Measurement of efficiency and its drivers in the Chilean banking industry[*,†]

Adriana Cobas[‡] Alexandros Maziotis[§¶] Andrés Villegas[‖]

December 16, 2021

Abstract

This paper estimates efficiency measures for the banking system in Chile during 2000-2019. Apart from data updating, we depart in many dimensions from previous studies, using input distance functions, introducing the non-parametric slack-based model to measure efficiency at input level, and choosing the intermediates approach in the determination of inputs and outputs. Most inference is conducted using both parametric and non-parametric efficiency scores to evaluate whether methodological selection affects empirical conclusions. Our findings suggest that the Chilean system achieved high efficiency levels, performing on average at 75-90%, with no significant variations during the sample. There is an important heterogeneity between size groups both in levels and trends with smaller banks presenting the worst performance. Ownership (state, foreign and public trading) and size had a positive impact on efficiency. Merger and acquisitions processes, on average, seem to have targeted highly efficient banks to improve overall efficiency of the controller institution in the short term. At input level, deposits, operative expenses and capital stand out respectively for reaching the frontier level, presenting an increasing and a decreasing trend. We did not find categorical results in the effects of efficiency on bank variables, mostly in return heterogeneity and dividend policy. Regarding the models, we find that parametric techniques yield similar results between them and a significant distance from the non parametric ones in efficiency averages, scores and rankings. However, differences did not affect the relation with other variables and, in consequence, did not have impacts on most inference tests.

Keywords: Banks efficiency . Intermediates approach . Stochastic Frontier Analysis . Data Envelopment Analysis . Slacks Based Model . Double Bootsrap DEA

1 Introduction

The efficiency level of the banking system in an economy is related to a variety of relevant processes from the consolidation of the industry,[1] to financial stability,[2] and even economic growth.[3] Measuring the efficiency of a set of productive units, however, is a challenging objective due to its

[*]We are grateful for valuable suggestions from Alejandro Jara, José Matus, Felipe Cordova and Rodrigo Alfaro, as from participants at the 37th EBES Conference, 23rd INFER Annual Conference and SECHI 2021 Conference. We thank Javier Moreno for his excellent research assistance in this project.

[†]The opinions expressed in this article are the exclusive responsibility of the authors and do not necessarily represent the opinions of the Central Bank of Chile or its Board.

[‡]Central Bank of Chile. Agustinas 1180, Santiago, Chile. email: acobas@bcentral.cl

[§]Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile. Avda. Vicuña Mackenna 4860, Santiago, Chile

[¶]Department of Business, New York College. Av. Vasilissis Amalias 38, 105 58 Athens, Greece. email: alexandrosmaziotis@gmail.com

[‖]Escuela de Agronomía, Facultad de Recursos Naturales y Medicina Veterinaria, Universidad Santo Tomás, Ejército 146, Santiago, Chile. email: avillegas5@santotomas.cl

[1]Focarelli et al. (2002), Wheelock and Wilson (2004), Berger et al. (1999).

[2]Wheelock and Wilson (2000), Kick and Koetter (2007), Bos et al. (2009), Fiordelisi et al. (2011).

[3]King and Levine (1993a,b), Greenwood et al. (2010, 2016), Creel and Labondance (2015).

non-observable nature, the availability of multiple robust non converging methodological approaches, and the lack of consensus across the theoretical literature towards any of them. In this paper we update efficiency measures for the Chilean banking system to assess both salient features and recent dynamics in the industry. To overcome the measurement controversy, we incorporate multiple estimation techniques, as first proposed in Ferrier and Lovell (1990), and compare our results across them whenever possible.[4]

Over the past thirty years, the Chilean banking system has experienced a substantial consolidation process, going from over 40 banks by the mid-80s to 18 financial institutions in 2021. Simultaneously, other radical changes occurred such as the increase of international competitors in the industry, the opening to public capitalization, changes in regulation and the emergence of new business models more reliant on technology. Meanwhile, the profitability of Chilean banks ranks among the highest across countries with similar financial development levels. Substantial heterogeneity across domestic banks' profitability, although, suggests that different levels of banks' efficiency could explain both the trend in concentration and the high profitability levels.

The purpose of this paper is four fold. First, we update previous studies on efficiency in Chilean banking system to analyze the main features and most recent dynamics. Second, we employ several efficiency measures simultaneously in order to evaluate the impacts of methodology on final results. Third, we evaluate the effects on efficiency of the merger and acquisition process observed in the last decade, both the public and state ownership of the institutions, the size of the units, and the origin of investing capitals. Finally, we test whether efficiency can account for both the level and observed heterogeneity of system profits and in addition if efficiency gains are directed towards increases in market share, dividend payments or both.

Technical efficiency captures the best practices within an industry. Thus the production level at production frontier represents the maximum output attainable for each input level (Coelli et al., 2005). The determination of the set of relevant inputs and outputs, in the case of banking industry, distinguishes between intermediates and production approaches. We use the intermediates approach, most frequent in the literature, which assumes banks are intermediary institutions offering financial services. In this approach, inputs represent the sources of funds and outputs the uses of these funds.[5] Besides, this position besides embraces an important technological change in the industry, where branches and consequently fixed costs has increasingly been replaced by sophisticated softwares and then becoming less critical to produce financial services. The alternative production approach considers banks as producers of loans and deposits and then the last ones are assumed outputs of the production function. It has mostly been used to compare within an institution between branches.

Multiple works attempted to measure banks' efficiency in the Chilean banking sector. Budnevich et al. (2010), based on the estimation of a cost function, argued that both scale and scope economies existed during the 90s. Still, efficiency gains due to larger scale or economies of scope were moderate and relevant for smaller banks.

On the other hand, Alfaro and Franken (2001) with quarterly data in 1989.I-2001.II applied both parametric (econometric) such as Ordinary Least Squares (OLS), Seemingly Unrelated Regression (SURE) and Stochastic Frontier Analysis (SFA), and non-parametric (linear programming) such as Data Envelopment Analysis (DEA) techniques to measure banks' efficiency in the Chilean banking industry. They found that the distributional properties associated with the efficiency measures from different estimation techniques such as OLS and SURE were similar. The authors reported an average efficiency of around 90%. Results were slightly lower when using SFA method to measure efficiency and higher when using the DEA technique (75% and 87% respectively). Vergara (2006) employed SFA techniques to assess the efficiency of the Chilean banking sector by specifying several functional forms for the underlying technology such as a fourier flexible, translog and cobb-douglas. The author showed that on average efficiency did not remain constant over time and that there were no significant differences across the SFA models when using alternative functional forms. Carreño et al. (2010) based on a profit frontier analysis, showed a much lower average level of efficiency than previous studies. Still, they emphasized that the banking industry as a whole had improved its efficiency levels dramatically since the late 1990s. Finally, Sepúlveda et al. (2019) used a non-

[4]For Chilean data, Alfaro and Franken (2001) have already followed a multi measure approach.

[5]First proposed in Sealey and Lindley (1977).

parametric technique to measure efficiency and showed that the Chilean bank sector's efficiency was around 85% on average.

We find many elements common across all the studies above. First, they used a cost or profit function approach which means that prices for inputs or outputs are required. Even if the data is available, it might not have enough variation thus resulting in biased estimates of input or output elasticities. Second, all previous studies use methodologies that do not allow for the inclusion of multiple inputs and outputs in the efficiency analysis. Third, all models assumed a proportional contraction of all inputs to generate the same level of output. Finally, all previous studies assumed a production approach when selecting inputs and outputs in the model estimation.

