs as the result of the capabilities of their managers, and what we broadly refer to as technological differences between the two types of entities. Previous lines of research have established the relationship between risk, capital and performance in banking grounded on different hypotheses. Approaches accounting for risk as an undesirable by-product of banking—as our work does—are unusual. Another contribution is the assessment of the differences in performance between commercial and investment banks and the sources of those differences, considering that any increase in the production of conventional outputs is limited not only by resource availability but also by the need to keep risk under control. Moreover, as far as we know, no previous studies have taken risk into account when examining the efficiency of Brazilian banks.

The remainder of this thesis is organised as follows. Section 2 briefly reviews the research objectives. Section 3 introduces the methodology used for the three empirical exercises carried out. Section 4 presents the empirical results and publications, Section 5 concludes and Section 6 draws possible future lines of research.

# 2. Research objectives

The LAC region shows certain common characteristics in relation to its economic development over the latter half of the twentieth century, with the evolution and convergence of its banking sector playing a particularly prominent role. Therefore, it is crucial to analyse and gain an understanding of the factors surrounding or playing a role in LAC banking activity.

The first essay of this thesis seeks to analyse the factors that may explain the differences in the levels of technical efficiency in commercial banking in the LAC region. Most studies on LAC take as their starting point the abovementioned reforms that were implemented in response to the recommendations of the Washington Consensus. Such studies of the factors influencing the banking industry reveal that there are still high levels of heterogeneity among some of the economies in the region. The development of new techniques and methodological models in analyses of technical efficiency makes it possible to contribute new knowledge that can help to explain which factors exert a significant causal influence on the proper functioning of the industry, measured through its levels of technical efficiency.

Subsequently, the analysis is aimed at showing how the differences between the activity of commercial banks and other types of banks, such as cooperative banks and investment banks, partly explain the distribution of the levels of inefficiencies in the different banking industries in the region.

The second essay of this doctoral thesis is aimed at analysing the levels of efficiency in the management of NPLs in the LAC region. As mentioned above, within the banking industry, different types of banking entities operate with similar purposes but they also have certain specific features purely due to how they are established. In this regard, this essay seeks to highlight the similarities and differences in the management and technology of commercial and cooperative banks operating in the LAC region. This client-member relationship that occurs in cooperative banks differs greatly from the relationship that exists between the customer and the shareholder of commercial banks. For the latter, the main aim of their business is more oriented towards maximising the interests of shareholders, and less towards meeting the needs of their customers. In this regard, commercial banks will be more likely to engage in risky activities. However, other authors believe that the fact that cooperative banks have closer links with local politics in the area where they operate—in some cases the local authority is represented in their corporate bodies—could affect their efficiency when compared to their competitors in the financial intermediation market.

Lastly, there is an analysis of efficiency levels in the Brazilian banking industry when the variable risk is included in the production function. The Brazilian banking industry is the largest in the Latin American and Caribbean region and has undergone an important structural transformation in recent decades, which makes an analysis of its performance particularly interesting. In this regard, a group of banks analysis has also been carried out in order to more fully understand the possible causes behind the levels of inefficiency previously identified. In the previous literature, the relationship between risk, capital and the performance of these entities has been extensively analysed (see Altunbas et al., 2007). In this regard, this essay attempts to provide new knowledge about how the allocation of resources to risk management leads to a reduction in the actual production of good outputs.

## Research objectives

Although the topic has been approached from different perspectives, the conclusions and recommendations drawn from the results are intended to provide an overview of the current state of the industry.

# 3. Methodology

Stemming from the studies published in the field of efficiency theory by Koopmans (1951), Debreu (1951) and Farrell (1957) in the 1950s, a wide range of techniques and methodologies have thus far been developed by the specialised academic community. Broadly speaking, these techniques can be classified into two major groups (parametric and non-parametric) depending on the form for specifying the technology or the distribution of efficiency levels.

To address the topic of this thesis—efficiency in the banking industry of Latin America and the Caribbean (LAC)—various forms of the technique known as Data Envelopment Analysis (DEA) have been applied. This method, which was developed by Charnes et al. (1978), is based on mathematical programming. It has been applied in many sectors of the economy, but its flexibility makes it especially suitable for application to the banking sector. DEA does not require restrictive assumptions about technology or the distribution of efficiency. Moreover, it permits the construction of a *surface* over the data that allows best producers to be compared with other producers by means of a performance index. These characteristics do not take anything away from the advantages offered by parametric techniques, which have also been widely applied in the literature on the banking sector (see Carvallo and Kasman, 2005), providing equally robust results when compared to non-parametric techniques.

In recent decades, methodological developments in the parametric and non-parametric groups have played a fundamental role in the literature aimed at analysing levels of technical efficiency in all the different regions of the world. The huge volume of publications in this field reflects the importance of these developments. Access to new global databases, computer software that enables complex mathematical programs using very large samples, as well as the application of new methodological techniques, have allowed the specialised literature on the banking industry to test some of the key strands of banking theory.

Throughout this thesis, both traditional and cutting-edge methods of efficiency assessment have been used appropriately to obtain results as robust as possible in each of the three empirical exercises carried out. The methodological models used have primarily been based on nonparametric frontier estimation methods that are based on data envelopment techniques. The methodological techniques chosen to explore the external and internal factors that affect the average levels of technical efficiency in the region should not be the same as those used when seeking a more specific understanding of any of these factors individually. The conditional efficiency and Simar and Wilson (SW) technique, the metafrontier analysis using directional distance functions (DDFs) or the strong and weak disposability scenarios analysis are some of the cutting-edge techniques used in this work. In this regard, the use of the appropriate tests has proved fundamental in confirming the reliability of the results obtained from the efficiency measurement techniques applied throughout this thesis.

So, in a first stage of this thesis, DEA and conditional efficiency analysis techniques are applied, before then carrying out a more in-depth analysis of the factors that influence these levels of efficiency. One of the main contributions this study makes to the literature on LAC is the use of conditional efficiency and the technique proposed by Simar and Wilson (SW) (2007) to study these factors. The empirical analysis in this work first shows how much these industries can reduce their consumption of inputs without altering the quantity of good outputs they produce. In order to ensure the results obtained are as robust as possible, in addition to a radial analysis accounting for the technology defined previously, a technique known as conditional efficiency analysis is applied to examine the levels of efficiency in the different economies in the region. This approach allows the researcher to quantify the part of the inefficiency estimated in the radial analysis that can be associated with external factors rather than the transformation of the production factors included in the study. Such external factors include market concentration, GDP per capita, inflation rates, the development of different financial systems in the region, and population density; as will be seen later, these factors have an impact on the levels of efficiency found in these industries. Next, the second-stage SW (2007) analysis explores the extent to which the variables that are within managerial control affect the distribution of efficiency levels obtained in this analysis. In this respect, the model includes the variables most commonly used in the previous literature(see Dietsch et al. (2000); Tecles et al. (2010) and Lozano-Vivas et al. (2002)), and which are understood to be the most relevant given the particular characteristics of the region. Such factors include Size (Total assets), Foreign or Domestic ownership, Public or Private banks, Loan to assets, and Risk (Loan loss reserves to total assets).

As indicated above, different types of banking entities operate with similar purposes but they also have certain specific features purely due to how they are established. In recent decades, there has been some development in the scientific methodology applied to this sector, which enables a more in-depth exploration of this debate. Access to new, more specific data on the activity of LAC commercial and cooperative banks also allows an up-to-date analysis of how these two types of banks are managing their NPLs. To that end, the first step is to perform a metafrontier analysis proposed by O'Donnell et al. (2008) using the nonparametric DEA technique (Charnes et al. 1978) and directional distance functions (DDFs) (Färe and Grosskopf 2000). A key assumption in the analysis is that when a bank produces a good output, a certain amount of bad output is also inevitably generated. The analysis of the metafrontier and the group frontiers through the metatechnology ratio makes it possible to distinguish between inefficiencies that are due to managerial performance and those that are due to being a certain type of bank.

Lastly, in order to analyse the efficiency of the Brazilian banking sector when the variable risk is included in the production function, the first step is to analyse, through DEA and the use of DDFs, output-oriented efficiency levels when accounting for risk under two different scenarios. On the one hand, there is the methodological scenario where the reduction of risk entails a reduction in the production of good outputs (weak disposability). On the other hand, the same analysis is performed under the strong disposability scenario, which assumes that the reduction of bad outputs has no cost in terms of the production of good outputs. In fact, the banking industry always works under the weak disposability scenario, but this comparison between the two scenarios allows an approximation of the opportunity cost in terms of good output production when accounting for the bad output. Different types of banks are included in the sample of banks collected in this study; the observations allow the sample to be classified into commercial and investment banks, foreign and domestic, as well as private and public. A more in-depth analysis of the differences by groups can provide us with a better understanding of how the Brazilian banking industry works. To find out if the differences are due to the fact that they belong to different groups or are simply a statistical artefact, a series of specific tests have been conducted that allow us to explain these differences in more detail. In order to further explore whether these differences are due to being a particular type of bank or due to managerial efficiency, the metatechnology approach is applied and verified through the tests mentioned above.

The main characteristics of the applied methodology are further developed in appendix 1-3 of this thesis.

# 4. Results and Publications

This section briefly presents the main results obtained in the three peer-reviewed and published papers that make up this doctoral thesis. It is organized around the three research objectives presented earlier and include a summary of the three essays included in the appendix. The valuable contribution to the literature is explained in greater detail in appendix 1-3 of this thesis.

### *4.1 Determinants of bank efficiency: evidence from the Latin American banking industry.*

This essay analyses the levels of technical efficiency of 409 commercial banks in 17 countries of the LAC region, during the years 2014-2016. The banking production function taken as a reference considers the banking business not only as a generator of good outputs through traditional production factors (labour and capital), but also as a financial intermediary (the intermediation approach) between savers and investors, using deposits and other funds to be able to generate different types of loans and other assets.

The results from the first stage of the analysis indicate the level of efficiency in each of the 17 industries included in the analysis, revealing a high degree of heterogeneity among the different economies that make up the LAC banking industry. Conditional efficiency calculations reveal the proportion of the levels of inefficiency driven by external factors. In line with previous articles focused on this region of the world, Chile, Brazil, Colombia and Mexico are shown to be the economies with the highest levels of technical efficiency. The conditional efficiency results also indicate large differences in the degree to which the external factors affect the efficiency levels of each industry. In relation to the variables that are within the control of the banks' managers, the results are in line with the previous literature. Size is positively related to our efficiency score. 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 with more complete data. 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.

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### *4.2 Are cooperative and commercial banks so different in their management of non-performing loans? Empirical evidence from the LAC banking industry.*

The empirical analysis includes 307 banks operating in the LAC region during the years 2013, 2014, 2015 and 2016. Of these 307 banks, 104 are cooperative banks and 203 are commercial banks, giving a final total of 924 observations. In line with the exercise developed in the previous essay, the banking production function taken as a reference is based on the intermediation approach.

The results of this study allow us to first analyse the levels of technical efficiency in the management of NPLs considering the set of commercial and cooperative banks operating in the region. In order to link the results obtained under the metatechnology approach with those estimated under a group approach, the metatechnology ratio is introduced into the analysis. This makes it possible to determine what proportion of the levels of inefficiency obtained in the metatechnology analysis is due to managerial inefficiencies and what proportion is due to technological inefficiencies. In order to be able to confirm that the results obtained are not a statistical artifact, a series of specific tests have been applied to determine whether or not the two types of bank belong to different distributions and populations.

Our principal results support the idea that the technology used by cooperative banks in the management of non-performing loans is more efficient than the technology of commercial banks. Therefore, taking into account the LAC structural characteristics, these results may indicate that in economies where cooperative banks can make use of their advantages as member-owned entities to significantly reduce asymmetric information compared to more profit-oriented entities, the promotion of the former by the responsible authorities could have a positive impact on the efficiency levels in these banking industries.

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*4.3 Performance and risk in the Brazilian banking industry.*

The empirical analysis includes 124 banks (543 observations) operating in the Brazilian banking industry in the years 2014, 2015, 2016, 2017, 2018 and 2019. Brazil's banking industry has been selected because of its substantial weight in the LAC region. Although the Brazilian economy has also been involved in the changes in the LAC region since the late 80s, it has been the subject of a series of reforms that make it a very interesting case to study. In line with the previous essays, the production function has been defined in reference to the intermediation approach mentioned above.

First of all, the results indicate that Brazilian banks could significantly increase their production of good outputs without having to increase the use of their inputs or increase their risk levels. Comparing these results with the results obtained under the scenario in which risk reduction has no additional cost for financial institutions operating in the industry, an opportunity cost can be identified, reflecting the proportion of the good outputs that are no longer produced because resources have to be allocated to risk management, which under other circumstances could be allocated to producing more good outputs.

The results confirm that, in addition to the high levels of inefficiency observed in the Brazilian banking industry, there is a cost in terms of production when we take into account the variable risk. This cost stems from diverting resources to control risk rather than using them in the production of good outputs. This analysis draws on the bad management hypothesis proposed by Williams (2004), as well as involving a more in-depth group analysis to check whether belonging to one type of bank or another leads to clear differences in the development of banking activity in the Brazilian industry.

When organising the results by groups, significant differences are observed between the different types of banks that comprise the sample. The superior managerial performance of investment bank managers compared to commercial bank managers may indicate that both the well-developed risk management practices involved in investment banking and the level of qualifications of the managers helps them to conduct their business more efficiently.

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# 5. Conclusions and recommendations

The aim of this chapter is to highlight the final conclusions reached after conducting the three empirical studies presented in the appendix of this thesis. These conclusions primarily centre around the levels of technical efficiency in the LAC banking industry, although in order to reach these conclusions the issue was addressed from a variety of perspectives and methodological approaches.

The three empirical studies deal with current periods, but they all reference the reforms that took place in the entire region in the late eighties and nineties. Indeed, it is clear that while all these studies attempt to explain the current reality in the LAC banking industry, accounting for different external and internal factors, it is also essential to look back and analyse the evolution of this industry. Thus, the results and conclusions presented in the three empirical essays of this thesis can help economic agents and the political authorities to better understand the current state of the LAC banking industry.

In line with previous studies, the analysis developed in the first essay, focusing on the factors that influence the levels of efficiency in the region, confirms the high levels of heterogeneity mentioned above, as well as the predominant role played by certain banking industries within the region—namely, the Chilean, Brazilian, Colombian and Mexican industries—in terms of technical efficiency. It is also interesting to note how external factors have an uneven effect on the different economies that make up the region. The results of the analysis indicate that the most affected banking sectors are the Brazilian, Chilean, Mexican and Panamanian. The results obtained by applying in a second stage the SW (2007) approach confirm the sign of the relationship between the levels of inefficiency in the LAC banking industry and a set of variables traditionally included in such analyses. In this regard, it seems clear that the application of new methodologies can help provide an understanding of the role that this region is currently playing on the international stage when compared with other, historically more developed banking industries. Furthermore, it can help indicate the potential evolution of banking industries belonging to other regions of the world that are currently less developed than LAC.

After the financial turbulence caused by the 2008 global crisis, the share of non-performing loans (NPLs) to total gross loans rose considerably. In this regard, the analysis of the management of NPLs and policies enacted to encourage entities to be more efficient in their production of mortgage loans or other financial products —without limiting the population's access to this type of product—offers a clearer understanding of the resulting economic and social effects on the economies where these entities operate.

The results from the analysis of differences in the management of NPLs between LAC commercial and cooperative banks in terms of technical efficiency, explained in the second essay, underscore the positive role played by cooperative banks compared to their competitors (commercial banks) in the LAC banking industry. These results cannot readily be extrapolated to other regions of the world, since—as discussed in essay 2—the relationships cooperative banks have with their customers are fundamental to the development of their business, and management in terms of the levels of NPLs in this type of bank will vary greatly depending on the local environment. In LAC society, these interactions are positively reflected in the efficiency shown by this type of bank compared to commercial banks.

Since the 2008 financial crisis, good risk management has become increasingly important, both for the financial system in particular and for the economy as a whole. As in other parts of the world, LAC financial markets face different sources of risk. In general terms, due to their lower levels of economic, financial and institutional development, the impact tends to be more pronounced in areas of the developing world than in more developed countries. The third essay of this thesis analyses the opportunity cost involved in risk management in the Brazilian banking industry, revealing that those entities that achieve high levels of efficiency in the use of the resources employed in the risk management function can take advantage of the risk management function as a value-generating tool for the banking business.

Significant differences were found in the analysis of the technical efficiency of the Brazilian banking industry when accounting for the type of bank—investment or commercial. Given that no statistically significant differences were found in the technologies of the two types of bank, but there was a difference in managerial efficiency, these findings open up a new line of research into the role that a universal type of bank could play in an industry where more qualified managers can achieve higher levels of efficiency by means of economies of scale, risk diversification through a wide range of products and services, and economies of scope fostered by a single market providing entities with more information on customers. In an environment where these institutions enjoy a strong reputation thanks to high levels of continued efficiency, or a very healthy capital position, the likelihood of bankruptcy related to their levels of debt issuance could be minimised.

The main recommendations and conclusions are explained in greater detail in essays 1-3 of this thesis.

# 6. Future lines of research

Like the other sectors that make up the economy, the financial industry is influenced by the global socio-economic changes that have been emerging in recent years. In this sense, the banking sector raises important questions to be addressed in the field of inclusive financing, green banking, women's empowerment in financing, corporate social responsibility, poverty alleviation or consumer protection measures. Lately, the banking industry (primarily commercial banking) has incorporated digitisation and the use of software into its relationships with customers, thereby demonstrating a dynamism not traditionally associated with this sector, which has been very conservative in certain aspects. This dynamism does not seem to be a one-off in the evolution of the sector, but rather a feature that the banking business will have to improve in the future and that will inevitably end up affecting how it provides its products and services.