Within this context, and besides the assessment with updated data, we make several contributions to the banking efficiency literature in Chile. First, we use an input distance function approach which does not require price data and allows us to incorporate multiple inputs and outputs simoultaneously. This model further permits us to assess the impact of several operating characteristics such as ownership type and mergers on banks' costs and efficiency. Second, we introduce the non-parametric slack-based model, which allows us to observe efficiency at input level using simultaneous contractions of inputs and expansion of outputs. Third, we apply the intermediates approach which we consider more aligned with current banking production technology. Finally, opposed to most studies (except Alfaro and Franken 2001), we estimate and compare across parametric and non-parametric models to assess whether methodological selection is relevant for empirical conclusions.

Overall, we found that the banking system achieved a high efficiency level on average (in line with previous studies) yet with some room for improvement. During the period of analysis, our models did not identify time trends for the system and, in contrast, they suggest that level persisted relatively constant in time. However, efficiency presents a substantial heterogeneity both in level and trends when analyzed at size clustered institutions.

Regarding environmental drivers, our estimates suggest that ownership (state, public trade and foreign) and size contributed to increase efficiency. Merger and acquisition processes had a significant effect on efficiency but only in the short term (at impact or up to one quarter lag). The impact was positive, which means that targeted institutions were already highly efficient when acquired, then contributing to overall efficiency at controlling institution.

Estimation at input level, allow us to identify deposits as those in which institutions perform most efficiently. Meanwhile, operative expenses appear as the one input that experienced the steepest increase in the period sample. Finally, capital efficiency is the only input with a decreasing trend accentuated in the banks oriented to consumption credit. In this particular case, risk hedging and extraordinary high returns explain the excess capital allocation and thus the low levels of efficiency in this group of banks.

In model selection, we found that methodology does have an impact on the level of efficiency obtained. Differences decrease among non parametric models and increase between them and the parametric results. On the contrary, model selection, did not substantially affect the conclusions of most econometric tests: environmental drivers of efficiency, effects of merger and acquisitions, and the identification of time trends. That, however was not the case of the relation between efficiency heterogeneity and the heterogeneity of returns where models yielded mixed non conclusive results.

Finally, we assessed the relationship with returns, dividends and market share and found (in the case of DEA efficiency) that efficiency dynamics impacts on returns up to 6 months afterwards. In addition, changes in efficiency precede by one quarter changes in market share which means that the pass through from efficiency to prices and then market share is not immediate. There was not, however a clear definition of precedence when we related efficiency and both dividend and dividend policy. Possibly it is because these decisions entail a much complex set of determinants.

The rest of the paper is organized as follows. In section 2 we present the main empirical alternatives to assess efficiency and discuss advantages and disadvantages of using each of them. Section 3 thoroughly presents each of the estimation models we used in the paper. Section 4 introduces the data used and presents empirical results. In Section 5 we include final considerations and conclude.

2 Discussion on efficiency measures

Empirical measures of efficiency coincide in the overall procedure: build an efficient frontier for the industry across time and then score each productive unit according to its distance to that. The differences among techniques arise from the amount of structure imposed, and the assumptions made for both the frontier's shape, and the error term's distributional properties. From the available methods, the most frequently applied group into parametric and non-parametric techniques.[6] In what follows, we briefly discuss the main features of each of them.

The Stochastic Frontier Analysis (SFA)[7] is the main parametric technique. It consists of the econometric estimation of either a costs, production, or profits relationship among inputs and outputs. Caiazza et al. (2016) summarize all these alternatives in an equation such as (1).

$$y_{it} = x_{it} + \epsilon_{it} \tag{1}$$

where i represents the productive unit, y stands for industry outputs (or costs or benefits), x is a vector of inputs. The error term is a composite in the form $\epsilon_{it} = \varepsilon_{it} + u_{it}$. The equation assumes a functional form to combine inputs, in general, a Cobb Douglas or a translog form. u_{it} represents total inefficiency and requires a distribution assumption[8] while ε_{it} captures some random noise following the standard normal distribution. Conditioned by the noise term, any departure from efficient level derives from the inefficiency score.

The main advantage of this method lies in the error term. First, the noise component allows for occasional deviations in efficiency due to unexpected events. Second, it admits the use of statistical inference on results.

The disadvantages originate in the assumptions required to run the model both the functional form of the interest relation and the distribution of the error term. For the underlying technology, translog, and Cobb-Douglas are the most widely used functional forms (other alternatives are Fourier flexible, composite or quadratic). The latter assumes constant returns to scale, can be used when the number of observations is small and is easy to converge. The translog functional form assumes that the size of the companies varies then introducing multiple returns to scale, takes into account interaction among variables which allow the measurement of substitutability/complementarity among inputs and outputs and is easy to estimate. For the functional form selected, the results only hold if all the sample units use the exact same technology to combine inputs and outputs. This assumption might be very strong when sample pools banks divergent in scale, market niche coverage, clientele, country, regulation, etc.

Non-parametric frontiers such as Data Envelopment Analysis (DEA) takes into account the productive unit heterogeneity by not assuming any frontier structure and eliminating the efficiency error. In terms of Berger and Humphrey (1997), DEA is a linear programming model where the frontier is determined by maximizing outputs, given available inputs, or minimizing inputs, given total outputs. The frontier results from the best convex combination of factors according to one of these goals. It does not require the assumption of an efficiency error and its main advantage is simplicity at implementation.

Thus the program in (2) determines all the linear combinations of inputs x_i and outputs y_i that yield the production set ψ.

$$\psi = \{x, y \in R_+^{p+q} : \; y \leq \sum_{i=1}^{n} \gamma_i y_i, \; x \geq \sum_{i=1}^{m} \gamma_i x_i, \; \sum_i \gamma_i = 1 \;\; \gamma_i \geq 0, \; i = 1...n\} \tag{2}$$

Where, $\gamma_1, \gamma_2, ..., \gamma_3$ are intensity variables that make ψ the smallest convex free-disposal cone enveloping all banks in the sample.

[6] In the specific case of bank efficiency, Bhatia et al. (2018) survey 15,192 studies in 1998-2017. They find that 49% used non-parametric methods, 40% used parametric methods and the rest divide between semi-parametric methods and a mixture of techniques.

[7] Proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

[8] Half normal, gamma, or truncated normal, uniform, beta and doubly truncated normal are the most used (Bhatia et al., 2018).

The main drawback here is that the linear optimization technique is deterministic and does not include random errors. In terms of efficiency, it implies that there is no room for randomness, and as a consequence, any deviation from the frontier is completely attributed to efficiency gains or losses. Moreover, any measurement error or unintended productivity shock in each unit will compute the system frontier affecting all the units' scores in the sample. Also, it is very sensitive to extreme values. A second problem is the inability to directly include other explanatory variables such as controls. This limitation is especially relevant in the framework of banks performance comparisons since it is well-known that several exogenous variables influence banking efficiency. To overcome this limitation, Simar and Wilson (2007) extended the bootstrap method on efficiency scores[9] and developed a double-bootstrap DEA (DBDEA) procedure that enables statistical inference and hypothesis testing in DEA models. In other words, reliable results are obtained with this approach since it helps to identify the determinants of efficiency.

The Slack Based Model (SBM),[10] is another non parametric technique. It shares with DEA the use of linear programming tools and the lack of an error term to allow for random deviations inheriting all the advantages and disadvantages discussed above. An advantage over DEA is that it measures non radial efficiency (non linear) and identifies deviations of efficiency at input/output level. The radial measure of efficiency in the previous models means that convergence towards the frontier implies a contraction of all inputs for a given level of outputs. In contrary, non radial models allows measure an efficiency score for each input and potential savings.

In summary, all available methods to estimate efficiency present caveats. Parametric approaches can produce misspecification errors, which might drive to over or underestimate efficiency. Non-parametric models attribute any deviation of the frontier to inefficiencies, avoiding economic, technical, or measurement shocks. The solutions proposed from the theoretical literature are to destructure parametric models or to randomize non-parametric ones (resampling). From an empirical point of view, although authors signal that results from DEA or SFA are similar (Cummins and Zi 1998, Casu et al. 2008) others recommend a parsimonious strategy to estimate using both methodologies first and then compare them in robustness checks.

3 Efficiency models

3.1 Stochastic Frontier Analysis

To estimate the stochastic frontier we follow an input minimization approach in which banks minimize their inputs to obtain a determinate level of output. Let's assume that the production technology consists of a set of several inputs, x, that is employed to produce a vector of outputs, y. The production technology T is determined as follows:

$$T = \{(x, y) : x\, can\, generate\, y\} \tag{3}$$

When the production technology consists of multiple inputs and outputs, it can be represented by either the input distance function[11] or the cost function approaches. In this case, we choose the first one which is a dual to cost function and overcomes the limitation of requiring input prices.[12] The input distance function in (4) measures the maximal radial contraction of all inputs for a given level of outputs (Coelli et al., 2005):

$$D_I(x, y) \equiv max\{\theta : \left(\frac{x}{\theta}, y\right) \in T, \theta > 0\} \rightarrow D_I(x, y) = \frac{1}{TE} \tag{4}$$

where θ denotes the technical efficiency score of each bank, which means that each bank can reduce the use of its resources by $1/\theta$ and still produce the same level of output (Coelli et al., 2013).

[9] For more details see Simar and Wilson (1998, 2000).
[10] Proposed in Tone (2001).
[11] Developed by Shephard (1953).
[12] Both data-intensive and hard to obtain (Das and Kumbhakar, 2012).

A bank is technically efficient when $D_I(x,y)=1$. If the bank is technically inefficient it follows that $D_I(x,y)=(1/TE)\geq 1$, where TE is Farrell's input-oriented measure of technical efficiency and $lnD_I(x,y)\geq 0$ is the technical inefficiency of the bank (Ferro and Mercadier, 2016). The input distance is non-increasing in outputs, non-decreasing in inputs and linear homogeneous in inputs.[13]

The next step in our analysis is to specify a functional form for the bank's input oriented distance function. Following several studies,[14] we use a translog functional form to present the technology as much flexible as possible and control for the different size of the banks (i.e. allow economies of scale to vary) in (5):

$$\begin{aligned}lnD_I(x,y) = a_j + \sum_{l=1}^{L} a_l\, lny_{ljt} + \sum_{k=1}^{K} \beta_k\, lnx_{kjt} + \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L} a_{lm}\, lny_{ljt}\, lny_{mjt} \\ + \frac{1}{2}\sum_{k=1}^{K}\sum_{n=1}^{K} \beta_{kn}\, lnx_{kjt}\, lnx_{njt} + \sum_{l=1}^{L}\sum_{k=1}^{K}\gamma_{lk}\, lny_{ljt}\, lnx_{kjt} + \psi_1 t \\ + \frac{1}{2}\psi_2\, t^2 + \sum_{k=1}^{K}\delta_k\, lnx_{kjt}t + \sum_{l=1}^{L}\xi_l\, lny_{ljt}\, t + \sum_{z=1}^{Z}\mu_z z_{jt} + \epsilon_{jt} \quad (5)\end{aligned}$$

where j represents the bank and t is the time period, L and K capture the total number of outputs and inputs, respectively, and α, β, γ, μ, δ, ξ are parameters that need to be estimated. The error is represented by ϵ_{jt} which follows the normal distribution, $\epsilon_{jt}\sim N(0,\sigma_\epsilon^2)$. a_j are firm-specific effects and capture firm unobserved heterogeneity such as managerial inability. This unobserved heterogeneity is assumed to be fixed and time invariant (Greene, 2005). This is the so-called "true" fixed effect model developed by Greene (2005) which separates unobserved heterogeneity from time varying technical inefficiency (please also see eq. (6)). Moreover, in expression (5) we include a set of operating characteristics (control variables) that could impact input requirements (Saal et al. 2007, Molinos-Senante et al. 2017).

After imposing homogeneity of degree 1 in inputs we get the final estimable form of the input distance function in (6):

$$\begin{aligned}-\, lnx_{Kj} = a_i + \sum_{l=1}^{L} a_l\, lny_{ljt} + \sum_{k=1}^{K-1} \beta_k\, lnx^*_{kjt} + \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L} a_{lm}\, lny_{ljt}\, lny_{mjt} \\ + \frac{1}{2}\sum_{k=1}^{K-1}\sum_{n=1}^{K-1} \beta_{kn}\, lnx^*_{kjt}\, lnx^*_{njt} + \sum_{l=1}^{L}\sum_{k=1}^{K-1}\gamma_{lk}\, lny_{ljt}\, lnx^*_{kjt}\,\psi_1 t \\ + \frac{1}{2}\psi_2 t^2 + \sum_{k=1}^{K=1}\delta_k\, lnx^*_{kjt}t + \sum_{l=1}^{L}\xi_l\, lny_{ljt}t + \sum_{z=1}^{Z}\mu_z\, z_{jt} + \epsilon_{jt} - u_{jt} \quad (6)\end{aligned}$$

where $x^*_{kj}=x_{kj}/x_{Kj}$ and u_{jt} is the technical inefficiency of each bank j at any time t and is assumed to follow the exponential distribution, $u_{jt}\sim\varepsilon(\sigma_u^2)$. Technical efficiency of each bank j at any time t is calculated as $TE_{jt}=exp(u_{jt})$.

Thus, Eq. (6) is the final SFA model because it includes both noise and inefficiency. It is estimated using maximum likelihood estimation (MLE) techniques (Greene 2005, Kumbhakar et al. 2015). Finally, the restrictions needed for the imposition of the homogeneity in +1 in inputs are as follows (Coelli et al., 2013):

$$\sum_{k=1}^{K}\beta_k = 1,\;\; \sum_{n=1}^{K}\beta_{kn} = 0\;\;\forall k, \sum_{l=1}^{L}\gamma_{lk} = 0\;\;\forall l, \sum_{k=1}^{K}\delta_k = 0\;\;\forall k \quad (7)$$

[13]For the properties of the distance function please see Färe and Primont (1995), Lovell et al. (1994), Färe et al. (1994).

[14]See for instance Orea (2002), Rezitis (2008), Das and Kumbhakar (2012), Coelli et al. (2013), Kumbhakar et al. (2015).

Finally, we impose conditions in (8) for symmetry (Das and Kumbhakar, 2012):

$$a_{lm} = a_{ml} \quad \forall m, \quad \beta_{kn} = \beta_{nk} \quad \forall n \tag{8}$$

3.2 DEA

In the framework of banking industry, previous studies (Nigmonov 2010, Zreika and Elkanj 2011, Arshinova 2014, Titko et al. 2014) have adopted input orientation. The argument is that the bank managers have more control over inputs rather than over outputs (Fethi and Pasiouras, 2010). In relation to scale assumption, variable returns to scale (VRS) is considered to be more appropriate than constant returns (CRS), because in banking sector such factors, as imperfect competition or government regulations, may cause the deviation from an optimal scale (Coelli et al., 1998).

Given a set of banks, $j = 1,\ 2, \ldots, N$ each one using a vector of S inputs $x_j = (x_{1j},\ \ x_{2j,\ldots,}\ x_{Sj})$ to produce a vector of L outputs $y_j = (y_{1j},\ \ y_{2j,\ldots,}\ y_{Lj})$. Assuming variable returns to scale (VRS) technology, the input-oriented DEA model employed to estimate efficiency scores is as follows (Banker et al., 1984):

$$\begin{aligned} Min\ \theta_j \\ s.t. \\ \sum_{k=1}^{N} \gamma_k x_{ik} \leq \theta_j x_{ij}, \quad 1 \leq i \leq S \\ \sum_{k=1}^{N} \gamma_k y_{rk} \geq y_{rj}, \quad 1 \leq r \leq L \\ \sum_{k=1}^{N} \gamma_k = 1 \\ \gamma_k \geq 0, \quad 1 \leq k \leq N \end{aligned} \tag{9}$$

when $\theta_j = 1$ banks are technically efficient, and they are inefficient when $\theta_j < 1$. Thus, $1 - \theta_j$ is the proportional inputs reduction that can be achieved by the j th bank given the output level and N denotes the number of banks. The γ_i represent a non-negative intensity variable used to scale individual observed activities for constructing the piecewise linear technology.