In this new scenario, banking is in constant competition with companies from all sectors. The arrival of new financial companies based on technological platforms heralds a profound change in the financial markets and at the same time poses a challenge to regulators. In response, most banks are incorporating new technologies to position themselves at the forefront of a very competitive market. In the future development of this industry, it will be crucial to build trust between customers and the financial companies that manage their personal data and economic activity. In this respect, the banking industry must be able to carry out its activity efficiently thus incentivising the demand side to meet its needs through the products and services the industry offers. As such, the implementation of regulations aimed at enriching the market for value-added services and improving consumer security can help the sector position itself as the main option to meet savers' and borrowers' needs. In addition, the increasing competition from the shadow banking system in the intermediation of credit provided to businesses and households is driving the search for new business models with major improvements in efficiency and customer centricity.

Although these lines of research provide an interesting starting point for future studies, our future lines of research will be aimed at addressing some aspects that have arisen over the course of this thesis.

As has been shown over the three essays of this thesis, defining the process through which the inputs used by the industry are ultimately transformed into outputs reflects the degree of complexity when it comes to gaining a clear understanding of how banking activity is conducted. We are witnessing a rapid expansion in off-balance-sheet activities (loan origination, sales, servicing, securitization, standby letters of credit, and derivative securities) and information about the asset quality and bank foreign operations involved in the bank production process. Any future studies that attempt to estimate bank efficiency without incorporating these activities and new information may not be completely accurate or entirely meaningful, and could understate the actual bank output. It is also worth exploring whether including in the production function the total resources employed by banks and the scope of their financial products and services leads to a difference in the average technical efficiency levels compared to those obtained under the traditional perspective on banking.

If banking operators and supervisors implement efficient mechanisms in terms of the supervisory and regulatory capabilities of risk management systems, this will have a positive effect not only on the technical efficiency of banking in the LAC region, but also in terms of fostering the sustained development of the economy. Banking policymakers have shown growing interest in the high levels of NPLs in the banking sector, which pose important risks to its financial stability. In a future line of research, considering the results reported in the second essay of this thesis, it will be important to understand the behaviour of NPLs in banks, identifying the factors (such as regulatory capital ratios, loan growth and business cycle fluctuation) that influence this performance.

Despite the ever-growing number of publications on credit risk, it is critical to analyse how operational, market, and liquidity risks also affect bank performance. However, this will depend on the data available for the LAC region. From a theoretical point of view, such studies of the banking sector should seek to test the "bad management" hypothesis analysed in the third essay, and the impact in terms of technical efficiency. These analyses should also include the effects of an overprotectiveness policy—implemented by banks seeking to reduce their risk—on competitiveness in the sector where they operate, as well as with other intermediaries. To that end, it will be essential to use the new methodology and to apply an appropriate test of the separability condition when regressing estimated efficiency scores on environmental variables in a second-stage regression. Whenever the test rejects separability, conditional efficiency estimators should be used instead of unconditional estimators in order to estimate distance to the relevant frontier.

Regarding the type of bank analysed here, as mentioned above, the inclusion of universal banking characteristics into the performance analysis could indicate whether such banks are currently bolstering their presence in the commercial and private banking business, implementing new models of customer segmentation, reducing the minimum requirements for the volume of financial assets needed to access such services, and more efficiently taking advantage of the relationships between customers and wealth management advisors traditionally offered by this type of business. The customer could thus access integrated services and products offered by one or other of the banking models. In terms of technical efficiency, this could expand the frontiers of the banking business to a greater extent than could be achieved by increasing the use of new productive resources.

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# Appendix

Essay 1: Determinants of bank efficiency: evidence from the Latin American banking industry.

Essay 2: Are cooperative and commercial banks so different in their management of non-performing loans? Empirical evidence from the LAC banking industry.

Essay 3: Performance and risk in the Brazilian banking industry.

# Essay 1: Determinants of bank efficiency: evidence from the Latin American banking industry


## Abstract

This paper analyses a variety of factors that can explain the differences in commercial bank efficiency among 17 countries in Latin America (LatAm). In a first stage, Data Envelopment Analysis (DEA) and conditional efficiency analysis techniques are employed to assess the relative efficiency level of 409 banks for the period 2014-2016. The conditional efficiency approach takes into account 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 a 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. To do so, we use an econometric approach developed by Simar & Wilson (2007). 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, 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. As far as we know, this is the first time that conditional efficiency and Simar & Wilson (2007) approaches have been applied at the same time in order to analyse the Latin American banking industry.

## 1.1 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 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 macroeconomic perspective.

In the last few decades, the structure of the banking industry and the relationships among its key players have changed substantially. 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 due to 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 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-Fernandez 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 period 1999–2013, 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 et al. (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 et al. (1997)]. Therefore, in the last few decades, numerous studies have appeared which 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 et al. (1996) and Lang et al. (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 et al. (2000); Tecles et al. (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 analyse 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 take into account cross-country differences in regulatory, economic and demographic determinants etc., which are beyond the control of bank managers. Given this weakness, in order to properly apply the well-known SW econometric approach to the resulting efficiency scores, we first examine which variables 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 taken into account in order to correctly select the factors used in the second stage of our analysis.

The remainder of this paper is organised as follows. Section 2 briefly reviews the existing literature. Section 3 outlines the methodology used for the measurement of banking efficiency and its determinants. Section 4 describes the sources of data and the variables. Section 5 presents and discusses the empirical results, and Section 6 concludes.

## 1.2. Performance in banking: A brief literature review

In this section, we review the relevant literature on bank efficiency, highlighting 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 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 et al. (1996)], scale and X-efficiency [Carbó et al. (2002)], allocative efficiency [Sathye (2001)], as well as cost and profit efficiency [Prior (2003); Ray et al. (2010)]. In this line, Aiello and Bonanno (2018) perform a meta-regression analysis of the empirical literature on banking efficiency that includes 120 papers published over the period 2000-2014, 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 et al. (2009)], origin of investors [Havrylchyk (2006)], banking regulations [Barth et al. (2013)], size [Bonin et al. (2005)] or ownership structure [Beck et al. (2013)], among others.

From a geographical point of view, some studies have examined banking performance on a global scale [Bhimjee et al. (2016)] while others have put the focus on emerging economies [Huang and Fu (2013)], transition economies [Weill (2003); Yildirim et al. (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 et al. (2018); Kasman et al. (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. (2018)]; the relationship between performance on the one hand, and public versus private ownership or foreign versus domestic ownership on the other [Figueira et al. (2009)]; and the impact of liberalisation on performance [Leightner et al. (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 et al. (2005)]. On the other hand, 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 et al. (2006); Pasiouras et al. (2006); Lozano-Vivas et al. (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, yielding inconsistent estimates. In this sense, the bootstrapping technique [Delis & Papanikolaou (2009)], the SW (2007) approach, the slacks-based measure [Tone (2001)], and second-stage Tobit regression [Grigorian & 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, United Kingdom, Malaysia, Vietnam, China, India, and frontier markets in Africa). However, no studies to date have focused on the LatAm region as a whole [Pancurova et al. (2013); Stewart et al. (2016)].

As we have indicated above, environmental variables may influence the production process, generating differences in the performance of production units. Recently, several models have been developed in order 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 et al. (2005, 2007, 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 [see 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)].

## 1.3. Methodology

Since the mid-20th century, efficiency studies have developed different methodologies to assess the efficiency of observed units [Koopmans (1951); Debreu (1951); and 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 in order 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 remains widely used in the relevant literature. Additionally, 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 et al., 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. It should also be noted that we use total operating expenses as the labour input instead of number of employees due to 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 which are beyond the control of the bank managers:

- <u>Market structure (The Herfindahl-Hirschman Index, HHI, using share of total assets)</u>: 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): Due to 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 employ 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 & 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.

### 1.3.1 DEA input-oriented technical efficiency model

To implement the method, let us first assume that we observe a sample of k = 1,…,K banks that make use of a set of N inputs, represented by x = ($x_1$,…,$x_N$), to produce a set of M outputs, namely y = ($y_1$,…,$y_M$). 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:

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

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:

$$Technical\ efficiency = Min\varphi \mid (\varphi x, y) \in T \qquad (2)$$

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:

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

Subject to:

$$\begin{array}{llll} \sum_{k=1}^{K} \lambda_k x_{kn} \leq \varphi^{k'} x_{k'n} & n = 1,\ldots,N & (i) & \\ \sum_{k=1}^{K} \lambda_k y_{km} \geq y_{k'm} & m = 1,\ldots,M & (ii) & (3) \\ \sum_{k=1}^{K} \lambda_k = 1 & k = 1,\ldots,K & (iii) & \\ \lambda_k \geq 0 & & (v) & \end{array}$$

where $\varphi^{k'}$ is the input-oriented technical efficiency of $DMU_{k'}$, $y_{km}$ is the amount of the m<sup>th</sup> output (m = 1,...,M) produced by $DMU_k$, $x_{kn}$ is the amount of the n<sup>th</sup> input (n = 1,...,N) consumed by $DMU_k$, and $\lambda_k$ is the weight assigned to $DMU_k$ (k = 1,2,…,K). Furthermore, variable returns to scale are assumed through restriction (iii), so that 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 due to supply and demand reasons, among other. 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)].

## 1.3.2 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 note 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 implement 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).

In order 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 et al. (2011)).

## 1.3.3 Simar and Wilson approach

SW (2007) proposed a procedure that allows the use of environmental variables as determinants of efficiency scores and corrects for the problem of serial correlation by means of bootstrapping and truncated regression. The bootstrap method is based on the idea of resampling the original data in order to assign statistical properties to the quantities of interest. It should be borne in mind that: (a) the efficiency scores are not observed but estimated, (b) they are relative rather than absolute scores, (c) the two-stage DEA procedure depends on other explanatory variables which are not taken into account in the first stage, (d) the efficiency score is restricted to the zero-one interval, which should be taken into account 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, 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 and the subset of DMUs with efficiency below one to estimate the parameters $\beta$ and $\sigma_{\varepsilon}$ in the truncated regression where bank efficiency scores (TEff) are the dependent variable and $z$ is a set of covariates related to the dependent variable. Formally:

$$\widehat{TEff}_k = \beta' z_k + \varepsilon_k \qquad \text{with, } \boldsymbol{\epsilon}_k = \varepsilon_k + \xi_k \qquad \text{and } \xi_k \equiv \widehat{TEff}_k - TEff_k$$

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

   - For each bank's efficiency scores, draw $\varepsilon_k$ from a normal distribution: $N = [0, \hat{\sigma}_\varepsilon]$, right truncated at $\left(1 - \hat{\beta}' z_k\right)$

   - Compute $TEff_k^b = \beta' z_k + \epsilon_k^b$ again

   - Estimate $\hat{\beta}^b$ and $\hat{\sigma}_\varepsilon^b$ 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 β and $\sigma_\varepsilon$.

## 1.4. 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 dataset 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 dataset includes

[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)].

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 due to tax haven and political instability concerns. Given that 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 dataset includes a total of 1124 observations.

Regarding the representativeness of our final sample, Table 1 presents some figures at the country level, as well as the representativeness for the whole sample of economies.

**Table 1. Representativeness of the banks in the sample (% for the 2014-2016 period).**

| | 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

The appropriate definition and measurement of banking inputs and outputs has been the subject of discussion in the literature. In order 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). On the other hand, 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 between liability holders and those who receive bank funds. Loans and other assets are considered bank outputs; deposits and other liabilities are inputs in the intermediation process [Berger et al. (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, on the other hand, are gross loans and financial assets [Bhatia et al. (2018)]. Some descriptive statistics are presented in Table 2. The high standard deviations seen in Table 2 highlight the large size differences among the banks operating in the region.

**Tabla 2. Sample descriptive statistics (in constant 2016 $US million)**

| | **Mean** | **Standard deviation** |
|---|---|---|
| ***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

## 1.5. 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 in order 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 dataset 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 3 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 Nicaragua in the case of radial efficiency case, while the corresponding values for

[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 6 in the appendix.

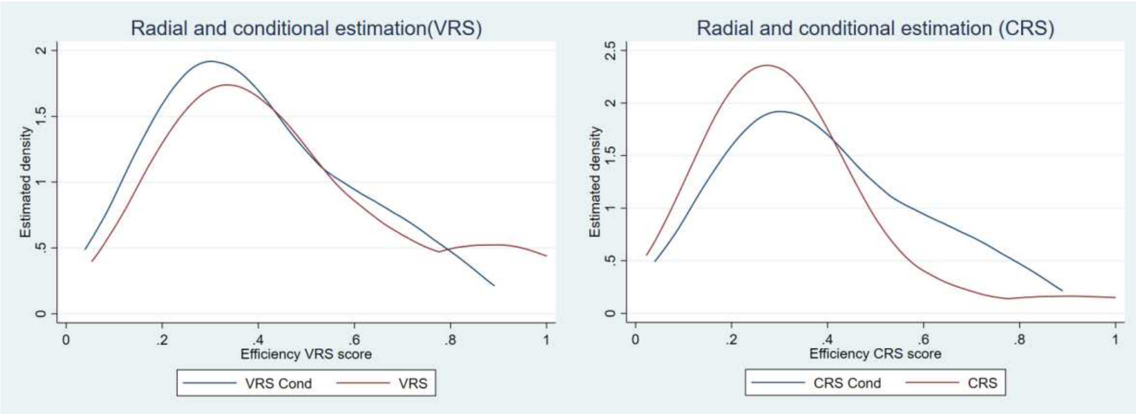
conditional efficiency scores are 0.798 and 0.270, respectively. The weighted mean efficiency score for all countries analysed is 0.839.

**Table 3. 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** | | |

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, in order to see the whole distribution of efficiency scores across banks and countries. In this regard, Table 6 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.

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




Source: Authors' own elaboration.

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 differences in the efficiency measures point to how environmental variables affect the efficiency level in these industries, and might indicate the importance of taking into account 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 2 and 3 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 1000 repetitions using the software

[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.

Stata 12 and the package developed by Tauchmann. This algorithm should improve the robustness of the second-stage analysis and ensure consistent results.

Table 4 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 in order to exclude the differences explained by economies of scale, as noted above. However, we replicate our analysis with CRS efficiency scores, obtaining qualitatively and quantitatively similar results[4]. All our regressions include time fixed effects.

**Table 4. Results of SW: Determinants of LatAm banks' efficiency (VRS)**

| VARIABLES | VRS | VRS | VRS | VRS | VRS | VRS |
|---|---|---|---|---|---|---|
| **ln(size)** | 0.0395***<br>(0.00337) | 0.0384***<br>(0.00316) | 0.0370***<br>(0.00340) | 0.0418***<br>(0.00384) | 0.0438***<br>(0.00383) | 0.0441***<br>(0.00372) |
| **Loan to assets** | | 0.101***<br>(0.0280) | 0.138***<br>(0.0306) | 0.130***<br>(0.0321) | 0.105***<br>(0.0337) | 0.104***<br>(0.0336) |
| **Risk** | | | -0.895***<br>(0.311) | -0.934***<br>(0.306) | -0.562*<br>(0.310) | -0.558*<br>(0.322) |
| **Private** | | | | -0.00440<br>(0.0254) | | 0.00806<br>(0.0251) |
| **Foreign** | | | | | -0.00749<br>(0.0120) | -0.00851<br>(0.0125) |
| Constant | -0.233***<br>(0.0502) | -0.267***<br>(0.0496) | -0.250***<br>(0.0532) | -0.301***<br>(0.0638) | -0.326***<br>(0.0580) | -0.335***<br>(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 4 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 a 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

[4] Tables 8 and 9 in appendix

nine countries with more complete data (Table 5). 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.

**Table 5. 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 |

## 1.6. 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 a 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 do 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.

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 which 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; that becoming more specialised in loans and credits also boosts efficiency; and that inadequate credit risk management involves a higher relative consumption of inputs. On the other hand, 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-Fernandez et al. (2015), who conclude that the entry of foreign banks in

LatAm, primarily in the 1990s, prompted the modernisation of the national banks, meaning that efficiency levels in the two types of entities are now fairly similar.

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# Appendix

**Table 6. Estimates of efficiency scores (9 countries)**

| | 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 7. Estimates of efficiency scores – descriptive statistics**

| | 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 |

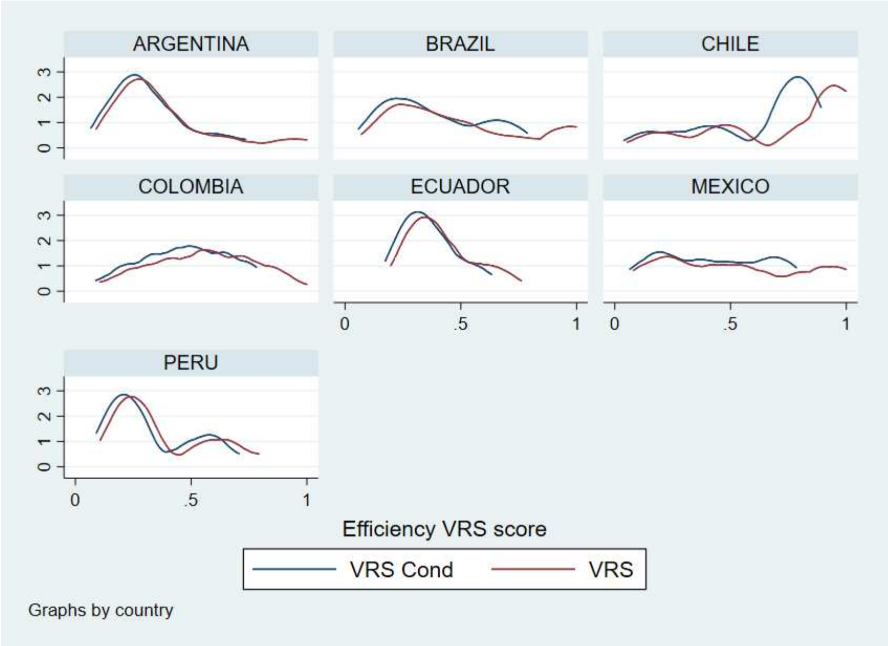
**Table 8. Results of SW: Determinants of LatAm banks' efficiency (CRS)**

| VARIABLES | CRS | CRS | CRS | CRS | CRS | CRS |
|---|---|---|---|---|---|---|
| ln(size) | 0.0395***<br>(0.00322) | 0.0384***<br>(0.00326) | 0.0371***<br>(0.00336) | 0.0418***<br>(0.00370) | 0.0439***<br>(0.00375) | 0.0441***<br>(0.00384) |
| Loan to assets | | 0.102***<br>(0.0267) | 0.138***<br>(0.0301) | 0.130***<br>(0.0330) | 0.104***<br>(0.0333) | 0.103***<br>(0.0348) |
| Risk | | | -0.884***<br>(0.301) | -0.921***<br>(0.311) | -0.555*<br>(0.306) | -0.553*<br>(0.320) |
| Private | | | | -0.00654<br>(0.0258) | | 0.00585<br>(0.0265) |
| Foreign | | | | | -0.00767<br>(0.0130) | -0.00841<br>(0.0131) |
| Constant | -0.234***<br>(0.0489) | -0.268***<br>(0.0503) | -0.252***<br>(0.0516) | -0.301***<br>(0.0635) | -0.328***<br>(0.0583) | -0.334***<br>(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 9. Results of SW: Determinants of LatAm banks' efficiency (CRS): Reduced sample**

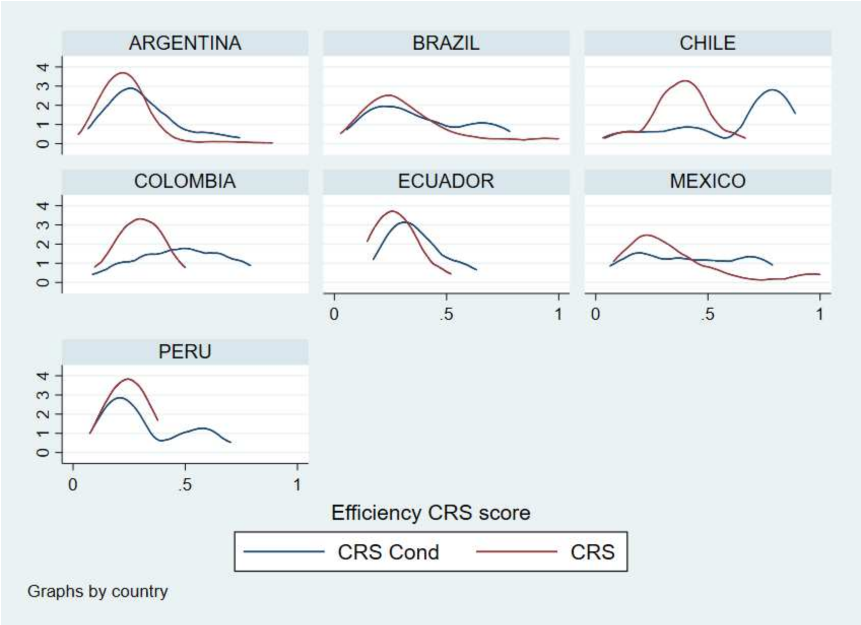
| VARIABLES | CRS | CRS | CRS | CRS | CRS | CRS |
|---|---|---|---|---|---|---|
| **ln(size)** | 0.0244***<br>(0.00454) | 0.0203***<br>(0.00389) | 0.0190***<br>(0.00391) | 0.0228***<br>(0.00442) | 0.0234***<br>(0.00443) | 0.0234***<br>(0.00450) |
| **Loan to assets** | | 0.401***<br>(0.0327) | 0.443***<br>(0.0356) | 0.426***<br>(0.0387) | 0.395***<br>(0.0396) | 0.395***<br>(0.0396) |
| **Risk** | | | -1.165***<br>(0.309) | -1.095***<br>(0.325) | -0.860**<br>(0.339) | -0.860**<br>(0.343) |
| **Private** | | | | -0.0132<br>(0.0285) | | 0.000750<br>(0.0293) |
| **Foreign** | | | | | -0.0259*<br>(0.0153) | -0.0260<br>(0.0161) |
| Constant | 0.152**<br>(0.0672) | 0.0138<br>(0.0596) | 0.0265<br>(0.0594) | -0.00274<br>(0.0740) | 0.00204<br>(0.0647) | 0.00130<br>(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 |

**Figure 2. Univariate kernel density estimation (VRS) – Selected countries**




Source: Authors' own elaboration.

**Figure 3. Univariate kernel density estimation (CRS) – Selected countries**




Source: Authors' own elaboration.

# Essay 2: Are cooperative and commercial banks so different in their management of non-performing loans? Empirical evidence from the LAC banking industry

**Abstract**

This paper assesses technical efficiency in the management of non-performing loans (NPLs) in the Latin American and Caribbean (LAC) banking industry. To that end, *Data Envelopment Analysis* techniques are employed with data from the years 2013 to 2016 on a sample of 307 LAC cooperative and commercial banks. Our main contribution to existing literature is that differences of efficiency between cooperative banks and commercial banks are assessed as the result of the different capacities of their managers *–managerial efficiency–*, and the so-called *programme efficiency*, which represents differences in the technology used by these two categories of entities. Our principal result suggests that the technology used by cooperative banks in the management of NPLs is more efficient than the technology of commercial banks.

## 2.1 Introduction and motivation

There is a deep-rooted tradition of performance analyses in the field of economics; furthermore, a comprehensive scientific literature has addressed the issue of the assessment of performance in the banking industry. Our paper contributes to this field of research by assessing the technical efficiency in the management of non-performing loans (NPLs) in the Latin American and Caribbean (LAC) banking industry. In particular, the technical efficiency of cooperative banks and commercial banks in the management of NPLs is assessed as the result of the capabilities of their managers, and what we broadly refer to as technological differences between the two types of entities. These technological differences might arise from a wide range of sources, including different business practices regarding risk management or relationships with customers, differences in stakeholders' interests, and different degrees of information asymmetry between borrowers and lenders.

The structure of the banking industry and the relationships among its players has changed in recent years, particularly since the 2008 global economic crisis. The internationalisation of banking activity has been one of the most important recent developments in the sector, and Latin America and the Caribbean is one of the world regions with the highest involvement of foreign companies (Musacchio *et al.,* 2015). Over the last 20 years, LAC banking systems have experienced a rapid and deep structural transformation process (Sáez-Fernández *et al.,* 2015), characterized by increasing deregulation aimed at boosting efficiency, several waves of privatisation of financial institutions, and increasingly active participation of foreign banks. Additionally, during these years, some LAC economies have experienced significant economic development, deeper regional integration as well as financial innovation (Saona, 2016). In this changing scenario, different types of banking entities have played quite different roles. Commercial banks have been more focused on high-risk and high-return business activities to maximise shareholder value. In contrast, cooperative banks have various stakeholders and are generally held to be more conservative in their business practices, preferring security over risk, and typically adopting a longer-run perspective (Mäkinen and Jones, 2015).

Cooperative banks are an important part of the Social Economy, and their importance and multiple facets are subject to intense discussion nowadays. Cooperatives put people first. They are member-owned entities governed by democratic principles, as well as collective enterprises driven by members' needs (Chaves and Monzón, 2001). Cooperative institutions are often specialized in agriculture, housing and life assurance markets. Furthermore, in many ways, cooperatives may also be particularly well-suited to providing financial services, especially those relating to longer-term contractual relationships such as mortgages and life assurance (Ayadi *et al.,* 2010). Historically, cooperative banks were operated as non-profit enterprises, where members knew about each other's economic activities (Gorton and Schmid, 1999); in fact, in many cases, people became a member of a cooperative in order to get easier access to loans. In this sense, the role of cooperative banks could represent a particular case within the banking industry, due to the overlap between customers and members. Closer relationships with customers could help to overcome information asymmetries and also lead to gains in allocative efficiency (Stiglitz and Weiss, 1981).

A parallel strand of literature has addressed the specific patterns of credit relationships between local and/or cooperative banks and small businesses. Some authors hold that individual customer relationships and group interactions within the local community affect credit conditions for small firms, which may improve the ability of cooperative banks to screen and monitor borrowers and to enforce debt contracts (Angelini *et al.,* 1998). Furthermore, it has also been maintained that when regulation is implemented with the aim of limiting banking activity, commercial banks may react to tougher regulatory burden by engaging in riskier activities and investing in ways that circumvent regulation, which ultimately would affect their performance (Jalilian *et al.,* 2007). Differences of performance might also arise between *shareholder value* banks, whose primary and almost exclusive business focus is on maximizing shareholder interests, and *stakeholder value* banks, which have a broader focus on serving the interests of a wider group of stakeholders: customer-members in the case of cooperative banks, and society in the case of savings banks and public banks (Ayadi *et al*., 2010).

Whereas most of the abovementioned arguments seem to suggest that cooperative banks enjoy certain advantages in the management of NPLs, several authors have contributed reasonable arguments that point towards the opposite conclusion. In this respect, cooperative banks could be more exposed to risk stemming from close ties to local politicians; in some cases, local authorities are represented on the board of cooperative banks, which could lead to problems of lower loan interest rates or soft information (Infante and Piazza, 2014; Uchida *et al*., 2012). Additionally, due to their smaller size, cooperative banks tend to have less diversified loan portfolios than commercial banks, and could also have commitments to operate in particular geographical areas with low levels of productive diversification. Lastly, legal restrictions to operate with no members and a more lenient risk assessment procedure for local firms might also increase concentration risk and reduce the credit quality of cooperative banks (Becchetti *et al*., 2016). In brief, the relative performance of cooperative banks and commercial banks in their management of NPLs is an open question, on which our research attempts to shed some light.

The remainder of the paper proceeds as follows. Section 2 briefly reviews previous literature. Section 3 outlines the methodology. Section 4 describes the data and variables. Section 5 presents and discusses the empirical results, and Section 6 summarises and concludes.

## 2.2 Performance in banking: A brief literature review

Over the last few decades, a great deal of scientific literature has examined performance in the banking industry from different angles, and also using a range of methodological approaches. Some reviews include Berger (2007), Fethi and Pasiouras (2010), and Paradi and Zhu (2013). Furthermore, in a recent paper, Aiello and Bonnano (2018) carry out a meta-regression analysis of the empirical literature on banking efficiency that includes 120 papers published over the period 2000-14. Different concepts of efficiency have been analysed, including technical efficiency (Cavallo and Rossi, 2002; Sáez-Fernández *et al*., 2015), scale and X-efficiency (Carbó *et al*., 2002), allocative efficiency (Curi *et al*., 2015), in addition to cost and profit efficiency (Prior, 2003; Ray and Das, 2010; Koutsomanoli-Filippaki *et al*., 2012; Xiang *et al*., 2015). Moreover, the impact of a wide set of environmental variables on banking efficiency has also been addressed, including the ownership of capital (Berger *et al*., 2009; Bokpin, 2013), the origin of investors (Havrylchyk, 2006; Sturm and Williams, 2010), or banking regulations (Chortareas *et al*., 2012; Barth *et al*., 2013).

As far as geography is concerned, some papers have studied banking performance on a global scale (Kösedağ *et al*., 2011), while others have specifically focused on developed economies (Chortareas *et al*., 2012; Tabak *et al*., 2013; Glass *et al*., 2014), emerging countries (Sun and Chang, 2011; Huang and Fu, 2013; Yin *et al*., 2013), transition economies (Weill, 2003; Yildirim and Philippatos, 2007; Fang *et al*., 2011), or other specific regions or economic areas. Accordingly, several papers have specifically focused on the LAC banking industry, whether the region as a whole or on individual countries. The issues addressed by these papers include the relationship between performance and ownership, whether public *versus* private or foreign *versus* domestic (Figueira *et al*., 2009; Tecles and Tabak, 2010; Jeon *et al*., 2011; Sáez-Fernández *et al.,* 2015); the relative efficiency of large and small banks (Chortareas *et al.,* 2011); the impact of liberalization on performance (Sanchez *et al*., 2013); the assessment of cost efficiency (Carvallo and Kasman, 2005); the relationship between efficiency and market power (Williams, 2012); the influence of firms' heterogeneity on performance (Goddard *et al*., 2014); or miscellaneous analyses focused on specific LAC economies (Taylor *et al.*, 1997; Staub *et al.,* 2010).

Furthermore, while several papers have studied different facets of the performance of cooperative banks (Esho, 2001; Battaglia *et al*., 2010; Kontolaimou and Tsekouras, 2010; Barros *et al*., 2010; Glass *et al*., 2014), just a few have analysed the relative performance of cooperatives and commercial banks. Among the latter, Brunner (2004) assessed both cost and revenue efficiency of European cooperative banks and concluded that they are not less efficient than commercial banks. Chortareas *et al.* (2011) and Fiordelisi and Mare (2013) found a direct relationship between the efficiency of both cooperative and commercial banks and risk-taking. Moreover, Chiaramonte and Oriani (2015) suggested that cooperative banks are less vulnerable to impaired loans and toxic assets than commercial banks. In parallel, some studies have included, in addition to conventional inputs and outputs, NPLs as a *bad* or undesirable output of the banking industry; these papers include Zago and Dongila (2005), Karim *et al*. (2010), Barros *et al.* (2012), Assaf *et al.* (2013), Fujii *et al.* (2014) and Zhu *et al*. (2015). As mentioned in the Introduction, our paper contributes to this literature by combining an assessment of technical efficiency in the management of NPLs with an evaluation of differences between cooperative banks and commercial banks. Besides, we evaluate whether or not observed differences of efficiency are the result of technological differences. To the best of our knowledge, no previous paper has used this approach to address the study of performance in the LAC banking industry.

## 2.3 Methodology: Assessing efficiency in the management of non-performing loans

The methodology that we use in this paper is based on the metafrontier approach proposed by O'Donnell *et al*. (2008), and later extended by Sáez-Fernández *et al*. (2012) with non-parametric *Data Envelopment Analysis* (DEA) techniques (Charnes *et al*., 1978) and directional distance functions (DDFs) (Färe and Grosskopf, 2000). Furthermore, we consider a banking technology that generates both desirable and undesirable outputs, the latter being represented by NPLs, which can be considered as by-products of the banking production function (Park and Weber, 2006).

DEA is a well-known approach to measuring efficiency based on mathematical programming that was pioneered by Charnes *et al*. (1978), and has been used in hundreds of empirical papers (a recent survey can be found in Emrouznejad and Yang, 2017). While DEA has been extensively employed to study performance in banking (reviews of this branch of literature include, as mentioned in Section 2, Berger and Merger, 1997; Fethi and Pasiouras, 2010; Paradi and Zhu, 2013; and Aiello and Bonnano, 2018), many other papers have used parametric stochastic frontier analysis (SFA) (Meeusen and Van den Broeck, 1977; Aigner *et al*., 1977); e.g., in a study closely related to our research, Karim *et al*. (2010) first estimated a stochastic cost frontier and, in a second stage, used regression analysis to assess the effect of NPLs on cost efficiency.

One of the leading advantages of DEA is its flexibility, as it does not require restrictive assumptions about technology or the distribution of efficiency. Accordingly, it permits the construction of a *surface* over the data that allows best producers to be compared with other producers by means of a performance index, which constitutes '... *an elegant way of simultaneously constructing frontier technology from data and calculating the distance to that frontier for individual observations or activities*' (Färe *et al*., 1994:11). Conversely, an attractive feature of the SFA approach is that it offers the possibility of richer specifications of the technology, while also allowing for statistical testing of hypotheses and the construction of confidence intervals for efficiency scores. In practice, however, according to Hjalmarsson *et al*. (1996:304), '… *the choice between different approaches* [referring to parametric and non-parametric approaches to performance assessment] *must be based on trade-offs concerning the purpose of the study, type of data, technology characteristics, etc.*'.

In light of the above arguments, and given the characteristics of our technology – which involves inputs and several good outputs as well as an undesirable output– along with the focus of our main research question, we have decided in favour of the flexibility of non-parametric DEA techniques. Furthermore, a particularly relevant feature of DEA for the purpose of our research is that, as mentioned above, it does not require the establishment of a specific functional form for the production technology, thus greatly facilitating the inclusion of NPLs as an undesirable output of the banking industry.

### 2.3.1 The metatechnology

In order to implement the methodology, let us first assume that we observe a sample of k = 1,…,K banks, either cooperative banks or commercial banks, that make use of a set of N inputs, represented by $x = (x_1,\ldots,x_N)$, to produce a set of M desirable or good outputs, namely $y = (y_1,\ldots,y_M)$. Transforming inputs into desirable outputs also generates NPLs as an undesirable or *bad* output, which is represented by the variable b. It is also assumed that inputs, desirable outputs and the *bad* output are all non-negative. The technology used by the banking industry to transform inputs into desirable outputs and NPLs, i.e., the so-called *metatechnology*, is formally defined as:

$$T = [(x, y, b) \in R_+^{N+M+1} \mid x \geq 0;\ y \geq 0;\ b \geq 0;\ x \text{ can produce } y \text{ and } b] \qquad (1)$$

Furthermore, we assume that the metatechnology 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. In addition, null-jointness and weak disposability of the *bad* output are also assumed (Färe *et al.*, 1989).