3.3 Double boostrap DEA

The DBDEA procedure applied is referred to as Algorithm 1 of Simar and Wilson (2007) which can be summarized in the following steps:

1. Compute $\hat{\theta}_j$ for all banks in the sample by using (9).
2. Use those M (with $M < N$) banks, for which $\hat{\theta}_j > 1$ holds, in a truncated regression (left-truncation at 1) of $\hat{\theta}_j$ on z_j to obtain coefficient estimates $\hat{\beta}$ and an estimate for variance parameter $\hat{\sigma}$ by maximum likelihood.
3. Loop over the following steps 3(a)–3(c) B times, in order to obtain a set of B bootstrap estimates $(\hat{\beta}^b, \hat{\sigma}^b)$, with $b = 1, ..., B$.
   (a) For each bank $j = 1, ..., M$, draw an artificial error $\tilde{\varepsilon}_j$ from the truncated $N(0, \hat{\sigma})$ distribution with left-truncation at $1 - z_j\hat{\beta}$.
   (b) Calculate artificial efficiency scores $\tilde{\theta}_j$ as $z_j\hat{\beta} + \hat{\varepsilon}_j$ for each bank $j = 1, ..., M$.
   (c) Run a truncated regression (left-truncation at 1) of $\tilde{\theta}_j$ on z_j to obtain maximum likelihood, bootstrap estimates $\hat{\beta}^b$ and $\hat{\sigma}^b$.
4. Calculate standard errors for $(\hat{\beta}, \hat{\sigma})$ from the bootstrap distribution of $(\hat{\beta}^b, \hat{\sigma}^b)$.

3.4 Slacks Based Model

Starting from the expression in (2), we define two vectors $v^+ \geq 0$ and $v^- \geq 0$, called slacks, that indicate input excess or output shortfall for each productive unit with inputs x_0 and outputs y_0:

$$\begin{aligned} x_0 &= \sum_i x_i \gamma_i + v^- \\ y_0 &= \sum_i y_i \gamma_i + v^+ \end{aligned} \tag{10}$$

A SBM of efficiency is applied to evaluate the efficiency together with the slack value. The following index κ

$$\kappa = \frac{1 - \frac{1}{S}\sum_{i=1}^{S} v_i^- / x_{i0}}{1 + \frac{1}{L}\sum_{r=1}^{L} v_i^+ / y_{i0}} \tag{11}$$

is defined in terms of the amount of slack, and has the value between 0 and 1.

Finally, efficiency measure obtains from minimizing (11) subject to conditions (10) in addition to $\lambda \geq 0$, $v^+ \geq 0$, $v^- \geq 0$.

The formula in (11) can be transformed into (12), where the ratios in the numerator and denominator indicate inputs and outputs inefficiencies respectively:

$$\kappa = \frac{\frac{1}{S}\sum_{i=1}^{S} (x_{io} - v_i^-) / x_{io}}{\frac{1}{L}\sum_{r=1}^{L} (y_{ro} + v_r^+) / y_{ro}} \tag{12}$$

According to Tone (1997, 2001), we can modify the denominator of the measure κ by introducing a small positive number, $\phi = 10^{-6}$, as:

$$\kappa = \frac{1 - \frac{1}{S}\sum_{i=1}^{S} v_i^- / x_{i0}}{1 + \frac{\phi}{L}\sum_{r=1}^{L} v_i^+ / y_{i0}} \tag{13}$$

This modification corresponds to the input-oriented model which establishes more relevance on the input slacks than the output ones.

4 Data and empirical findings

4.1 Data

We use monthly accounts from balance sheet and income statements of Chilean banks from 2000 to 2019 available at Comisión para el Mercado Financiero (CMF). The sample was restricted to big, medium, and consumption banks according to clustering in Jara and Oda (2015) (reproduced in Appendix A). All income statement variables are 12 months accumulated and the whole set of variables were deflacted using July 2005=100 which minimizes the distance to period's average inflation.

Inputs and outputs, were selected applying the intermediates approach,[15] most frequent in banking efficiency literature. It consists of assuming a financial intermediaries production function according to which banks receive funding from different sources and allocate it in multiple investment alternatives, such as credits or market assets.[16] Table 1 lists the variables used across the models. The inputs are deposits, regulatory capital, issued bonds and operating expenses (includes salaries, buildings rent, utilities, information plus interests paid). The outputs are loans and other earning assets (liquid assets plus financial investments). Finally, we have other variables such as cluster, ownership in several dimensions (public, state, foreign), inflation, GDP growth (using monthly IMACEC Index at Central Bank of Chile). For the cases of merger and acquisitions, we have a dummy equal to one the entire year of occurrence.

[15] First proposed in Sealey and Lindley (1977).

[16] The alternative production approach assumes both deposits and credits as outputs of the production function while employees and fixed assets are the main inputs. It has mostly been used to compare attained efficiency between branches within an institution.

Table 1: Sample description.

	Variable		Obs.	Avge.	SD
Inputs (CLP mm)	Operating expenses		3683	287	299
	Deposits		3683	3210	3780
	Capital		3683	574	694
	Issued Bonds		3683	677	1220
Outputs (CLP mm)	Loans		3683	4330	5190
	Financial earning assets		3683	1500	1880
Continuous Explanatory Variables	IMACEC Index		3683	84	18
	Variable		**Obs.**	**% of total**	
Categorical Explanatory Variables	Cluster	Big	1015	28	
		Medium	2006	54	
		Consumption	662	18	
	State owned		240	6.5	
	Foreign		1331	36	
	Public Traded		1652	45	

Average exchange rate 2000−2019 is CLP1.00 =USD586.47.

4.2 Stochastic Frontier Analysis

Table 2.a presents the estimated results from the input distance function. Variables were normalized around their mean so that the first-order estimated coefficients of inputs and outputs can be interpreted as elasticities at the sample mean. As expected, output elasticities have a negative sign and are statistically significant, which means that increases in outputs cut the distance to the frontier (Ferro and Mercadier, 2016). Input elasticities have a positive sign and are statistically significant from zero, so that increases in inputs augment the distance to the frontier. We can then conclude that the input distance function is both non-increasing in outputs and non-decreasing in inputs which implies that the model is well-specified (Ferro and Mercadier, 2016).

From the elasticities of loans and financial earning assets we can say that, keeping other things equal, a 1% increase in loans and financial earning assets could lead to average increases in operating costs of 0.8712% and 0.1366%, respectively. The finding suggests that loans are a major cost driver for the banking sector.

The elasticities of deposits, capital, bonds and operating expenditures suggest that deposits and capital are major determinants of input requirements in the Chilean banking sector.

Both loans and financial earning assets have been increasing costs at a rate of 15% and 5.6%, respectively as indicated by the negative sign of their squared term. The positive sign in the interaction term between loans and financial earning assets, which is significant, signals a cost complementarity between them. On average, an increase in the provision of more loans could lead to an increase in financial earning assets which could lead to lower costs and thus push up the performance of the bank. Moreover, on average as deposits grow its elasticity increases, whereas the opposite is true for capital as indicated by the squared terms of these variables.