On the one hand, null-jointness means that both good outputs and the *bad* output are jointly produced (Färe *et al.*, 2005). In less technical terms, if a positive amount of good outputs –that should include loans to customers– is produced, some NPLs ought to also be produced. On the other hand, weak disposability of the *bad* output allows the modelling of the idea that reducing NPLs is not costless, but rather involves a cost that can be measured either as an increase in the use of inputs or as a reduction in the desirable outputs. This is a very reasonable assumption to make in the banking industry since reducing NPLs would require consuming productive inputs that could otherwise be devoted to generating good outputs. Put less technically, in order to minimise NPL rates, bank managers need to reduce information asymmetries, make better assessments and risk selection by forecasting future borrowers' cash flow, and build good relationships with customers. It means that productive resources, e.g., employees and/or some capital resources, need to be diverted to these undertakings instead of using them to produce desirable outputs.

Let us now define the *directional metadistance function* (Färe and Grosskopf, 2000) as:

$$M\vec{D}[x, y, b; g = (-g_x, g_y, -g_b)] = \text{Sup } [\varphi \mid (x - \varphi g_x, y + \varphi g_y, b - \varphi g_b) \in T], \quad (2)$$

with $g = (-g_x, g_y, -g_b)$ being the so-called direction vector.

This directional metadistance function generalises Shephard's input and output distance functions (Shephard, 1970), and provides a complete representation of the metatechnology. It seeks the maximum attainable expansion of desirable outputs in the $g_y$ direction, and the largest feasible contraction of both inputs and NPLs in the $-g_x$ and $-g_b$ directions, respectively. Moreover, the directional metadistance function is lower bounded to zero (other properties of DDFs are discussed in Chambers *et al.*, 1998); that is:

$$M\vec{D}[x, y, b; g = (-g_x, g_y, -g_b)] \geq 0 \Leftrightarrow (x, y, b) \in T \quad (3)$$

An important feature of DDFs is that they allow the modelling of different scenarios in performance analyses that might represent the preferences of researchers, managers, policymakers or society as a whole. In our case study, we are interested in assessing the performance of the LAC banking industry in the management of NPLs. This pattern of preferences can be modelled through the following direction vector:

$$g = (0, 0, -b), \quad (4)$$

which looks for the maximum feasible reduction of NPLs without increasing inputs and/or reducing the production of desirable outputs.

Using this direction vector, the directional metadistance function becomes:

$$M\vec{D}[x, y, b; g = (0, 0, -b)] = \text{Sup}\ [\varphi \mid (x, y, (1- \varphi)b) \in T] \quad (5)$$

As noted above, this metadistance measures the extent to which NPLs could be reduced while maintaining the resulting production plan within the metatechnology set. For example, a computed score for a particular bank of, let us say, 0.2 means that it could reduce its volume of NPLs by 20% without additional use of inputs or a reduction of the desirable outputs. In other words, this would mean that there is another bank in the sample –or a *virtual* production plan resulting from a convex combination of two or more observed plans– that generates 20% fewer NPLs without using more inputs or producing fewer desirable outputs.

## 2.3.2 Group frontiers

Let us now consider that banks in the sample can be split into two groups according to their legal nature: commercial banks and cooperative banks. The key issue here is that belonging to a particular group might prevent banks from choosing the entirety of technologically-feasible production plans contained in the metatechnology. This allows specific technologies to be defined for group j = 1, 2, which would represent all feasible production plans available to banks classified in that group. In particular, the *technology* for group j is given by:

$$T^j = [(x, y, b) \in R_+^{N+M+1} \mid x \geq 0; y \geq 0; b \geq 0; \text{x can be used by banks in group j to produce y and b}] \quad (6)$$

It is also assumed that the properties of the technology of each group j are the same as those described for the metatechnology. Furthermore, the DDF that allows the computation of the maximum feasible proportional reduction of the *bad* output, namely NPLs, with respect to the technology of group j while maintaining inputs and desirable outputs is:

$$\vec{D}^j [x, y, b; g = (0, 0, -b)] = \text{Sup}\ [\varphi^j \mid (x, y, (1 - \varphi^j)b) \in T^j] \quad (7)$$

Moreover, it is worth highlighting that, by construction, the distance function computed with respect to the technology of group j will always be equal to or lower than the metadistance function relative to the metatechnology. In other words, the potential of a particular bank to reduce NPLs when it is compared to best practices in the group it belongs to will always be equal to or lower than its potential when compared to the overall technology represented by the metatechnology, which includes banks in both groups.

## 2.3.3 Metatechnology ratio

Both directional metadistance and distance functions computed with a direction that reduces NPLs while maintaining inputs and desirable outputs can be directly employed to compute groups' metatechnology ratios. The *metatechnology ratio* for group j is defined as:

$$\text{Metatechnology ratio}^{j}\ [x, y, b; g = (0, 0, -b)] = \frac{\text{Technical efficiency}}{\text{Technical efficiency}^{j}} = \frac{(1-\varphi)}{(1-\varphi^{j})} \quad (8)$$

In order to avoid infeasibilities in the computation of the metatechnology ratio in cases where banks are fully efficient with respect to the technology of the group they belong to, i.e., with distance functions equal to zero in expression (7), the metatechnology ratio has been formulated in terms of conventional technical efficiency scores, i.e., efficiency in the Farrell sense (Farrell, 1957).[5] That said, the metatechnology ratio of expression (8) would measure how close the technological frontier of group j is to the metafrontier, measured in a direction that reduces NPLs while maintaining inputs and desirable outputs. By way of example, a metadistance ratio of 0.9 would indicate that the efficient level of NPLs relative to the metafrontier is just 90% of the efficient level relative to the technological frontier of group j.

As mentioned by O'Donnell *et al.* (2008:237), this approach provides a suitable decomposition of technical efficiency measured with respect to the metafrontier –

[5] For example, a computed distance function of 0.2 means, as already mentioned, that NPLs could be reduced by 20% without additional inputs and/or a reduction of desirable outputs. The corresponding score of Farrell's technical efficiency would be one minus the distance function; in this case 0.8, meaning that the same level of good outputs could be achieved without using additional inputs and producing only 80% of currently observed NPLs.

representing the existing state of knowledge in the banking industry, in our case study– into the components of technical efficiency measured with respect to the technology of group j –which represents the state of knowledge and the physical, social and economic environment of group j, either cooperative banks or commercial banks–, and the metatechnology ratio for group j –which measures how close the frontier of group j is to the metafrontier. Formally:

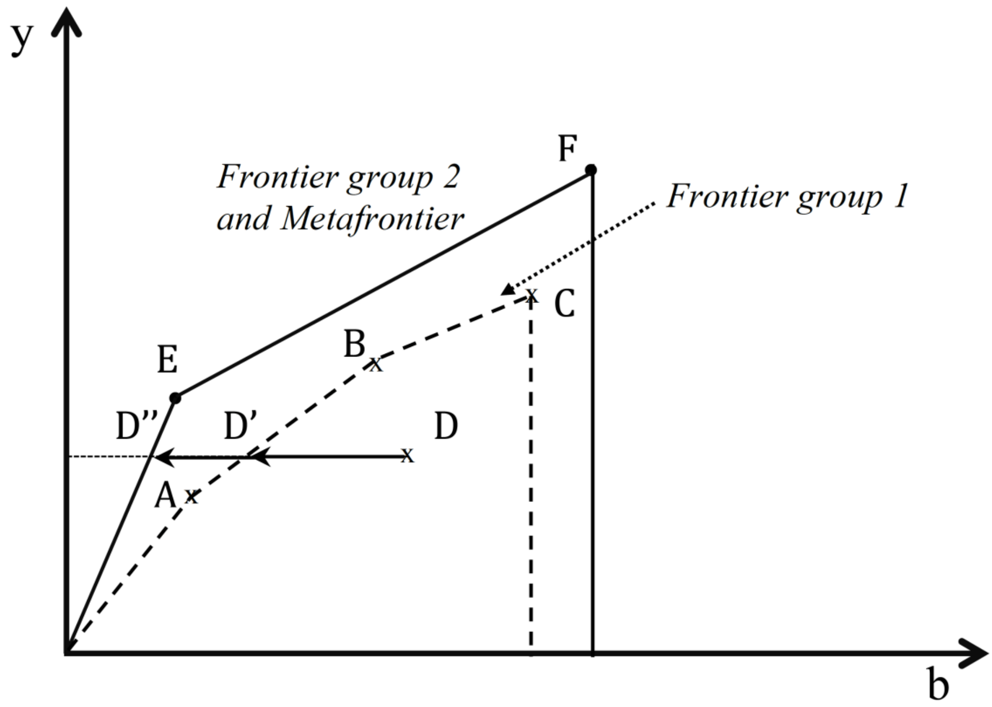
$$\text{Technical efficiency} = \text{Technical efficiency}^{j} \cdot \text{Metatechnology ratio}^{j} \qquad (9)$$

Or, in other words:

$$\text{Technical efficiency} = \text{Managerial efficiency} \cdot \text{Programme efficiency} \qquad (10)$$

*Figure 4* provides a graphical illustration of this decomposition. Let us assume that we observe six banks that use a set of inputs x to produce one desirable output y and one *bad* output b, namely NPLs. Furthermore, banks A, B, C and D (represented by crosses) are commercial banks (group 1), while banks E and F (represented by dots) are cooperative banks (group 2). The metatechnology and the groups' technologies are represented by the corresponding output sets, which embody all combinations of the good and *bad* outputs that can be obtained from a given endowment inputs. Considering the assumptions made on the technology, the productive plans of efficient banks A, B and C and their convex combinations determine the technological frontier of group 1 (commercial banks), while efficient banks E and F and their convex combinations give shape to the technological frontier of group 2 (cooperative banks), which for the sake of simplicity also coincides with the metatechnology or frontier for the whole sample of banks.

**Figure 4. Efficiency, distance/metadistance functions and metatechnology ratios.**




Let us now focus our attention on commercial bank D, which is unequivocally inefficient as it is located at an inner point of the output set. Projecting the productive plan of this bank onto the technological frontier of its own group, namely commercial banks, with a direction that reduces NPLs while maintaining the good output at its observed level –always for a given amount of inputs– yields point D', showing that D is not using the technology of the group it belongs to efficiently. Furthermore, projection of this bank onto the metafrontier with the same direction vector would yield point D'', which means that once technical efficiency in the management of NPLs with respect to the best practices available to commercial banks has been attained (*managerial efficiency*), further reductions of the bad output could still be feasible by using the best available practices that the existing state of technology allows (*programme efficiency*), i.e., those represented by the metatechnology. In other words, a part of the (overall) technical inefficiency of bank D in the management of NPLs is attributable not to the skills of their managers, but rather to the gap that exists between the technology available to managers of commercial banks and the metatechnology or overall technology.

Finally, using DEA techniques, the mathematical program required to compute the directional metadistance function of expression (5) for a bank k´ in the sample is (Cooper *et al.*, 2007):

$$\text{Maximise}_{\varphi^{k'},\, \lambda_k,\, \mu_k}\ \varphi^{k'}$$

Subject to:

$$
\begin{array}{llll}
\sum_{k=1}^{K} \lambda_k y_{km} \geq y_{k'm} & m = 1,\ldots,M & \text{(i)} & \\
\sum_{k=1}^{K} \lambda_k b_k = (1-\varphi^{k'}) b_{k'} & & \text{(ii)} & (11) \\
\sum_{k=1}^{K} (\lambda_k + \mu_k)\, x_{kn} \leq x_{k'n} & n = 1,\ldots,N & \text{(iii)} & \\
\sum_{k=1}^{K} (\lambda_k + \mu_k) = 1 & & \text{(iv)} & \\
\lambda_k,\ \mu_k \geq 0 & k = 1,\ldots,K & \text{(v)} &
\end{array}
$$

In this program, we have assumed variable returns to scale through restriction (iv) (see Banker *et al.*, 1984), so that 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. Furthermore, we have employed the formulation initially proposed by Kuosmanen (2005) (see also Kuosmanen and Podinovsky, 2009) to assess performance with variable returns to scale and weak disposability; accordingly, $\mu_k$ denotes the part of the output of bank k that is abated through scaling down the activity level –the so-called scale effect– and $\lambda_k$ stands for the remaining output –the efficient effect (further technical details are in Kuosmanen, 2005:1079-80). Finally, the distances involved in program (11) have been computed using the DJL package in R software.

Formulating the program that allows the computation of the distance function of expression (7) for bank k' belonging to group j is very straightforward, as it only requires restricting the sample of observations used to construct the technological frontier to banks belonging to that group. This is left to readers.

## 2.4 Data, variables and sample

Our empirical analysis is based on data from *Orbis Bank Focus*, a database that includes information on about 43,000 institutions worldwide, including commercial banks and cooperative banks. The information is sourced by Bureau van Dijk from a mixture of annual reports, information providers and regulatory sources, and the resulting dataset provides a source of 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. Our data refer to the years 2013, 2014, 2015 and 2016 and include information about 307 banks from the following LAC countries: Argentina, Bolivia, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Paraguay, Peru and Uruguay.[6] It is worth highlighting that all the countries in our sample have a shared legal tradition: the civil-law system developed in continental European countries, rather than the common-law system. In this respect, it is reasonable to believe that banking efficiency in the management of NPLs might differ between civil- and common-law countries (see Beck *et al*., 2006; Breuer, 2006).

In the process of selecting our sample of LAC banks, we have taken the following steps. In the first place, we extracted all information available in the *Orbis Bank Focus* dataset on cooperative banks and commercial banks operating in the banking industries relevant to our case study. We then eliminated the observations –banks– that lacked information about any of the variables used to characterize the banking production function. The third step was to exclude the so-called common-law countries, as well as any countries that did not have both types of banks or that had very few of one type, as in the case of cooperative banks in Mexico[7] and Chile.[8] As a final step, we eliminated outliers by means

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[6] The data were accessed at *https://www.bvdinfo.com/en-gb/our-products/data/international/orbis-bank-focus* on 23rd March 2018.

[7] More than 95% of the cooperative banks in this country lacked information on the labour input.

[8] Moreover, in order to ensure the sample of entities analysed is as homogeneous as possible, we also excluded Panama and Brazil. The fact that Panama is considered a tax haven by several international institutions means that its banking entities differ from the rest of the sample in terms of the structure of the balance sheet and the production function. Likewise, the particular nature of cooperative

of scatter plots and the TRIMMEAN function applied to 10% of the sample resulting from the previous stage. As a result of this filtering of the original data, we obtained a final sample –as mentioned above– of 307 banks, which includes 104 cooperative banks and 203 commercial banks Thus, taking into account the fact that we observe these entities over a four-year period and that some of them have no available data in a particular year, our final dataset includes a total of 924 observations, of which 275 are for cooperative banks and 649 for commercial banks.[9] Furthermore, as noted above, the final sample includes observations of both types of banks from all the abovementioned countries.

Regarding the representativeness of our final sample, *Table 10* includes some figures at the country level as well as for the sample as a whole. These percentages reflect all observations of all entities in the four-year period analysed. While some differences of representativeness across individual countries and years are observed (see Appendix A) – which are entirely due to the availability of information–, given the extensive coverage of the *Orbis Bank Focus* dataset, our opinion is that the sample is sufficiently representative at the level of the aggregate LAC banking market studied. In this respect, 68.4% of all entities in our source of data and 71.6% of all assets are covered in the case of cooperative banks, while the corresponding figures for commercial banks are 72.6% and 71%, respectively.

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banks in Brazil (*Orbis Bank Focus* reports almost six times more cooperatives in this country alone than in all the 10 countries included in our final sample) prompted us to exclude them from the analysis for reasons of homogeneity.

[9] This means that, over our four-year period, each cooperative bank has an average of 2.6 observations whereas each commercial bank has 3.2 observations. As rightly noted by one referee, this difference could be introducing some bias in the sample if there were reason to believe that it arises from a sample selection problem. In this respect, identifying why *Orbis Bank Focus* does not report the information for particular entities in some years is far from easy. At any rate, it is our belief that the reporting in the *Orbis Bank Focus* dataset might be more irregular for cooperative banks than for commercial ones, which is a drawback that should not significantly bias the results of our research.

**Table 10. Representativeness of the entities in the sample (*% for the 2013-2016 period*)**

| | Over total entities [(1)] | | Over total assets [(1)] | |
|---|---|---|---|---|
| Country | Cooperative banks | Commercial banks | Cooperative banks | Commercial banks |
| Argentina | 60.0 | 78.0 | 99.7 | 61.1 |
| Bolivia | 50.0 | 54.5 | 52.9 | 60.1 |
| Colombia | 100.0 | 58.9 | 100.0 | 21.8 |
| Costa Rica | 66.1 | 73.4 | 54.8 | 68.9 |
| Dominican Republic | 92.1 | 80.4 | 72.3 | 92.1 |
| Ecuador | 72.5 | 77.2 | 69.6 | 87.6 |
| El Salvador | 55.6 | 64.7 | 71.0 | 77.5 |
| Paraguay | 50.0 | 93.3 | 50.0 | 81.3 |
| Peru | 50.0 | 80.8 | 59.0 | 77.5 |
| Uruguay | 87.5 | 64.4 | 87.0 | 82.1 |
| TOTAL | 68.4 | 72.6 | 71.6 | 71.0 |

*[(1)] Total entities and assets reported by the Orbis Bank Focus database.*

Finally, in order to characterise the banking production function, we have followed the intermediary approach (Sealey and Lindley, 1977), according to which, banks use production factors and gain resources such as deposits or capital –inputs–, to invest in financial products such as credits, loans or securities –desirable outputs. This is the most commonly-used financial approach in analyses of performance in the banking industry in previous literature (Berger and Mester, 1997). Accordingly, and in line with other previous papers, the inputs included in our characterisation of the technology are personnel expenses as a proxy of labour, non-earning assets as a proxy of physical capital, and equity plus customer deposits as one financial input. The desirable outputs, on the other hand, are gross loans and financial assets. Finally, as repeatedly mentioned throughout the paper, we also consider NPLs as a *bad* output that inevitably accompanies the production of desirable outputs. Some descriptive statistics are in *Table 11*.