Increases in loans are accompanied by increases in deposits and capital as indicated by the statistically significant and positive sign of their cross input-output terms (not alike is the case of financial earning assets which resulted non significant). Consequently, this could lead to lower input requirements on average which could have a positive impact on the performance of the bank. A similar result is observed from the interaction term between bonds and loans.

Furthermore, the interaction term between both deposits and capital and deposits and bonds is negative and statistically significant from zero. This means that there were some substitution possibilities between these two inputs which might not have led to lower costs on average.

The time variable, that captures technical change was not statistically significant. It has a negative sign which means that the banking sector experienced a technical regress of 0.03% per year on average. The same occurs in the case of technical regress with a positive although non

Table 2: Empirical model results.

2.a SFA model, dependent variable: Opex

Frontier	**Coefficient**	**St.Er.**
Loans	-0.8712***	0.0096
Fin. ear. as.	-0.1366***	0.0064
Deposits	0.4251***	0.0147
Capital	0.3991***	0.0142
Bonds	0.0284***	0.0032
Loans^2	-0.1509***	0.0059
Fin. ear. as.^{2}	-0.0558***	0.0037
Loans*Fin. ear. as.	0.0677***	0.0043
Deposits^2	0.0320***	0.0009
Capital^2	-0.0063	0.0154
Bonds^2	0.0028***	0.0003
Deposits*Loans	0.0316***	0.0040
Deposits*Fin. ear. as.	0.0018	0.0051
Capital*Loans	0.0158**	0.0075
Capital*Fin. ear. as.	0.0059	0.0063
Bonds*Loans	0.0058***	0.0004
Bonds*Fin. ear. as.	-0.0024***	0.0003
Deposits*Capital	-0.0829***	0.0089
Deposits*Bonds	-0.0053***	0.0007
Capital*Bonds	0.0023***	0.0007
Loans*Time	0.0007	0.0006
Fin. ear. as.*Time	-0.0009*	0.0006
Deposits*Time	0.0060***	0.0012
Capital*Time	-0.0037***	0.0012
Bonds*Time	-0.0002***	0.0000
Time	-0.0003	0.0005
Time^2	-0.0001	0.0003
Medium	-0.0589**	0.0250
Consumption	-0.2234***	0.0528
State	0.1071***	0.0250
Foreign	0.1436***	0.0123
Public trading	0.0969***	0.0143
Imacec	0.0004	0.0003
M&A ocurred	0.0693**	0.0293
L3.M&A ocurred	0.0394	0.0269
L6.M&A ocurred	0.0126	0.0260
L12.M&A ocurred	0.0066	0.0234

2.b DBDEA, dependent variable: DEA scores

Frontier	**Coefficient**	**St.Er.**
Medium	-0.2698***	0.0124
Consumption	-0.4679***	0.0139
State	0.1115***	0.0244
Foreign	0.0825***	0.0075
Public Trading	0.0002	0.0062
M&A ocurred	0.1301	0.1139
L3.M&A ocurred	0.2007*	0.1088
L6.M&A ocurred	0.0983	0.0926
L12.M&A ocurred	0.0493	0.0695
2001.year	-0.0185	0.0194
2002.year	-0.0138	0.0210
2003.year	0.0187	0.0238
2004.year	0.0847***	0.0322
2005.year	0.0511	0.0389
2006.year	0.0080	0.0496
2007.year	0.0068	0.0572
2008.year	-0.1131*	0.0645
2009.year	-0.0901	0.0619
2010.year	0.0378	0.0721
2011.year	-0.0548	0.0854
2012.year	-0.0955	0.0972
2013.year	-0.0840	0.1063
2014.year	-0.1227	0.1100
2015.year	-0.1221	0.1152
2016.year	-0.1046	0.1190
2017.year	-0.0691	0.1229
2018.year	-0.0498	0.1336
2019.year	-0.0857	0.1362
cons	1.0175***	0.1398
σ	0.1320***	0.0025

significant coefficient of 0.01%. Moreover, the interaction term of deposits with time is positive, whereas the interaction term between capital and bonds with time are negative. This means that technical change has been deposits saving and capital and bonds using.

The discussion on the control variables, cluster, ownership and merger and acquisition, is in subsection 4.3 along with DBDEA results on that matter.

4.3 Efficiency drivers using a multimodel approach

In this section we use our estimations to analyze the evolution of efficiency at both aggregate and disaggregate levels, the effect of environmental variables and of corporate events. In all cases we use both parametric and non parametric estimates in order to identify eventual implications of methodology in results.

4.3.1 System efficiency

Chilean banking system performs in the top quarter efficiency range across models as depicted in Figure 1, leaving some room for improvement. Average system efficiency ranges between 75% in SBM and 90% in SFA model. We also estimated SFA model without other explanatory variables for a fair comparison with non parametric models. Nevertheless, this estimate yielded only negligible differences with the general version, as the figure shows. An interesting feature is that in both models mean and median diverge in the last decade, which will discuss further below.

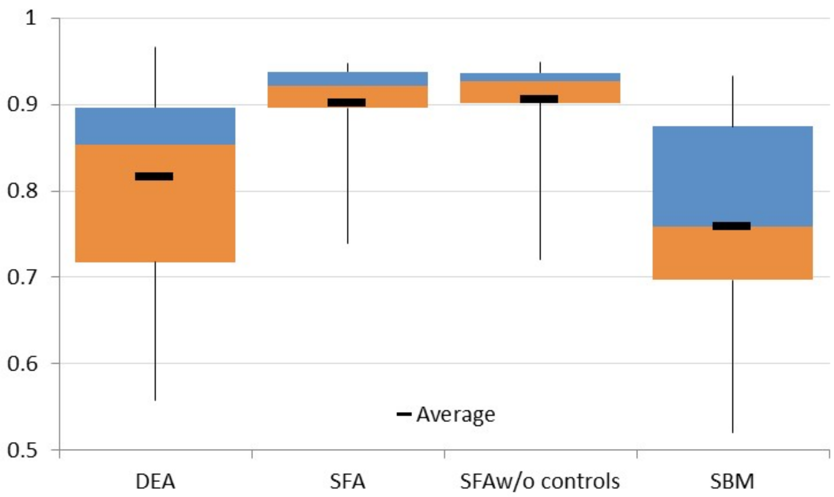

Figure 1: Boxplots overall efficiency 2000-2019 across models. Boxes represent interquartilic range. Colors change at median value.

In addition, as in Berger and Humphrey (1997) parametric models present more concentrated results than non parametric ones. In effect, SFA with and without controls achieve an interquartile range between 3.5% and 4.2% while in parametric models it situated above 17%. Moreover, dispersion originates in the lower portion of the distribution. While maximums across models gather between 93.3% and 96.6% minimums spread between 51% and 73%, the lowest at SBM and DEA models.

There is no evident time trend when system performance is analyzed through the whole period as depicted in Figure 2. Just in the case of the DEA estimation in panel 2.a the median efficiency exhibits a consistent increase after 2012. On the contrary, mean efficiency reduces with persistence after 2010 in SFA model in 2.b.

Estimations in both models suggest there is an important impact in year 2010 coincident with an important regulatory reform in the system.

4.3.2 Efficiency at Institutional level

Efficiency models allow us to construct efficiency scores and rankings. Just as observed above, there are strong similarities between non parametric results and significant differences between them and the parametric ones. In Table 3 we present a set of cross correlations of both efficiency scores and institutional rankings using annual averages. For instance, the correlation between DEA and SBM scores and rankings is 90% and 92% respectively (Tables 3.a and 3.b respectively). On the contrary, DEA and SFA correlation reduces to 42% when scores are considered and to 22% when rankings are observed instead (Tables 3.a and 3.b respectively).

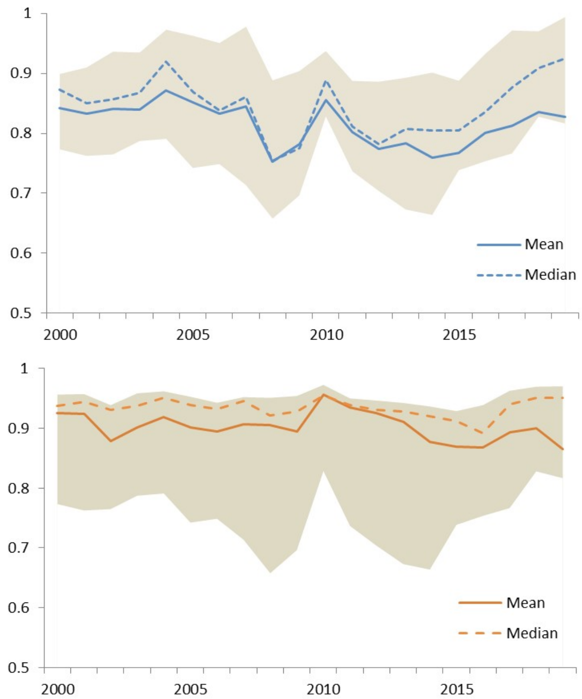

Figure 2: System efficiency dynamics 2000-2019. a) DEA model results. b) SFA model results.

In addition, we evaluated ranking correlations in the top and bottom five institutions across models. In this case we used average efficiency along the 2000-2019 period. As depicted in Tables 3.c and 3.d DEA and BSM present the highest correlation in the top five of the ranking and a high correlation in the bottom five (around 40% in both cases). DEA and SFA are negatively correlated in the top list and highly positively correlated in the bottom one (-60% and 51% respectively). Finally BSM and SFA show the lowest correlations at top and bottom rankings (19% and 25% respectively).

Focusing on institutional performance, we identify a significant heterogeneity by cluster hidden in the aggregate measure as it evidences Figure 3. Despite the differences across models, big and medium banks achieve the highest efficiency levels and converge in the last decade. In these groups, efficiency differs 11% on average in DEA while the gap reduces to 3% in SFA, in both cases dominated by big banks in most of the period. Meanwhile consumption banks stand out for being the worst performers with a sharp drop in the most recent term. Increasing inefficiency persists along the whole

Table 3: Correlations between efficiency scores and efficiency rankings.

3.a Efficiency vectors

	DEA	SFA	SBM
DEA	1		
SFA	0.42	1	
SBM	0.90	0.39	1

3.b Ranking vectors

	DEA	SFA	SBM
DEA	1		
SFA	0.22	1	
SBM	0.92	0.26	1

3.c Top 5 ranking

	DEA	SFA	SBM
DEA	1		
SFA	-0.60	1	
SBM	0.41	0.19	1

3.d Bottom 5 ranking

	DEA	SFA	SBM
DEA	1		
SFA	0.51	1	
SBM	0.43	-0.25	1

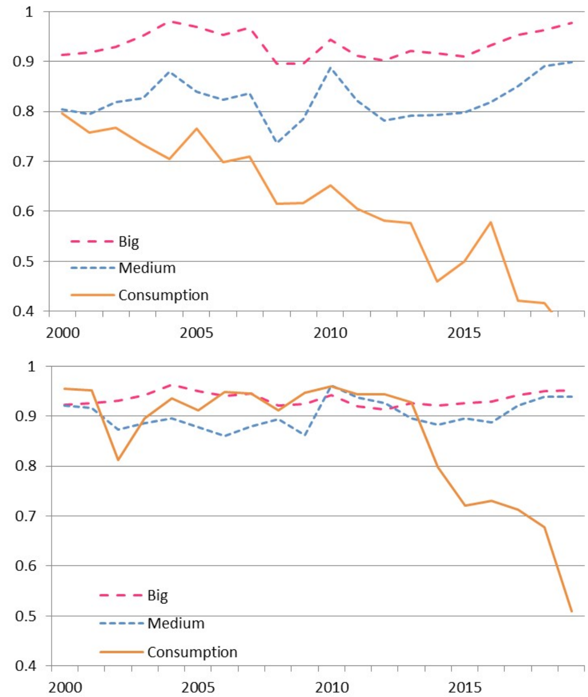

Figure 3: Average efficiency by cluster. a) DEA model. b) SFA model.

period in DEA and only after 2010 in SFA.[17] (In Subsection 4.4, we discuss on the determinants of this phenomenon).

SFA results suggest that system reached a high level of efficiency, with an average of 0.90 in the last two decades. Nevertheless, we observe a significant heterogeneity across units which renders an average interquartile range of almost 0.03 in the sample. The heterogeneity produce divergent time trends when we consider average or median performances.

4.3.3 Environmental effects

We now discuss the effects of size, and ownership using SFA and BDEA models, presented in Tables 2.a and 2.b. In both models, negative and significant coefficients in medium and consumption banks indicate that size does impact on system efficiency. In particular, efficiency reaches the highest rates in big banks followed by medium and consumption institutions.

State ownership dummy is significant and positive (in line with results in Sepúlveda et al. 2019), which means that state banks are on average 11% more efficient than private banks in both estimated models. Foreign ownership also has a significant positive effect on efficiency, increasing it by 14% in the SFA model and 8.25% in DBDEA. This result aligns with findings at Berger et al. (2009) finding that Chinese banks in 1994-2003 were more efficient if owned by foreigners, although there is plenty evidence of the opposite case.[18]

Regarding publically traded shares, we found a positive effect in both models but not significant in the case of DBDEA. According to Berger and Humphrey (1997) firms with stockholder ownership face stronger incentives to control costs or increase efficiency, and then we should expect them to be more efficient. Nevertheless, empirical results have turned out mixed.[19]

[17]Efficiency obtained with SBM at cluster level, in Appendix B, preserves the features observed in the other models.
[18]See for instance Wezel (2010), Berger et al. (2000).
[19]See Isik and Hassan (2003) for a positive relationship in Turkish banking system.

4.3.4 Mergers and acquisitions

We found a positive impact of merger and acquisitions on overall efficiency although mixed in terms of timing. SFA model reports that mergers had a positive effect on the year of occurrence (at 10% significance), but there are no significant impacts on the following three quarters. DBDEA model, on the contrary, does not report impact at occurrence but only one quarter after (at 10% significance) and again with a positive sign. That said, it is important to note that both models suggest that effects only impact the controlling institution in the short term.

Overall, the results suggest that on average, the merger and acquisition strategy targeted already efficient institutions benefiting directly controller institution at purchase (a negative sign would have suggested that on average low efficient institutions are targeted by more efficient institutions). The same result was found for instance by Wheelock and Wilson (2000) in US banking system during the eighties, where the probability of being acquired was lower for cost inefficient banks.

4.3.5 Summary on multi model results

We did find that methodology impacts on system average estimate, locating parametric models results above those of no parametric ones. Nevertheless, models coincided in that none detected any clear time trend over the period. A direct comparison of correlations among the efficiency scores shows that non parametric measures are quite similar between them and different from parametric results. We then observed cluster averages, DEA reports higher heterogeneity in efficiency levels and scores ordering varies in 2000-2012 when comparing against SFA.

In environmental effects, both models obtain the same directions in all significant variables (only in the case of public trading we obtain mixed results at significance). Regarding mergers and acquisitions, both models identify an impact but disagree on the timing of it. Indeed SFA model detects a response just as event occurs while DBDEA reports effects in the first quarter.

In summary, we found that model selection does have an impact on the resulting level of efficiency, which is mainly a consequence of the fact that both are based on different assumptions. However, model estimations were indistinctly capable of identify the relationship between efficiency and other variables at most econometric tests we performed.