**Table 11. Sample descriptive statistics (*in constant 2016 $US million*)**

| | All banks | | Cooperative banks | | Commercial banks | |
|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| *Desirable outputs* | | | | | | |
| Gross loans | 1095.4 | 2510.6 | 156.0 | 344.4 | 1493.4 | 2897.4 |
| Financial assets | 244.9 | 739.0 | 53.0 | 213.4 | 326.2 | 858.1 |
| *Bad output* | | | | | | |
| Non-performing loans | 40.0 | 109.3 | 5.7 | 10.4 | 54.5 | 127.5 |
| *Inputs* | | | | | | |
| Personal expenses | 51.2 | 110.2 | 8.7 | 38.4 | 69.2 | 124.8 |
| Non-earning assets | 350.0 | 815.2 | 30.2 | 136.6 | 485.6 | 936.4 |
| Equity and customer deposits | 1414.5 | 3076.2 | 208.3 | 633.4 | 1925.6 | 3525.7 |

## 2.5 Results and discussion

In this Section, we discuss the results obtained for both technical efficiency in the management of NPLs, and metatechnology ratios representing the differences of technologies of the LAC cooperative banks and commercial banks in our sample. The directional metadistance/distance functions involved in our analysis, i.e., those in expressions (5) and (7), have been computed for each one of the 924 observations in the sample, whether cooperative or commercial bank, using program (11) for the metadistances and its equivalent in the case of the distance functions. In this respect, it is worth noting that in order to obtain our performance scores, observations for all years –2013, 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 dataset and the discrimination capacity of our DEA-based models (see Cooper *et al*., 2007), it also requires assuming that no technical progress has occurred during this four-year period. In our opinion, this is a realistic assumption since 2013-16 is a fairly short period of time. That said, *Table 12* reports descriptive statistics for NPL technical efficiency and the metatechnology ratios, while *Table 13* displays the results of some statistical tests for differences of performance between cooperative banks and commercial banks.[10]

**Table 12. Estimates of NPL technical efficiency (*0 lower, 1 higher*)**

| | Mean | Standard deviation | Maximum | Minimum |
|---|---|---|---|---|
| *Technical efficiency with respect to the metafrontier* $(1-\varphi)$ | | | | |
| Cooperative banks | 0.511 | 0.365 | 1 | 0.014 |
| Commercial banks | 0.486 | 0.301 | 1 | 0.018 |
| *Technical efficiency with respect to the group frontiers* $(1-\varphi^{j})$ | | | | |
| Cooperative banks | 0.540 | 0.373 | 1 | 0.020 |
| Commercial banks | 0.529 | 0.310 | 1 | 0.018 |
| *Metatechnology ratio* $(1-\varphi)/(1-\varphi^{j})$ | | | | |
| Cooperative banks | 0.943 | 0.117 | 1 | 0.240 |
| Commercial banks | 0.924 | 0.154 | 1 | 0.168 |

**Table 13. Differences of efficiency: Cooperative banks *versus* commercial banks**

| | Kolmogorov-Smirnov test (1) | Mann-Whitney test (2) | Simar-Zelenyuk-Li test (3) |
|---|---|---|---|
| | *KS-statistic* (4) | *Z-statistic* (5) | *Li-statistic* |
| NPL technical efficiency | 0.151 (0.000)*** | 0.013 (0.908) | 16.054 (0.000)*** |
| Metatechnology ratio | 0.172 (0.000)*** | 11.134 (0.001)*** | 4.268 (0.000)*** |

*Note: p-values are in parentheses; *** means significant at 1%.*

*(1) The null hypothesis is that the two samples have the same distribution.*
*(2) The null hypothesis is that the two samples are drawn from the same population.*
*(3) Original estimates are smoothed using the algorithm II in Simar and Zelenyuk (2006:508).*
*(4) Exact p-values are computed.*
*(5) The Z-statistic is adjusted for ties.*

[10] Conover (1999) provides a detailed description of the *Kolmogorov-Smirnov* and the *Mann-Whitney* non-parametric tests. Details on the *Simar-Zelenyuk-Li* test are in Li (1996), and Simar and Zelenyuk (2006).

Let us start, on the one hand, with the results for NPL technical efficiency computed with respect to the metafrontier. The average for cooperative banks is 0.511, indicating that banks in this group could reduce their NPLs by 48.9% while maintaining their level of desirable outputs and also without requiring additional inputs. In the case of commercial banks, average NPL technical efficiency is 0.486, indicating a reduction potential of 51.4%. Furthermore, according to the results of the *Kolmogorov-Smirnov* test, the distribution of technical efficiency in cooperative and commercial banks is statistically different at standard confidence levels; however, the *Mann-Whitney* test suggests that both samples are drawn from the same population. Additionally, we have computed the *Simar-Zelenyuk-Li* test, which is specifically designed for testing the equality of distributions of technical efficiency scores calculated using DEA; it shows that the distribution of technical performance of cooperative banks is statistically different from that of commercial banks at a confidence level of 1%.[11]

On the other hand, regarding NPL efficiency assessed with respect to the group frontiers, when cooperative banks are compared to the best practices observed within their own group, the average for managerial efficiency is 0.540. This score suggests an average potential to reduce NPLs by 46%, while maintaining desirable outputs and inputs. Average managerial efficiency for commercial banks is 0.529, pointing to a potential reduction of NPLs of 47.1%. However, it is important to remark here that averages of managerial efficiency are not comparable between cooperative banks and commercial banks. The

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[11] Following the suggestion of one referee, we have assessed the relationship between the technical efficiency of banks and the level of development in their respective countries. To do so, we have used the *Kruskal-Wallis* test (see Conover, 1999) to analyse differences of efficiency among three groups of countries classified according to their income, measured by GDP per capita; i.e., high income (Argentina and Uruguay), middle income (Colombia, Costa Rica, Dominican Republic and Peru) and low income (Bolivia, Ecuador El Salvador and Paraguay). The results show that these differences are statistically significant at standard confidence levels for both commercial banks and cooperative banks. However, the study of the relationship between performance and development lies far beyond the scope of this paper, as does the analysis of banks' efficiency at the country level, which, in our opinion, would require a different framework of analysis to that used in this research. Furthermore, the abundant empirical literature aimed at studying efficiency in banking and development –in several economic areas and using an array of methodologies– is inconclusive (e.g., see Altunbas *et al*., 2001, and Maudos *et al*., 2002 for the case of Europe; Fries and Taci, 2005 for transition economies; or Chortareas *et al*., 2011 for LAC countries).

reason for this is that efficiency is always a *relative* concept assessed with respect to a technology of reference, and scores of NPL managerial efficiency for the two groups of entities have been obtained with respect to different technological frontiers, i.e., their respective technologies. The only meaningful comment that can be made about these results is that, on average, cooperative banks are operating closer to their technological frontier than commercial banks are to theirs.

Comparing the scores of NPL technical efficiency relative to both the metafrontier and the group frontiers permits the computation of the metatechnology ratio for all banks in the sample. As explained in Section 2, these ratios measure how close the technologies of cooperative banks and commercial banks are to the metatechnology, allowing an assessment as to which technology is more efficient in the management of NPLs. According to our results, the average for cooperative banks is 0.943; in other words, the efficient level of NPLs relative to the metafrontier is, on average, 94.3% of that measured with respect to the frontier of cooperative banks. Conversely, the average for the metatechnology ratios of commercial banks is 0.924, suggesting that their technology is farther from the metatechnology than that of cooperative banks. Furthermore, the difference of metatechnology ratios between cooperative banks and commercial banks is statistically significant at conventional confidence levels, according in this case to the results from the three tests included in *Table 13*. In less technical terms, our results suggest that the technology used by cooperative banks in the management of NPLs is more efficient than the technology of commercial banks.

Finally, following the advice of one referee, we have used parametric regression analysis to further check the robustness of our results regarding differences in performance between cooperative banks and commercial banks. Specifically, we have run two random-effects Tobit panel regressions with the scores for technical efficiency and program efficiency as dependent variables, respectively. As far as the explanatory factors are concerned, our key variable is a dummy that takes a value of 1 for cooperative banks and 0 for commercial banks; several controls have also been used, including year and country dummies and total assets. The estimations have been carried out using Stata 15 software, and the results are reported in Appendix B. As expected, the estimated sign for the parameter of the dummy for cooperative banks is positive and statistically significant at standard confidence levels in both regressions –at 10% and 1%, respectively–, thus indicating that being a cooperative bank has a positive and significant effect on both technical efficiency and program efficiency.

## 2.6 Summary and conclusions

Literature in the field of financial economics has identified and documented several reasons why cooperative banks and commercial banks might perform differently in certain business areas. The nature of cooperative banks as member-owned businesses and their objective of boosting members' consumer surplus, as opposed to commercial banks that seek to maximise profits, might have an important impact on their performance, e.g., reducing asymmetric information between lenders and borrowers. Furthermore, additional features of cooperative banks such as longer-term contractual relationships, specific government control and regulations, specialization in products such as agriculture loans, mortgages and life assurance, and also their integration into local communities, could help their managers to improve forecasted lender cash flow and its consequences. Conversely, several authors have suggested that, compared to commercial banks, cooperative banks could face more difficulties in managing non-performing loans, particularly because of the geographical or sectorial concentration of their activity, and also due to the influence that close connections with local policymakers could have on certain managerial decisions.

Accordingly, all the abovementioned arguments seem to suggest that the relative performance of commercial banks and cooperative banks regarding the management of non-performing loans is an open empirical question. In this context, this paper analyses the technical performance in the management of non-performing loans by a sample of Latin American and Caribbean cooperative and commercial banks. Using *Data Envelopment Analysis* techniques and directional distance functions, technical efficiency is assessed as the result of both managerial capabilities and differences in the technology used by cooperative and commercial banks, understood in a broad sense that includes differences in production environments and regulations, among others. Our principal results support the idea that the technology used by cooperative banks in the management of non-performing loans is more efficient than the technology of commercial banks. However, conclusions about why cooperative banks perform better in the management of non-performing loans than commercial banks are still based on a limited number of studies, and only further investigation will clarify the validity of the theoretical hypothesis suggested by literature in this field of research.

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# Appendix A

**Table 14. Number of entities in the sample [(1)] and representativeness over total entities [(2)] by country and year (%)**

| | Cooperative banks | | | | Commercial banks | | | |
|---|---|---|---|---|---|---|---|---|
| | 2013 | 2014 | 2015 | 2016 | 2013 | 2014 | 2015 | 2016 |
| Argentina | 50.0 (1) | 50.0 (1) | 66.7 (2) | 66.7 (2) | 74.1 (40) | 76.4 (41) | 83.0 (42) | 86.5 (44) |
| Bolivia | 0.0 (0) | 0.0 (0) | 100.0 (1) | 100.0 (1) | 42.9 (6) | 50.0 (7) | 69.2 (8) | 64.3 (9) |
| Colombia | 100.0 (2) | 100.0 (3) | 100.0 (4) | 100.0 (4) | 50.0 (8) | 50.0 (9) | 68.4 (13) | 65.0 (13) |
| Costa Rica | 60.7 (17) | 64.3 (18) | 67.9 (20) | 67.9 (19) | 66.7 (10) | 66.7 (10) | 76.5 (13) | 82.4 (14) |
| Dominican Republic | 100.0 (9) | 100.0 (9) | 100.0 (8) | 100.0 (9) | 79.4 (26) | 73.5 (25) | 87.9 (29) | 86.5 (31) |
| Ecuador | 71.1 (26) | 63.9 (22) | 79.1 (33) | 79.6 (43) | 66.7 (12) | 75.0 (15) | 77.8 (14) | 87.0 (20) |
| El Salvador | 75.0 (3) | 25.0 (1) | 60.0 (3) | 60.0 (3) | 75.0 (9) | 25.0 (3) | 84.6 (11) | 71.4 (10) |
| Paraguay | 100.0 (1) | 0.0 (0) | 0.0 (0) | 100.0 (1) | 100.0 (14) | 100.0 (14) | 86.7 (13) | 100.0 (15) |
| Peru | 100.0 (1) | 100.0 (1) | 0.0 (0) | 0.0 (0) | 73.7 (14) | 84.2 (16) | 84.2 (16) | 81.0 (17) |
| Uruguay | 100.0 (2) | 100.0 (2) | 50.0 (1) | 100.0 (2) | 66.7 (10) | 66.7 (10) | 71.4 (10) | 53.3 (8) |

[(1)] *Number of entities in parentheses.*

[(2)] *Total entities reported in the Orbis Bank Focus database*

**Table 15. Representativeness of assets in the sample over total assets [(1)] by country and year (%)**

| | Cooperative banks | | | | Commercial banks | | | |
|---|---|---|---|---|---|---|---|---|
| | 2013 | 2014 | 2015 | 2016 | 2013 | 2014 | 2015 | 2016 |
| Argentina | 99.6 | 99.6 | 99.8 | 99.7 | 44.6 | 46.8 | 99.3 | 70.1 |
| Bolivia | 0.0 | 0.0 | 100.0 | 100.0 | 49.7 | 64.5 | 67.1 | 58.1 |
| Colombia | 100.0 | 100.0 | 100.0 | 100.0 | 24.3 | 17.4 | 27.6 | 18.1 |
| Costa Rica | 24.8 | 68.3 | 55.7 | 65.7 | 69.9 | 52.4 | 85.4 | 66.3 |
| Dominican Republic | 100.0 | 100.0 | 100.0 | 100.0 | 95.7 | 72.0 | 99.6 | 99.4 |
| Ecuador | 60.9 | 54.4 | 77.0 | 82.6 | 77.2 | 93.2 | 78.2 | 98.2 |
| El Salvador | 89.1 | 51.7 | 71.5 | 72.4 | 90.8 | 45.3 | 99.1 | 73.4 |
| Paraguay | 100.0 | 0.0 | 0.0 | 100.0 | 100.0 | 100.0 | 63.2 | 100.0 |
| Peru | 100.0 | 100.0 | 0.0 | 0.0 | 77.3 | 78.6 | 76.4 | 77.6 |
| Uruguay | 100.0 | 100.0 | 48.1 | 100.0 | 85.1 | 85.5 | 86.6 | 72.2 |

[(1)] *Total assets reported in the Orbis Bank Focus database.*

# Appendix B

**Table 16. Determinants of performance from random-effects Tobit panel regressions**

| | Dependent variable | |
|---|---|---|
| | Technical efficiency | Program efficiency |
| Constant | 0.251 (0.002)*** | 0.933 (0.000)*** |
| Dummy for cooperative banks | 0.076 (0.083)* | 0.120 (0.000)*** |
| Dummy for year 2013 | 0.019 (0.278) | 0.012 (0.400) |
| Dummy for year 2014 | 0.032 (0.066)* | 0.013 (0.376) |
| Dummy for year 2015 | 0.044 (0.008)*** | 0.007 (0.619) |
| Dummy for Argentina | 0.062 (0.477) | 0.037 (0.588) |
| Dummy for Bolivia | 0.209 (0.073)* | -0.099 (0.259) |
| Dummy for Colombia | 0.417 (0.000)*** | 0.022 (0.779) |
| Dummy for Costa Rica | 0.567 (0.000)*** | 0.103 (0.157) |
| Dummy for Dominican Republic | 0.326 (0.000)*** | -0.047 (0.488) |
| Dummy for Ecuador | -0.036 (0.680) | 0.007 (0.927) |
| Dummy for El Salvador | 0.267 (0.010)** | 0.062 (0.477) |
| Dummy for Paraguay | 0.231 (0.025)** | 0.095 (0.233) |
| Dummy for Peru | -0.028 (0.779) | -0.002 (0.975) |
| Total assets | 3.74e-8 (0.000)*** | 3.64e-8 (0.000)*** |
| Number of observations | 924 | 924 |
| Number of groups | 307 | 307 |
| Log likelihood | -157.71 | -77.18 |
| Wald $Chi^2$ | 204.59 (0.000)*** | 55.40 (0.000)*** |

*Notes: The year and country omitted variables are 2016 and Uruguay, respectively; p-values are in parentheses; *, ** and *** stand for significance at 10%, 5% and 1%, respectively.*

# Essay 3: Performance and risk in the Brazilian banking industry


## Abstract

This paper assesses the technical performance of Brazilian banks while accounting for risk, which is considered as an undesirable outcome of banking. To this end, frontier techniques based on Data Envelopment Analysis and directional distance functions are applied to a sample of 124 banks and data for the six-year period 2014-19. Our main finding is that the Brazilian banking industry could notably increase its production of conventional outputs without additional input usage and while maintaining the same levels of risk. Besides, investment banks are found to be more efficient than commercial banks mainly because of their superior managerial performance.

## 3.1 Introduction

The banking industry plays a key role in modern economies. Banks are financial intermediaries that gather deposits and other liabilities from savers and transfer them to borrowers in the form of loans and other financial assets. They share certain functions with financial markets, such as resource allocation, reducing credit risk, intermediating maturity differences, or bearing interest rate and exchange rate risk. Furthermore, the banking industry faces three main sources of risk: credit risk, operational risk, and market risk. Banks' productive process as financial intermediaries and the risk inherent to banking should not be considered individually, but rather jointly analysed. In this regard, existing research shows that risk exerts a major influence on both the level and variability of banks' performance; besides, these effects differ over time and across countries (Sun et al., 2011).