4.4 Efficiency disaggregated at input level

SBM results evidence a significant heterogeneity in the efficiency of the considered inputs, both in levels and trends as depicted in Table 4 and in Figure 4. Considering the system as a whole, the banking industry can improve its efficiency by reducing its inputs by 24% (1-0.76). In particular, the optimal combination of adjustments consists of reducing opex by 33%, deposits by 23%, capital by 13% and bonds by 27%.

Table 4: Inputs efficiency resulting from SBM (averages).

Efficiency level	Op. Exp.	Deposits	Capital	Bonds	Inputs
System	0.67	0.77	0.87	0.73	0.76
Big	0.75	0.96	0.95	0.86	0.88
Medium	0.74	0.80	0.82	0.64	0.75
Consumption	0.36	0.43	0.86	0.77	0.60

At cluster level, Big and Medium banks achieve the best performance in deposits and capital leaving room for improvement in operative expenses and bonds (especially in the case of Medium banks). The group of Consumption banks underperforms in all inputs, in particular in operative expenses and deposits, being the last one the main efficiency driver inside the inputs set (see subsection 4.2).

The most notable trend is in operative expenses which present a steady increase in efficiency almost duplicating its level over the whole sample (Figure 4). The efficiency in the use of deposits is almost stable across the period at 80%, while capital efficiency, that starts at a very high level in 2000 (94%) follows a persistent decrease ending 2019 at 74%. Note that the use of bonds as a "novel" source of founds remains at low efficiency levels (in the 30% to 50% range) which explains overall efficiency decrease when data is pooled after 2008. Nonetheless bond efficiency presented a sharp augment after 2016.

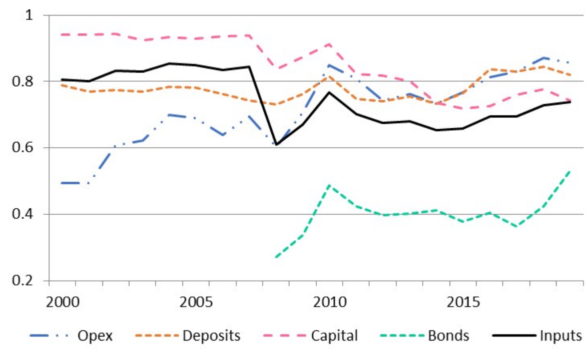

Figure 4: Input average efficiency SBM during 2000-2019.

So as a summary capital and bonds, in particular the latter, keep room for efficiency improvement in the overall sample. Deposits remain highly efficient and operative expenses present the most significant increase in efficiency in the period. Let us now see what happens with each component at cluster level.

Operative expenses have been a major driver for efficiency growth in the case of Big and Medium banks across the whole period, according to Figure 5.a. Both groups present a sharp persistent increase and converge to very high levels at the end of the sample. That contrasts with the dynamics at Consumption banks which do not evidence a clear time pattern in the long term, and persist at low efficiency levels during the whole sample.

In the case of deposits, Figure 5.b depicts three very different patterns. Big banks sustain at very high levels, with a slight increase to end up the period at the frontier. Regarding the Medium banks, they achieve an 10% improvement over the sample yet situating below the previous ones. On the contrary, the performance of Consumption cluster does not show a clear time pattern. Digging further, we find that Consumption banks experience the steepest upwards trend in their share of sight deposits, going from an average of 3.2% before 2010 to 13.8% after that year (a total six fold across the sample). For the banking industry, that means an increase in legal reserves and as a consequence less funding available per unit of deposit for both lending or investing.[20] (In Appendix C we present a comparison for the trajectory of the share of sight deposits by cluster).

Capital efficiency, in Figure 6.a, is the first occasion in which all clusters present a decreasing trend. The effect is the mildest among Big banks, where efficiency reduces only 3% and yet keeps above 90% at the end of the period. That is not the case for Medium banks in which capital efficiency reduces from 94% in 2000 towards 80% in 2019. But Consumption banks, in the extreme, experience a capital efficiency plummeting of almost 80% across the sample accelerating the drop after 2013. Our hypothesis for this group of banks is that as it is strongly related to retail activity (all these banks are part of retail conglomerates) and thus to consumption credit, they obtain high returns even while keeping capital in excess (which might be necessary in case of a negative shock increasing non performing loans in riskier credit portfolio). In fact, the return on equity of the cluster persistently overperformed that of the other groups since 2015 when keeping high capital levels. The riskier activity, which requires more capital, reflects on higher rates of provisions to assets. Indeed Consumption banks doubled system level of provisions to assets in 2005-2015 and started to converge to them only after 2015. (See Appendix D for more detail)

[20]In particular in the case of Chile sight deposits require a 9% of legal reserves while term deposits only require 3.6%.

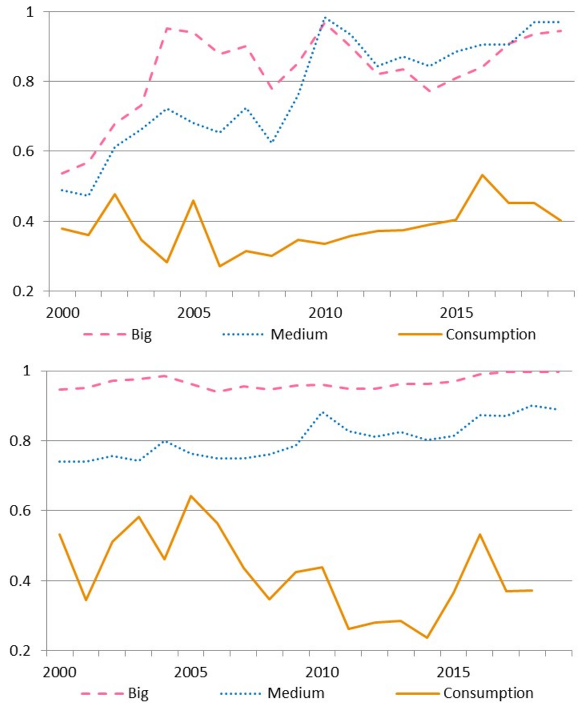

Figure 5: Cluster average efficiency in inputs with SBM during 2000-2019. a) Operative expenses. b) Deposits.

In the case of bonds efficiency, we only have data in the period 2007-2019, as it shows in Figure 6.b. We found that efficiency has been increasing steadily in the case of Big banks, which coincidentally behave as the most active group in the bond market.[21] There is a recent increase in bonds efficiency in the case of Medium banks although it only keeps at half the level of Big banks. Finally, for Consumption banks, our model again signals excess funding strategy, resulting in the low efficiency in bonds which deepens along the available data.

In summary, at inputs level, the cluster of Big banks sustained the highest efficiency across the period, with significant improvements from operative expenses and the issuance of bonds for extra funding. Medium banks kept 10% below due to mostly a lower efficiency on deposits, capital and loans (yet in most cases converging towards the previously mentioned group). Consumption banks present low efficient levels in the dimensions this paper assumed, mostly as a consequence both of deposit behavior and excess capitalization strategy.

4.5 Efficiency effect on market share and returns

In the previous subsections, we obtained measures of efficiency and examined its main determinants. In this last subsection, we will empirically assess how efficiency gains or losses affect other system variables, such as market share and dividend distribution policies.

4.5.1 Efficiency and return heterogeneity

In Appendix E we present our results on that monthly efficiency does help predict monthly return on equity (Granger precedence). Now we want to know whether this precedence extends to the heterogeneity dimension so that efficiency dispersion explains return dispersion. We estimated and

[21] Note that while the average ratio of issued bonds to assets in 2010-2019 reached 14% and 16% in Big and Medium banks respectively, it located in 8% in the case of Consumption banks (with a maximum level of 13.6% in September 2018 followed by a contraction to 9.5% afterwards).