In this research, we assess the technical efficiency of Brazilian banks while accounting for risk, which is considered as an undesirable outcome of banking. Besides, we study the difference in performance between groups of banks and the sources of these differences, particularly distinguishing commercial banks from investment banks. In doing so, we use non-parametric Data Envelopment Analysis (DEA) techniques on a sample of 124 Brazilian banks, and data for years 2014 to 2019. Regarding the contributions of the paper, while the analysis of efficiency in the banking industry has received a great deal of attention in recent decades, approaches accounting for risk as an undesirable by-product of banking—as our paper does—are much scarcer. Another contribution is the assessment of the differences in performance between commercial and investment banks and the sources of those differences, considering that any increase in the production of conventional outputs is limited not only by resource availability but also by the need to keep risk under control. Moreover, as far as we know, no previous studies have taken risk into account when examining the efficiency of Brazilian banks.

The Brazilian banking industry is the largest in the Latin American and Caribbean region. Furthermore, the banking system has historically played an important role as financial intermediary in Brazil given the lack of development of financial markets, and particularly the corporate bond market (Staub et al., 2010). The banking industry in this country has undergone important structural transformation in recent decades, which makes an analysis of its performance particularly interesting.

As in other major Latin American emerging countries, the 1990s in Brazil were characterized by rapid economic development largely motivated by the Washington Consensus. Moreover, privatizations, foreign direct investment incentives, financial liberalization, price stabilization and other reforms contributed to the integration of Brazil's domestic financial market into international financial markets (De Paula, 2011). The new regulation of the financial system enacted in 1988 allowed banks to offer different financial services, universalizing their business. In June 1994, the Brazilian government instituted a monetary reform aimed at stabilizing prices—the so-called Real Plan—which led to a profound reformulation of the banking sector (Almeida and Divino, 2015), and a notable increase in credit. The banking industry also witnessed a number of mergers and acquisitions involving both domestic and foreign banks (Baer and Nazmi, 2000). In August 1996, the Central Bank of Brazil launched the PROES (Program of Incentives for the Reduction of the State's Participation in Banking Activities), which was aimed at restructuring public banks; as a result of this programme only 12 of the 32 public banks that existed in 1994 remained operative in 2012 (Wolters et al., 2014).

Following this Introduction, Section 2 reviews existing literature on banking performance and risk; Section 3 explains the methodology; Section 4 describes the sample and the data; Section 5 presents and discusses the results; finally, Section 6 concludes.

## 3.2 Background

Previous literature has addressed the study of performance in the banking industry from different angles and using a range of methodological approaches. Surveys in the field include Berger (2007), which reviews the extant literature on the sources of differences in performance, including measurement method and a number of bank, market, and regulatory features; Paradi and Zhu (2013), which conducts a survey on bank branch efficiency and performance research in 24 countries or economic areas carried out with DEA; and, more recently, Aiello and Bonanno (2018), which reviews the empirical literature on banking efficiency by conducting a meta-regression analysis from 120 papers published over the period 2000–14. Without aiming to be exhaustive, papers focused on the Brazilian banking industry include: Ceretta and Niederauer (2001), Silva (2001), Silva and Neto (2002), Becker et al. (2003), Macedo et al. (2005), Tabak et al. (2005), Ghilardi (2006), Souza et al.

(2006), Chabalgoity et al. (2007), Périco et al. (2008), Ruiz et al. (2008), Souza et al. (2008), Souza and Macedo (2009), Staub et al. (2010), Tecles and Tabak (2010), Wanke and Barros (2014), Wanke et al (2015), Périco et al (2016), De Freitas Branco et al. (2017), Gomes et al. (2017), and Henriques et al. (2018).

Regarding the contributions and main findings of these papers, Silva (2001) analysed X-efficiency of Brazilian banks in the period 1994-99—after the implementation of the Real Plan—discovering a certain variability in efficiency, mostly stemming from public banks. Tecles and Tabak (2010) studied the post-privatization period 2000–07 finding that the negative profits reported by many banks in Brazil were closely related to prior privatization waves; these authors also suggested that large banks are the most cost and profit efficient, which supports the concentration process observed in previous years. Staub et al. (2010) found that the efficiency of the Brazilian banking industry in 2000-07 was lower than that of European and North American banks; and that state-owned banks in Brazil were the most cost efficient. Wanke and Barros (2014) analysed the efficiency of major Brazilian banks and its drivers in 2012. The results brought to light the heterogeneity of the banking industry in Brazil; also, mergers and acquisitions were found to be the main driver of both productive and cost efficiency. Henriques et al. (2018) evaluated the efficiency of 37 Brazilian banks in 2012-16 with DEA, and the causes of inefficiency. The authors found large inefficiencies that are slightly more related to technical issues than to the scale of operations; they also recommended fostering mergers and acquisitions as a strategy to improve performance.

The structure of the banking industry worldwide and the relationships among its players changed substantially from 2008, as a result of several regulatory reforms oriented to addressing the moral hazard problem arising from banks aiming to increase returns by taking increasingly risky positions in the securities markets. In September 2010, the Basel Committee for Banking Supervision passed new regulations for capital requirements—Basel III. Back in 1988, Basel I had tackled the impact of banks' capital regulations on their risk-taking performance. These regulatory changes stimulated a line of research focused on explaining the relationship between risk, capital and performance in banking. The theoretical models underpinning empirical work are mainly grounded on three hypotheses: i) the bad management hypothesis, which holds that managing risk requires the use of resources that could otherwise be dedicated to other productive activities (Williams, 2004);

ii) the bad luck hypothesis, which emphasizes the role of external triggers instead of managers' skills (Berger and De Young, 1997); and iii) the moral hazard hypothesis, which posits that managers tend to take on more risk when banks have lower levels of capital or they are less profit efficient (Jeitschko and Jeung, 2005).

Kwan and Eisenbeis (1997) analysed the interrelationships among banks' interest rate and credit risk-taking, capitalization, and efficiency; their results support the moral hazard hypothesis. Williams (2004) examined the intertemporal relationships between loan loss provision, efficiency and capitalization for European banks between 1990 and 1998, with the findings supporting the bad management hypothesis. In this regard, managers who engage in skimping behaviour reduce the use of bank resources that are oriented to monitoring the lending business; this influences the quality of loans and cost efficiency because bank managers face a trade-off between short-term operating costs and future loan quality. Fiordelisi et al. (2011) examined the inter-temporal link between bank efficiency, capital and risk in European commercial banks in 1997-2005. The results suggest that lower cost and revenue efficiency causes higher bank risk. Tan and Floros (2013) studied the relations among bank efficiency, capital and risk in Chinese commercial banks over the period 2003–09. Their findings suggest that there is a positive significant relationship between risk and efficiency, while the relationship between risk and capitalization is negative and also significant.

In a different framework, Hughes et al. (1998) found empirical evidence that the man-agers of US banks use more labour and physical capital in order to ensure better risk management and capital preservation, according to the bad management hypothesis. Altunbas et al. (2007) studied the relation between capital, risk and efficiency of European banks in the period 1992–2000, finding no empirical evidence of a relationship between efficiency and bank risk-taking. Recently, Colesnic et al. (2019) analysed the effect of risk on Middle East banks' efficiency levels before and after the financial cri-sis of 2008. In doing so, they defined an indicator of banks' risk efficiency which ac-counts for the inefficiency due to risk abatement cost—i.e., risk is considered as an undesirable or bad output in the banking production function (see Assaf et al., 2013). The empirical findings suggest that large banks' risk management was more flexible during the financial crisis; most notably, the authors advise that omitting risk may lead to biased estimates of banks' efficiency.

## 3.3 Methodology

The study of performance in banking has been addressed using different methodological approaches, notable among which are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Both of these approaches have their pros and cons. DEA is a non-parametric technique based on mathematical programming developed by Charnes et al. (1978), which has been employed in hundreds of empirical papers on efficiency assessment (for a recent survey see Emrouznejad and Yang, 2018; see Paradi and Zhu, 2013 for those focused on banking). Conversely, SFA is an approach simultaneously proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), which is grounded in the estimation of parametric production or cost functions. According to Hjalmarsson et al. (1996, p.304), *'...the choice between different approaches [to performance assessment] must be based on trade-offs concerning the purpose of the study, type of data, technology characteristics, etc.'*.

In our paper, we have decided in favour of non-parametric DEA primarily due to its flexibility. In this regard, DEA does not require a particular functional form to be established for either the technology or the distribution of efficiency, which greatly facilitates the task of accounting for risk as an undesirable output of banking (Jiménez-Hernández et al., 2019b). Instead, this technique allows a surface to be built over a set of observed data on productive units—banks in our case study—representing the best observed practices. All the productive units in the sample are then projected onto this technological frontier, yielding an indicator of performance (see details in Cooper et al., 2007). As noted by Färe et al. (1994, p.11), this approach constitutes '...an elegant way of simultaneously constructing frontier technology from data and calculating the distance to that frontier for individual observations or activities'. Furthermore, a notable feature of DEA—which is particularly relevant for the purpose of our research—is that it enables the computation of a range of measures of performance that might represent the preferences of researchers or managers; in the case of this paper, how the production of conventional outputs could be increased without employing additional resources and also maintaining risk at observed levels.

## 3.3.1 Using DEA to assess performance in banking while accounting for risk

Let us assume that we observe a sample of b = 1,...,B banks using a set of N inputs $x \in \mathcal{R}_{+}^{N}$ to obtain a vector of M good outputs represented by $y \in \mathcal{R}_{+}^{M}$. Transforming inputs into good outputs necessarily generates a certain level of risk, which is represented by a set of H variables $r \in \mathcal{R}_{+}^{H}$; moreover, risk is considered as an undesirable or bad output from banking.

The technology that models the transformation of inputs into good outputs and bad outputs (risk) is represented by:

$$T = [(y, r, x) | \, x \text{ can produce } (y, r)] \quad (1)$$

It is assumed that the technology satisfies the axioms proposed by Shephard (1970), including possibility of inaction, no free lunch, strong disposability of inputs and good outputs, and convexity. Inputs, good outputs and *bad* outputs are all considered to be non-negative. Furthermore, in order to model the joint production of good outputs and *bad* outputs two further axioms are needed: null-jointness and weak disposability of outputs, both good and *bad*.

*Null-jointness* models the idea that good outputs and *bad* outputs (risk) are jointly produced (Shephard and Färe, 1974). Put simply, if banks produce a positive amount of good outputs, some risk will also unavoidably be assumed. In formal terms:

$$\text{If } (y, r, x) \in T \text{ and } r = 0, \text{then } y = 0 \quad (2)$$

*Weak disposability of outputs*—desirable and undesirable—means that reducing risk is not free, but it has an opportunity cost that can be assessed in terms of a reduction in the potential amount of good outputs produced. This is because resources such as employees or physical capital that could otherwise be dedicated to producing good outputs ought to be diverted to activities devoted to reducing risk. Formally:

$$\text{If } (y, r, x) \in T \text{ and } 0 \leq \alpha \leq 1, \text{ then } (\alpha y, \alpha r, x) \in T \quad (3)$$

The relative position of each bank in the sample with respect to the technology defined in expression (1) can be assessed, in terms of an indicator of performance, using directional distance functions (DDFs). The more general formulation of the DDF is (Färe and Grosskopf, 2000):

$$\overrightarrow{\mathrm{DDF}} = \left[\mathrm{y}, \mathrm{r}, \mathrm{x}; \mathrm{g} = \left(\mathrm{g_y}, -\mathrm{g_r}, -\mathrm{g_x}\right)\right] = \mathrm{Sup}\left[\beta \middle| \left(\mathrm{y} + \beta \mathrm{g_y}, \mathrm{r} - \beta \mathrm{g_r}, \mathrm{x} - \beta \mathrm{g_x}\right) \in \mathrm{T}\right] \quad (4)$$

This DDF generalizes both Shephard's input and output distance functions (Shephard 1970) by jointly modelling good outputs, risk and inputs. It thereby provides, in the most general setting, a measure of the extent to which the good outputs could be increased in a direction $\mathrm{g_y}$, while risk and inputs are respectively reduced in directions $-\mathrm{g_x}$ and $-\mathrm{g_r}$. By construction, DDFs are lower bounded to zero. Other properties are detailed in Chambers et al. (1998).

Let us now consider that we are interested in assessing banks' performance in the presence of risk as the maximum proportional attainable increase in the good outputs while maintaining the same level of risk and input usage[12]; i.e., the good output-oriented approach. In this scenario, the DDF of expression (4) becomes:

$$\overrightarrow{\mathrm{DDF}} = [\mathrm{y}, \mathrm{r}, \mathrm{x}; \mathrm{g} = (\mathrm{y}, 0,0)] = \mathrm{Sup}[\beta | \langle (1 + \beta)\mathrm{y}, \mathrm{r}, \mathrm{x} \rangle \in \mathrm{T}] \quad (5)$$

where $\mathrm{g} = (\mathrm{y}, 0,0)$ is the direction vector that represents our preferences on how to measure banks' performance.

By way of example, a computed score for the DDF from expression (5)—parameter β—for a given bank of, let us say, 0.25 would mean that by behaving efficiently this bank could proportionally increase its good outputs by 25% without increasing risk and/or input usage. In terms of the expression $(1 + \beta)$, the potential or efficient level of the good outputs would be 1.25 times their observed level.

Alternatively, the technology can be characterized by assuming that *bad* outputs (risk) are strongly (or freely) disposable, which allows us to compute an indicator of the

[12] Banking performance could also be assessed with alternative direction vectors; e.g., reducing risk while maintaining the same level of inputs and good outputs, or simultaneously reducing risk and inputs while maintaining or even increasing good outputs.

opportunity cost of reducing risk at the bank level. Strong disposability of the *bad* outputs can be formalized as:

$$\text{If } (y, r, x) \in T \text{ and } 0 \leq \alpha \leq 1, \text{ then } (y, \alpha r, x) \in T \qquad (6)$$

The assumption of *strong disposability* of *bad* outputs means, as proposed by Färe et al. (1989), that reducing *bads* is costless; in simpler words, risk can be reduced at no cost. Moreover, strong disposability disrupts the physical link between good outputs and risk, rendering the null-jointness hypothesis unnecessary. In the *real world*, this would make little sense since there is always an association between good outputs and risk in banking; e.g., no loans can be made without assuming some risk, no matter how small. Accordingly, strong disposability needs to be understood in terms of costs, as Färe et al. (1989) themselves emphasized.

By comparing the DDFs of expression (5) computed with respect to technologies characterized by both weak ($\overrightarrow{\text{DDF}}^{\text{W}}$) and strong disposability ($\overrightarrow{\text{DDF}}^{\text{S}}$), we can compute an indicator of the opportunity cost of reducing risk at the bank level, expressed in terms of potential good output losses. Formally, for good output m, this indicator is:

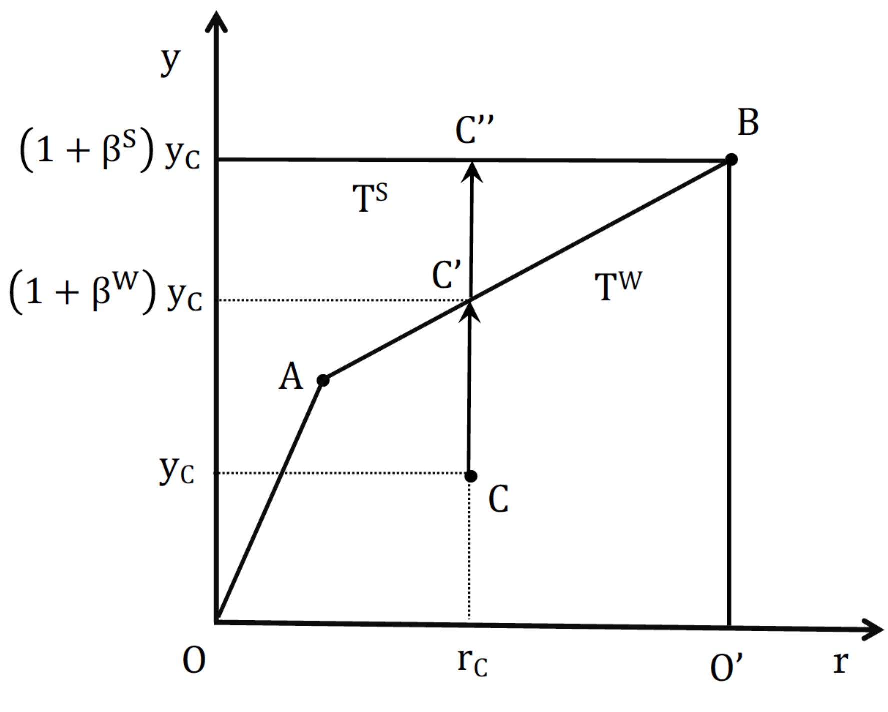
$$\text{Good output loss } y_m = y_m\left(\overrightarrow{\text{DDF}}^{\text{S}} - \overrightarrow{\text{DDF}}^{\text{W}}\right), \qquad (7)$$

This indicator measures potential losses of good outputs due to weak disposability, and by construction is equal to or larger than zero. A positive value indicates that weak disposability of *bads* is reducing the potential increases in the good outputs; i.e., reducing risk requires the use of resources that otherwise could be dedicated to producing the good outputs.

Figure 5 graphically depicts the technologies under weak and strong disposability, and the assessment of potential output losses. For the sake of simplicity, let us consider that we observe banks A, B and C, which all use the same vector of inputs to produce one good output (y) and one *bad* output (risk) (r). The technology that satisfies the assumptions of weak disposability and null-jointness ($T^W$) is bounded by OABO’, whereas the technology where the good and *bad* outputs are strongly (freely) disposable ($T^S$) is bounded by OO’B and the horizontal segment that goes from B until the vertical good-output axis. Furthermore, bank C is inefficient with respect to both technologies, as it is producing in an inner point of the output set.

Projecting the observed production plan of bank C toward the frontier of $T^S$ in the good output direction yields—according to expression (5)—point C''. This means that when reducing risk is assumed to be costless, the potential good output of bank C would be $(1+\beta^S)$ times its observed level if it acted efficiently; in other words, the good output could be increased by a proportion of $\beta^S$, a quantity equivalent to the segment CC''. On the other hand, when it is assumed that reducing risk is costly, the potential increase in the good output when point C is projected onto the frontier of $T^W$ comes down to the proportion $\beta^W$; or by the corresponding quantity CC'. This reduction of the *efficient* good output due to the weak disposability of risk is just what expression (7) measures; i.e., the loss of potential good output given by C'C''.

**Figure 5. Strong and weak disposability of outputs.**




In practice, computing the DDFs involved in our assessment of banking efficiency under the weak disposability axiom ($T^W$) and a direction that increases the good outputs, while maintaining productive resources and risk at observed levels, entails solving the following program for each bank b´:

$$\overrightarrow{\text{DDF}}^{\text{W}}[\text{y}, \text{r}, \text{x}; \text{g} = (\text{y}, 0{,}0)] = \text{Max}_{\text{z}^{\text{b}}, \mu^{\text{b}}, \beta_{\text{b}'}^{\text{W}}} \ \beta_{\text{b}'}^{\text{W}} \tag{8}$$

Subject to:

$(1 + \beta_{b'}^{W})y_{mb'} \leq \sum_{b=1}^{B} z_b y_{mb}$ $\quad m = 1,\ldots,M \quad$ (i)

$r_{hb'} = \sum_{b=1}^{B} z_b r_{hb}$ $\quad h = 1,\ldots,H \quad$ (ii)

$x_{nb'} \geq \sum_{b=1}^{B} (z_b + \mu_b) x_{nb}$ $\quad n = 1,\ldots,N \quad$ (iii)

$\sum_{b=1}^{B} (z_b + \mu_b) = 1$ $\quad$ (iv)

$z_b, \mu_b \geq 0$ $\quad b = 1,\ldots,B \quad$ (v)

In program (8) variable returns to scale (VRS) are imposed through restriction (iv) (Banker et al., 1984).[13] Nonetheless, as noted by Zago and Donceli (2011, p.542), the standard DEA-based specification grounded on VRS prevents the technology from satisfying weak disposability of both good and *bad* outputs (risk), thus hindering the usage of our risk-augmented model of performance. In order to overcome this weakness, we have used the approach proposed by Kuosmanen (2005) (see also Kuosmanen and Podinovsky, 2009), which allows performance assessment with VRS and weak disposability; accordingly, $\mu_b$ denotes the so-called *scale effect*, and $z_b$ stands for the *efficient effect* (further technical details are in Kuosmanen, 2005, p.1079–80).

Likewise, computing the DDFs against a technology with strong disposability ($T^S$) and the abovementioned direction vector that increases the good outputs, while maintaining inputs and risk, requires solving the following program, also for each bank b´:

[13] VRS is a common assumption in performance analyses in the banking industry (Barros et al., 2012). In practice, VRS means that each bank is compared against other observed banks of a similar size—or linear combinations of the production plan of two or more such observed banks—instead of against all banks in the sample. Given the large differences in size that exist in the Brazilian banking industry, in our opinion VRS is the most sensible assumption.

$$\overrightarrow{DDF}^S[y, r, x; g = (y, 0,0)] = \text{Max}_{\lambda^b, \beta^S_{b'}} \ \beta^S_{b'} \qquad (9)$$

Subject to:

$$(1 + \beta^S_{b'})y_{mb'} \leq \sum_{b=1}^{B} \lambda_b y_{mb} \qquad m = 1,\ldots,M \qquad (i)$$

$$r_{hb'} \leq \sum_{b=1}^{B} \lambda_b r_{hb} \qquad h = 1,\ldots,H \qquad (ii)$$

$$x_{nb'} \geq \sum_{b=1}^{B} \lambda_b x_{nb} \qquad n = 1,\ldots,N \qquad (iii)$$

$$\sum_{b=1}^{B} \lambda_b = 1 \qquad (iv)$$

$$\lambda_b \geq 0 \qquad b = 1,\ldots,B \qquad (v)$$

with $\lambda_b$ standing for the elements of the so-called intensities vector.

## 3.3.2 The metatechnology approach

One crucial assumption in Section 3.3.1 is that all banks in the sample share a common technology. However, certain banks may have no access to some production plans within the common technology due to regulations or other physical, social or economic factors in their environment. In such cases, the question arises as to whether their inefficiency is due to poor management or rather to the restrictions imposed by these environmental factors. The metafrontier approach by O'Donnell et al. (2008) allows some light to be shed on this question.

Let us define the *metatechnology* (MT) as the set of all feasible combinations of inputs, good outputs and risk available to the banking industry according to the state-of-knowledge, as defined in expression (1). It is assumed that the metatechnology also satisfies the axioms of null-jointness and weak disposability of outputs. The *directional metadistance function* (DMDF) can be computed against the metatechnology according to expression (5) in the particular case of assuming a direction that increases the good output while keeping inputs and risk the same. These DMDFs are assumed to fulfil the same properties as DDFs.

Furthermore, let us consider that the banks in our sample can be grouped into g = 1,…,G categories, according to criteria relating to features of their operating environment. As already noted, the central issue is that belonging to a given group might prevent banks from having access to the entire set of feasible production plans in the metatechnology.

That said, the technology of group g under weak disposability[14] representing the set of feasible production plans available to banks in that group is:

$$T^{Wg} = [(y, r, x)|\ x \text{ can be used by banks in group g to produce } (y, r)] \qquad (10)$$

Having defined the technology for group g, the DDF that allows us to compute the potential increase in the good outputs while maintaining the same level of inputs and risk with respect to the technology of that group is:

$$\overrightarrow{DDF}^{g} = [y, r, x; g = (y, 0,0)] = \text{Sup}[\beta^{Wg}|\langle(1 + \beta^{Wg})y, r, x\rangle \in T^{Wg}] \qquad (11)$$

By way of example, a computed score for the expression $(1 + \beta^{Wg})$ for a bank belonging to group g of, let us say, 1.1 would indicate that it could increase its good outputs by 10%, while maintaining the same level of risk and with no additional input usage, when compared to best observed practices within its own group. The DDF computed with respect to the technology of group g will be, by construction, always equal to or lower than the DMDF relative to the metatechnology; i.e., the potential of a bank to expand its good outputs when it is compared to the metatechnology will always be greater than that obtained when it is compared to banks in its own group.

Comparing the DMDFs obtained with respect to the metatechnology with the DDFs computed relative to the group frontiers allows us to define the metatechnology ratio for group g as:[15]

$$\text{Metatechnology ratio}^{g} = \frac{1 + \overrightarrow{DMDF}}{1 + \overrightarrow{DDF}^{g}} = \frac{(1 + \beta^{W})}{(1 + \beta^{Wg})} \qquad (12)$$

Expression (12) measures how close the technological frontier of group g is from the metafrontier, assessed in a direction that increases the good outputs while keeping both input usage and risk the same. As pointed out by O'Donnell et al. (2008, p.237), this approach allows for a suitable decomposition of *overall performance*, assessed with respect

[14] In the metatechnology approach we only define the technology with the assumption of weak disposability since it represents the *real world* in which reducing risk is costly.

[15] In order to avoid infeasibilities due to banks with DDFs equal to zero with respect to the technology of their own group, both the numerator and the denominator of the metatechnology ratio are formulated as one plus the directional function, either distance or metadistance function.

to the metafrontier, into i) *managerial performance*, measured with respect to the group technology; and ii) *group performance*, measured by the metatechnology ratio. In formal terms:

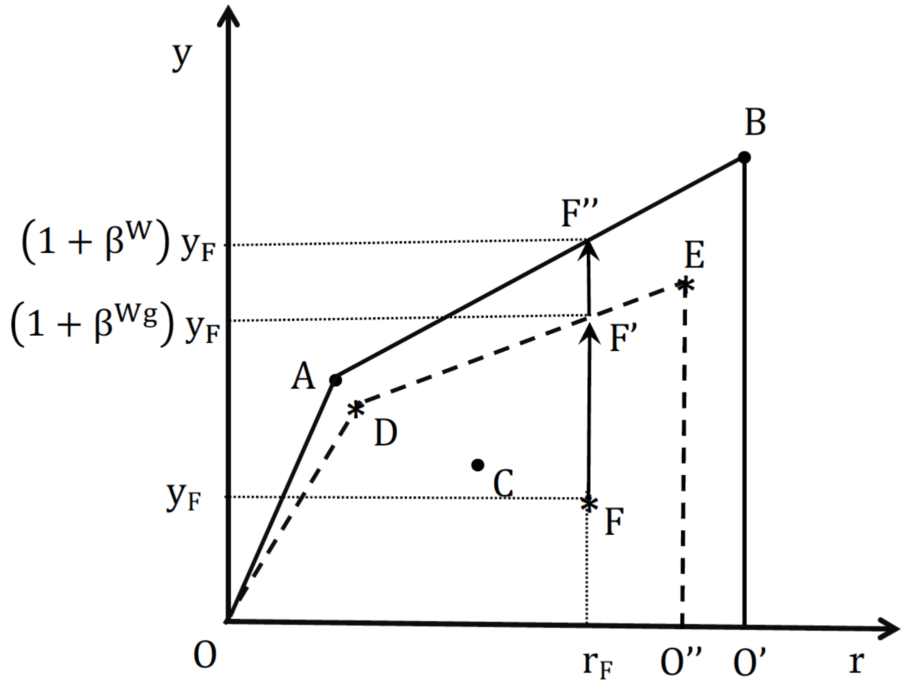
$$\text{Overall performance} = \text{Managerial performance}^{g} \text{ x Group performance}^{g} \qquad (13)$$

For illustrative purposes, an overall performance score of 1.5 for a given bank would mean that it could increase its good outputs by 50% for given inputs and risk. This score could be the result of, let us say: i) a managerial performance score of 1.2, meaning that using the best practices available to banks in its own group, the good outputs could be increased by 20%; and ii) a group performance score of 1.25, which means that, once the *efficient* levels of the good outputs against the group technology have been reached, an additional increase of 25% over those levels could be achieved if this bank used the best practices in the entire set of production plans available to the banking industry, given by the metatechnology.

Figure 6 graphically depicts this decomposition. Let us assume that banks in our sample can be classified into two groups: banks A, B and C (represented by dots) belong to group 1, while banks D, E and F (denoted by asterisks) belong to group 2. Efficient banks A and B and their convex combinations shape the technological frontier of group 1, which is given by the segment OABO'; likewise, the technological frontier of group 2 is ODEO'', which is shaped by efficient banks D and E and their convex combinations. It is also assumed that the metatechnology, or technological frontier for the whole sample, coincides with the frontier of group 1.

Let us now assess the performance of bank F belonging to group 2. Projecting its production plan onto the technological frontier of the group to which it belongs in, let us say, a North direction, yields point F'; i.e., by efficiently using the technology available to banks in its group bank F could attain a potential good output $(1 + \beta^{Wg})$ times its observed level; in other words, the good output could be increased by a proportion of $\beta^{Wg}$ (*managerial performance*). Similarly, projecting onto the metafrontier yields point F'', indicating that if bank F had access to the entire set of production plans in the metatechnology, it could achieve a good output of $(1 + \beta^{W})$ times its observed level; or a proportional increase of $\beta^{W}$ (*overall performance*). The difference between the good outputs at points F' and F'' is a measure of the effect on performance of belonging to a particular group (*group performance*).

**Figure 6. Performance, distance/metadistance functions and the metatechnology ratio.**




Using DEA, the metadistance functions involved in the calculation of the technology ratio of expression (12) can be directly computed from program (8) using the entire sample of banks; likewise, computing the distances with respect to group technologies requires running program (8) using only the sample of banks belonging to each group.

## 3.4 The production function in banking: Data, variables and sample

### 3.4.1 The production function in the banking industry

The existing literature has considered two main approaches to characterize the production function in the banking industry: the production approach and the intermediation approach. The former considers banks as firms that produce deposits and loan account services from traditional inputs; e.g., physical capital and labour. Conversely, the intermediation approach regards banks as financial intermediaries between savers and investors, which secure deposits and other funds and use them to produce different types of loans and other assets.

In this research, we use the intermediation approach (Sealey and Lindley, 1977), which is the most habitual in analyses of banking performance. Besides, we follow the asset approach for the selection of inputs and outputs, which considers banks as financial intermediaries only between liability holders and those who receive bank funds. Loans and other assets are considered bank outputs, whereas deposits and other liabilities play the role of inputs in the intermediation process (Berger and Humphrey, 1992).

Based on the abovementioned arguments, the inputs included in our characterization of the banking production function are i) staff expenses, to account for labour, and ii) non-earning assets, as a proxy of physical capital; in addition, we incorporate three financial inputs iii) equity; iv) customer deposits; and v) market liabilities, calculated as the sum of bank deposits, derivative financial instruments and trading liabilities. It should be noted that we have included a wide range of bank liabilities in order to account for the inputs of both commercial banks—which usually have a bigger role in the retail market—and investment banks—which are traditionally more market-oriented. On the other hand, conventional or good outputs are i) gross loans and ii) securities.

Finally, our variable accounting for the risk intrinsic to banking activity is the standard deviation of the return on assets (ROA), computed at the bank level over a five-year window. Furthermore, in order to perform a robustness analysis of our results we also consider the standard deviation of the return on equity (ROE) as an alternative measure of risk (see Liu et al., 2012). In both cases, a larger deviation represents higher risk.

## 3.4.2 Data and sample

The empirical analysis carried out in this research is based on data from Moody's Analytics BankFocus, a database that includes information about 55,700 banks worldwide. It is managed by the Bureau van Dijk and Moody’s Investors Service and the data come from a mixture of annual reports, information delivered by banks and regulatory sources. The dataset includes accounting and financial statistics that are highly suitable for making comparisons between banks, and also offer good coverage of the Brazilian banking industry.

According to this dataset, a total of 165 banks were operating in Brazil in the year 2019. The industry is highly concentrated as the five largest banks account for about 80% of total banking assets. Furthermore, the market is largely dominated by domes-tic institutions, both private and public. In fact, the five largest banks in terms of as-sets—Banco do Brasil, Itaú, Caixa Economica Federal (CEF), Bradesco and BNDES—are domestic; moreover, CEF and BNDES are majority state-owned. It is also worth highlighting the notable role in the Brazilian banking industry played by banks providing several banking services, including retail services, investment banking ser-vices, and brokerage services.

To build our sample, we have used yearly data from 2014 to 2019 inclusive for Brazilian banks in the BankFocus dataset.[16] At the time of writing this paper, 2019 was the last year for which data were available. Moreover, given the serious lack of data for some banks prior to 2014, it was considered advisable not to extend the sample any further back as its representativeness could be affected. It is important, however, to highlight that the use of data from several years is not primarily intended to analyse the time dimension of performance in the Brazilian banking industry, but to overcome a common limitation of DEA. This approach suffers from a lack of discrimination power when there is a small number of observations relative to the number of inputs and outputs; and this could be the case with our empirical application[17] (see Dyson et al., 2001, for details). Including more observations in the sample by considering the time dimension of the data is expected to greatly improve the discrimination power of our DEA-based models (Cooper et al., 2007; Jiménez-Hernández et al., 2019a). That said, it also entails the assumption that no significant technical change occurred over the period 2014-2019, which, in our view, is fairly plausible.

[16] Last access to the data was carried out through https://www.bvdinfo.com/en-us/our-products/data/international/bankfocus on January 14, 2021.

[17] Since our sample includes banks performing different activities, an unusually large number of inputs and outputs—including risk—need to be considered in the technology. Moreover, the metatechnology approach requires separately computing scores of performance for particular groups of banks—e.g., commercial and investment—which also reduces the sample size in some programs.

Thus, after removing banks with missing data for some of the variables defined in Section 4.1, and detecting and eliminating outliers by means of scatter plots and the *trimmean* function applied to 5% of the observations, our final dataset includes information on 124 Brazilian banks over the abovementioned six-year period. All bank and year observations have been pooled into a single sample. Moreover, given that data for some of the banks are not available in particular years, our final dataset includes a total of 543 observations. This final sample represents 97% of the total assets of Brazilian banks included in the Moody's Analytics BankFocus dataset for the period analysed; and 67% of the banks—a percentage that goes up to 75% in the year 2019, for which more data are available. Table 17 provides some descriptive statistics for the variables that represent the production process in banking. The high standard deviations of some of these variables brings to light the large size differences among the banks operating in the Brazilian banking industry.

**Table 17. Sample description (*constant 2018 $US million*)**

| | Mean | Standard deviation |
|---|---|---|
| *Inputs* | | |
| Staff expenses | 334 | 1,196 |
| Non-earning assets | 3,779 | 13,894 |
| Equity | 1,804 | 5,788 |
| Customer deposits | 6,179 | 23,792 |
| Market liabilities | 1,406 | 4,642 |
| *Good outputs* | | |
| Loans | 8,922 | 33,008 |
| Securities | 4,929 | 18,893 |
| *Risk* | | |
| Standard deviation of ROA | 1.91 | 3.54 |
| Standard deviation of ROE | 8.87 | 16.94 |

Source: Authors' elaboration from Moody's Analytics BankFocus.

## 3.5 Results and discussion

The results for the technical efficiency of Brazilian banks in the sample under both weak and strong disposability assumptions, in addition to potential good output losses, are in Table 18. These results have been obtained from programs (8) and (9) with the standard deviation of ROA computed over a five-year window, which includes the year to which the observation belongs and the four previous years, as a measure of risk; and from expression (7) for the potential output loss.[18] Above all, the low technical efficiency of the banking industry in Brazil stands out. In the scenario where it is assumed that reducing risk requires the use of resources that otherwise could be devoted to producing good outputs, banks in the sample could increase their loans and securities by a proportion of 65.1%, on average, without further usage of inputs and maintaining the same level of risk. The low efficiency of Brazilian banks has also been reported in previous studies such as Tabak et al. (2005), Souza et al. (2006) and, more recently, Henriques et al. (2018). However, the contribution of our research is that technical efficiency is evaluated while accounting for risk, which allows a more accurate assessment of performance.

Conversely, when it is assumed that reducing risk is a costless activity, the average proportional potential increase in the good outputs that could be achieved without consuming additional inputs is 69.1%, regardless of the level of risk. This finding clearly shows how reducing risk has a sizeable opportunity cost measured as a lower feasible expansion of the good outputs, thus supporting the bad management hypothesis, proposed by Williams (2004). The extent of the potential output loss due to weak disposability of risk can be interpreted as a reduction of 4 percentage points in the efficient level of the good outputs, on average.[19]

**Table 18. Estimates of technical efficiency (*1 best*) and potential output loss**

| | Mean | Standard deviation |
|---|---|---|
| Weak disposability assumption ($1 + \beta^W$) | 1.651 | 0.780 |
| Strong disposability assumption ($1 + \beta^S$) | 1.691 | 0.809 |
| Potential good output loss ($\beta^S - \beta^W$) | 0.040 | 0.157 |

Source: Authors' elaboration.

Several papers focused on the analysis of performance in the Brazilian banking industry have assessed the differences in efficiency between groups of banks. According to

[18] The DDFs have been computed using the DJL package in R software.

[19] This output loss would amount to an average potential increase in loans by bank and year of 356.8 million constant 2019 $US; and 197.1 million of securities.

the information provided by the Moody's Analytics BankFocus dataset, in our sample of 543 observations, 427 correspond to commercial banks whereas 116 are categorized as investment banks.[20] Moreover, 240 observations are identified as belonging to domestic banks, while 196 correspond to foreign banks; finally, 445 observations belong to private banks and only 12 to public ones.[21]

Table 19 displays the estimated scores of technical efficiency by groups of banks. It is worth highlighting that these scores of technical efficiency correspond to the scenario of weak disposability, which represents the *real world* where reducing risk consumes productive resources. At first glance, investment banks (score of 1.563, indicating that by behaving efficiently banks in this group could proportionally increase their good outputs by an average of 56.3%, without additional input usage and also maintaining the same level of risk) seem to perform better than commercial banks (score of 1.675); domestic banks (1.626) also achieve better performance than foreign ones (1.687); and finally, public banks (1.198) seem to be more technically efficient than private ones (1.693). These results are in line with Souza et al. (2006), which found Brazilian domestic banks to be more efficient than foreign ones, and Wanke and Barros (2014), which concluded that public ownership correlates with larger efficiency. However, given the large standard deviations of our efficiency scores, the question arises as to whether the abovementioned differences are statistically significant.

**Table 19. Estimates of technical efficiency (*1 best*) by groups of banks under the weak disposability assumption $(1+\beta^{W})$**

| | Mean | Standard deviation |
|---|---|---|
| Commercial banks | 1.675 | 0.785 |
| Investment banks | 1.563 | 0.753 |
| Domestic banks | 1.626 | 0.690 |
| Foreign banks | 1.687 | 0.860 |
| Private banks | 1.693 | 0.794 |
| Public banks | 1.198 | 0.293 |

Source: Authors' elaboration.

[20] Brazilian banks normally provide several banking services, including retail services, investment banking services, and brokerage services, as noted in Section 4.2. However, they have been categorized as commercial or investment banks according to their main activity reported to Moody's Analytics.

[21] For some of the banks in the sample, information regarding the ownership of capital—domestic *versus* foreign, or private *versus* public—is not provided by our source of data.

In order to further investigate this issue, we employ the Kolmogorov-Smirnov test of the equality of distributions, and the Mann–Whitney test that checks the hypothesis that two samples come from the same population (see Conover, 1999). In addition, we apply the Simar–Zelenyuk–Li test (Simar and Zelenyuk, 2006), which was explicitly designed for testing the equality of distributions of technical efficiency scores calculated using DEA. In essence, the algorithm of this test is based on the computation and bootstrapping of the Li statistic (Li, 1996) using DEA estimates, where scores equal to unity have been previously smoothed by adding a small noise component. The results are in Table 20. All three tests suggest that the difference of performance between commercial and investment banks is statistically significant. Besides, the results from both the Kolmogorov-Smirnov and Mann–Whitney tests point to the lack of significance of the difference in performance between domestic and foreign banks, although the Simar–Zelenyuk–Li test suggests weak significance, only at 10%. Finally, the technical efficiency of Brazilian private banks is statistically different from that of public ones, according to the results of the Kolmogorov-Smirnov and Mann–Whitney tests, but not the Simar–Zelenyuk–Li test.

**Table 20. Statistical significance of the differences in technical efficiency(1)**

| | Kolmogorov-Smirnov test (*KS-statistic*)(2) | Mann-Whitney test (*Z-statistic*)(3) | Simar-Zelenyuk-Li test (*Li-statistic*)(4) |
|---|---|---|---|
| Commercial *versus* investment | 0.168 (0.010)*** | -2.128 (0.033)** | 2.676 (0.003)*** |
| Domestic *versus* foreign | 0.105 (0.164) | -0.182 (0.855) | 1,363 (0.086)* |
| Private *versus* public | 0.359 (0.073)* | -2.140 (0.032)** | 0.188 (0.425) |

(1) *P-values* are in parentheses; ***, ** and * mean significance at 1%, 5% and 10%, respectively.

(2) Null hypothesis: the two samples have the same distribution; the exact *p-values* are computed.

(3) Null hypothesis: the two samples are drawn from the same population. *Z-statistic* adjusted for ties.

(4) Original estimates are smoothed using the algorithm II in Simar and Zelenyuk (2006, p.508).

Source: Authors' elaboration.

Given the aforesaid results, we can state with a high degree of confidence that Brazilian commercial banks perform differently from investment banks. However, reasonable doubts arise concerning the differences in performance between domestic and foreign banks, on the one hand, and between private and public banks, on the other. In the first case, only the Simar–Zelenyuk–Li test finds the difference to be (weakly) statistically significant. In the second, the reason is twofold: the Simar–Zelenyuk–Li test does not support the statistical significance of this difference, and this test is specifically designed for efficiency scores such as those calculated in this research; and there are only 12 observations in the group of public banks—belonging to the 2 banks observed over the period 2014-2019—which seriously limits the representativeness in this group. Accordingly, the following question arises: Why do Brazilian investment banks perform better than commercial ones?

### 3.5.1 Commercial versus investment banks: Managerial or group performance?

In Section 3.1 it was assumed that all banks in the sample share a common technology, regardless of the group to which they belong. However, in practice it might be the case that, due to particular environmental circumstances, some banks do not have access to the complete set of production plans available in the common technology. Thus, the question arises as to whether their inefficiency is due to poor management or to the technological restrictions imposed by such environmental factors. In this regard, the metafrontier approach developed in Section 3.2. helps us to further investigate the differences in performance between Brazilian commercial and investment banks.

Table 21 displays the results of decomposing the overall technical efficiency of commercial and investment banks as the result of managerial efficiency and group efficiency.[22] As already pointed out, the averages of overall efficiency for commercial and investment banks are 1.675 and 1.563, respectively, with the difference being statistically significant. Furthermore, when commercial banks are compared to best observed practices in their group, their managerial efficiency is, on average, 1.503; this score indicates that if all managers of commercial banks in the sample performed as efficiently as the best managers in the group, the good outputs could be increased by an average of 50.3% while

[22] Jiménez-Hernández et al (2019b) also employed this approach to assess the differences of efficiency in the management of non-performing loans between cooperative and commercial banks in the Latin American and Caribbean banking industry; see also Jiménez-Hernández et al (2019a).

maintaining input usage and risk the same. Average managerial efficiency for investment banks is 1.224, suggesting a potential increase in the good outputs of 22.4%. Although these figures cannot be directly compared to each other since they have been computed relative to different frontiers—i.e., the technologies of commercial banks and investment banks, respectively—they allow us to assert that, on average, the managers of investment banks are operating closer to their technological frontier than commercial bank managers are to theirs.

**Table 21. Managerial efficiency *versus* group efficiency (*1 best*)**

| | Commercial banks | | Investment banks | |
|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation |
| Overall efficiency $(1 + \beta^{W})$ | 1.675 | 0.785 | 1.563 | 0.753 |
| Managerial efficiency $(1 + \beta^{W_g})$ | 1.503 | 0.638 | 1.224 | 0.398 |
| Group efficiency $(1 + \beta^{W})/(1 + \beta^{W_g})$ | 1.109 | 0.227 | 1.250 | 0.367 |

Source: Authors' elaboration.

Comparing the scores of technical efficiency relative to both the metafrontier and the group frontiers allows the calculation of the metatechnology ratio for all banks in the sample, or group efficiency. As explained in Section 3.2, these ratios evaluate how close the technologies of investment banks and commercial banks are to the metatechnology or common technology, thus permitting an assessment of which technology is more efficient. According to our results, the average group efficiency of commercial banks is 1.109; this score indicates that even after reaching the level of the good outputs enabled by the best practices available to managers of commercial banks, a further increase of 10.9% over this level could still be achieved if the banks had access to the entire set of production plans in the metatechnology. Average group efficiency for investment banks is 1.250, pointing to an additional potential increase in the good outputs of 25%.

But is the difference in group efficiency between commercial and investment banks statistically significant? According to the results from the Kolmogorov-Smirnov and Mann-Whitney tests reported in Table 22, it is significant. Nonetheless, it is not significant according to the Simar-Zelenyuk-Li test, which, let us once again recall, is specifically designed for the type of efficiency scores computed in this research. Hence, we cannot robustly demonstrate that the technologies of Brazilian commercial and investment banks are different. In this regard, there have been historical technological differences between commercial banks and investment banks, mostly due to regulation and different operational capabilities. However, banking legislation has become less restrictive over the years, with a global trend towards the universal banking model; this shift has narrowed the technological differences between commercial and investment banks.

**Table 22. Statistical significance of the differences in group efficiency(1)**

| | Kolmogorov-Smirnov test (*KS-statistic*)(2) | Mann-Whitney test (*Z-statistic*)(3) | Simar-Zelenyuk-Li test (*Li-statistic*)(4) |
|---|---|---|---|
| Commercial *versus* investment | 0.190(0.002)*** | 2.871 (0.004)*** | 0.371 (0.355) |

(1) *P-values* are in parentheses; *** mean significance at 1%.

(2) Null hypothesis: the two samples have the same distribution; the exact *p-values* are computed.

(3) Null hypothesis: the two samples are drawn from the same population. *Z-statistic* adjusted for ties.

(4) Original estimates are smoothed using the algorithm II in Simar and Zelenyuk (2006, p.508).

Source: Authors' elaboration.

All in all, our results suggest that when technical efficiency is assessed while accounting for risk, Brazilian investment banks are more efficient than commercial banks. The reason is that investment banks have better managers—in the sense that they operate closer to their technological frontier representing best practices in the group—since no significant differences are found in the technology used by the two groups of banks.

Finally, the sensitivity of our findings to changes in the variable used to measure risk has been assessed by using the standard deviation of ROE instead of the deviation of ROA. This alternative scenario yields the same conclusions as those set out in the previous paragraphs. The numerical results are in the Appendix.

## 3.6 Conclusions

The study of performance in the banking industry has a deep-rooted tradition in the field of Economics. Since the 1980s, a bourgeoning literature has arisen devoted to analysing banks' performance from diverse approaches and perspectives. However, the related literature is less prolific when it comes to analysing the relationship between performance and risk. Although this matter has received increasing attention from researchers in the last two decades, there are still gaps that require further investigation.

This paper assesses the technical efficiency of Brazilian banks while accounting for risk. Our theoretical background is the *bad management* hypothesis posed by Williams (2004), which stresses that the management of risk requires the use of resources that could otherwise be dedicated to other productive activities; accordingly, efficiency is not independent of the risk levels that banks assume. Risk is proxied by the standard deviation of the return on assets (ROA). Furthermore, risk-conditioned scores of technical efficiency are calculated under two key assumptions, namely, that banking intermediation services cannot be produced without assuming a certain level of risk, whether high or low; and that risk can be treated as an undesirable or *bad* output from banking to be minimized. Regarding the methodology, non-parametric frontier techniques based on Data Envelopment Analysis (DEA) are applied to a sample of 124 Brazilian banks and data for the period 2014-19.

In line with some previous studies, we find that Brazilian banks are, on average, rather inefficient, although cross-bank differences are important. Moreover, an opportunity cost of maintaining risk at observed levels is found, which provides empirical support to the *bad management* hypothesis, and shows how assessing banking efficiency without properly accounting for risk could lead to biased results. Furthermore, we find robust statistical evidence that Brazilian investment banks perform better than commercial ones. Besides, domestic and foreign banks do not exhibit significant differences in performance; this result—which is in line with the findings reported by Sáez-Fernández et. al. (2015) for the Latin American and Caribbean banking industry—is perhaps a consequence of the successful adaptation of Brazilian domestic banks to the process of external opening and liberalization that began in the 1990s with the Washington Consensus.

Additionally, we find that investment banks outperform commercial ones because their managers are operating closer to the best practices available to them than commercial bank managers are to theirs; accordingly, no robust empirical evidence is found that the technologies of the two groups of banks are different. Put more simply, investment banks are more technically efficient because of their superior managerial performance. Although we have no clear-cut explanations for this finding, it could be related to the greater degree of specialization of investment banks, which would generate comparative advantages.

Investment banks may also have better qualified managers, which would seem essential given the type of clients they serve and the set of banking services offered.

It is our hope that the results from this research will provide bank managers and regulators of the banking industry in Brazil with sound information that can help them to improve both management and regulatory policies. In this regard, up to the best of our knowledge, we contribute the first assessment of Brazilian banks' performance accounting for risk, an intrinsic feature of financial activity that is displaying a growing trend in this turbulent new stage of the globalization era. Beyond this contribution, our research is not without its limitations, which may however pave the way for future work. We consider that further investigation is needed into the risk-conditioned performance of the Brazilian banking industry, using different methodological approaches and concepts of efficiency and risk. Moreover, a more in-depth analysis—i.e., using larger samples and more powerful statistical tests—of the possible differences in technology between groups of entities, as well as the causes of investment banks' superior performance in managerial efficiency, would also be welcome.

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# Appendix

**Table 23. Robustness check: Scores of technical efficiency (1 *best*) and potential output loss with ROE**

| | Mean | Standard deviation |
|---|---|---|
| Weak disposability axiom $(1 + \beta^W)$ | 1.639 | 0.774 |
| Strong disposability axiom $(1 + \beta^S)$ | 1.695 | 0.816 |
| Potential good output loss $(\beta^S - \beta^W)$ | 0.056 | 0.197 |

Source: Authors' elaboration.

**Table 24. Robustness check: Statistical significance of the differences in technical efficiency(1)**

| | Kolmogorov-Smirnov test (*KS-statistic*)(2) | Mann-Whitney test (*Z-statistic*)(3) | Simar-Zelenyuk-Li test (*Li-statistic*)(4) |
|---|---|---|---|
| Commercial *versus* investment | 0.174 (0.007)*** | -2.165 (0.030)** | 2.878 (0.002)*** |
| Domestic *versus* foreign | 0.101 (0.198) | -0.356 (0.721) | 1.406 (0.079)* |
| Private *versus* public | 0.363 (0.068)* | -1.990 (0.046)** | 0.163 (0.434) |

(1) *P-values* are in parentheses; ***, ** and * mean significance at 1%, 5% and 10%, respectively.

(2) Null hypothesis: the two samples have the same distribution; the exact *p-values* are computed.

(3) Null hypothesis: the two samples are drawn from the same population. *Z-statistic* adjusted for ties.

(4) Original estimates are smoothed using the algorithm II in Simar and Zelenyuk (2006, p.508).

Source: Authors' elaboration.

**Table 25. Robustness check: Managerial efficiency *versus* group efficiency (*1 best*), with ROE**

| | Commercial banks | | Investment banks | |
|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation |
| Overall efficiency $(1+\beta^{W})$ | 1.664 | 0.780 | 1.549 | 0.746 |
| Managerial efficiency $(1+\beta^{Wg})$ | 1.490 | 0.623 | 1.174 | 0.348 |
| Group efficiency $(1+\beta^{W})/(1+\beta^{Wg})$ | 1.110 | 0.231 | 1.295 | 0.425 |

Source: Authors' elaboration.

**Table 26. Robustness check: Statistical significance of the differences in overall efficiency and group efficiency[(1)] between commercial and investment banks, with ROE**

| | Kolmogorov-Smirnov test (*KS-statistic*)[(2)] | Mann-Whitney test (*Z-statistic*)[(3)] | Simar-Zelenyuk-Li test (*Li-statistic*)[(4)] |
|---|---|---|---|
| Group efficiency | 0.211 (0.001)*** | 3.101 (0.001)*** | 0.452 (0.325) |

(1) *P-values* are in parentheses; *** mean significance at 1% .

(2) Null hypothesis: the two samples have the same distribution; exact *p-values* are computed.

(3) Null hypothesis: the two samples are drawn from the same population; *Z-statistic* adjusted for ties.

(4) Original estimates are smoothed using the algorithm II in Simar and Zelenyuk (2006, p.508).

Source: Authors' elaboration.

Los coautores de los artículos que conforman esta tesis doctoral declaran que no los han presentado en otra tesis doctoral y manifiestan su renuncia a hacerlo en cualquier otra. Así mismo, informan que el trabajo llevado a cabo por el doctorando ha sido desarrollado conjunta y gradualmente con los demás coautores, por lo que la totalidad de los resultados novedosos de la tesis contienen una aportación atribuible al doctorando.