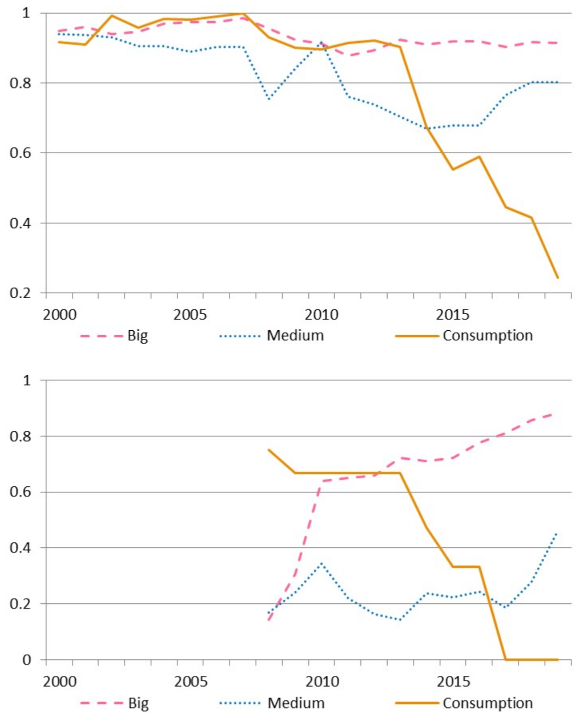

Figure 6: Cluster average efficiency in inputs with SBM during 2000-2019. a) Capital. b) Bonds.

compared standard deviations of return on equity and efficiency scores. Table 5 presents testing results in both cases using year and bank fixed effects.

Table 5: Empirical model results.

5.a SFA model, dependent variable: sd(roe)

Variable	**Coefficient**	**St.Er.**
sd(Efficiency)	14.5698***	2.4761
FE bank	yes	
FE year	yes	

5.b DBDEA, dependent variable: sd(roe)

Variable	**Coefficient**	**St.Er.**
sd(Efficiency)	-77.1124***	7.4489
FE bank	yes	
FE year	yes	

Using SFA efficiency we obtain a positive significant relationship, which means that the more banks differentiate themselves in efficiency, the more they differ in observed return on equity in the period. DEA efficiency, however, obtains a negative result. A possible explanation for this divergence might derive from differences in estimation among both models. Indeed SFA uses panel data for estimation while BDEA pools monthly bank data.

4.5.2 Efficiency dividends and market share

Now we ask whether efficiency improvements are applied to price reductions in order to gain market share or if in contrast, efficiency gains (losses) are fully channeled towards to shareholders dividends with little impact on the relation to customers. This second hypothesis would contribute to explain high return in Chilean industry when compared with peer markets.

Thus we tested Granger causality pairing efficiency with the variables dividend payments (and dividend policy) and market share using annual data (in Appendix E we reproduce the test with monthly data substituting dividend policy with ROE). Note that this test does not inform about causality in the regular sense of the term but instead it responds how much each variable in the pair helps predict the other, then we say it precede or "Granger cause" it.

We used the Non Granger Causality test in Dumitrescu and Hurlin (2012) suitable for unbalanced panel data. Results for up to 2 and 3 lags (maximum available according to sample) in each case are presented in Table 8.[22] Note that the lag time limit restricts us to test at most medium term relations, not long term plans.

Table 6: Panel Granger Non-Causality test, $\tilde{Z}$ values. Annual data.

6.a Test using DEA efficiency measure

max	**x**	*dividends*	ef_{DEA}	*d.policy*	ef_{DEA}	*mktsh*	ef_{DEA}
lags	**y**	ef_{DEA}	*dividends*	ef_{DEA}	*d.policy*	ef_{DEA}	*mktsh*
1		30.2500***	-0.8964	2.6065***	1.9281*	2.3337***	0.3803
2		7.5250***	-0.1730	2.1330**	-0.5369	4.0402***	-0.5137
3		-	-	-	-	1.7982*	-1.0765

6.b Test using SFA efficiency measure

max	**x**	*dividends*	ef_{SFA}	*d.policy*	ef_{SFA}	*mktsh*	ef_{SFA}
lags	**y**	ef_{SFA}	*dividends*	ef_{SFA}	*d.policy*	ef_{SFA}	*mktsh*
1		12.9060***	-0.4051	0.9952	-0.6289	1.0303	0.4476
2		6.2504***	0.9696	-0.3816	-1.5383	1.0660	0.4147
3		-	-			0.3802	-0.6558

H_0 : x does not Granger cause y. H_1 : Granger Causality for at least one individual. $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Regarding the relationship between efficiency and dividends, both models fail to identify a precedence relation from efficiency to dividends and only DEA detects a weakly significant relation at one lag. This result suggests that dividend payments are complex decisions depending in multiple variables other than efficiency itself (such as capital accumulation decisions, economic expectations, policy restrictions, etc). As a consequence, efficiency gains or loses are not enough to predict them, while they do predict returns (see Appendix E).

However, there is Granger causation in the relation which goes in the opposite direction, that is from dividends and dividend policy to efficiency. We find this to be an unexpected striking result. A possible explanation, is that both variables might be Granger caused by a third one but at different time stages. For instance, would it be loans, an increase in loans determines an increase on return for higher interest revenues and possibly higher dividends. At the same time, higher loans increase our efficiency measure which then appears to be preceded by dividends.

Finally, DEA efficiency score is Granger caused by market share. This result might be related with the fact that we measure market share as the percentage of market assets so it is related to size. At the same time, we found that size has a positive effect on efficiency so that it might be a spurious relationship we are detecting there.

5 Conclusions

In this paper we update efficiency measures for the Chilean banking system covering the period 2000-2019. In contrast to previous works, we employed distance functions, the intermediates approach and combine different empirical strategies for estimation objectives.

[22] All variables are stationary according to panel data Fisher-type test based on Augmented Dickey Fuller.

We found significant heterogeneity across measures most between parametric and non-parametric techniques which has to be regarded in following works. That however, did not have significant impact on empirical tests on environmental variables, trend or mergers and acquisitions results.

The Chilean banking system achieved high efficiency levels in all models estimated. According to our measures, Big and Medium banks are the best performers with the latter converging towards the former over the sample. That is not the case in Consumption cluster which presents a bad performance in most measures. A breakdown by input signals operative expenses as the major driver behind efficiency gains in the sample while capital characterize by a downwards evolution in the same period.

In addition, our results suggest that size, foreign and state ownership have a positive significant impact on efficiency. Public trading, also positive, resulted significant only at the SFA specification. In the case of mergers and acquisitions we got positive significant short term results. The heterogeneity of efficiency does have an impact on the observed heterogeneity on returns, although our models yielded opposed directions.

Finally, we run non causality tests between efficiency, market share, return and dividends to identify precedence relations between such variables. Our results depend on the efficiency series employed. In the case on DEA efficiency, we find that efficiency dynamics precede the return on equity up to seven lags while the impact on market share only occurs after one quarter. Short term causality from market share to efficiency does not surprises us as assets is part of inputs. Regarding SFA efficiency we got bidirectional causality in all the tested pairs. Finally, we obtained some unexpected results when testing dividends and dividend policy. Future analysis should dig deeper to better understand the relationship among these variables.

References

Aigner, D., Lovell, K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier function models. *Journal of Economics*, 6:21–37.

Alfaro, R. and Franken, H. (2001). Eficiencia-X en la banca chilena. *Mimeo.*

Arshinova, T. (2014). The banking efficiency measurement using the frontier analysis techniques. *Journal of Applied Mathematics*, 4(3):165–176.

Banker, R., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, (30):1078–1092.

Berger, A. N., Demsetz, R. S., and Strahan, P. E. (1999). The consolidation of the financial services industry: causes consequences and implications for the future. *Journal of Banking and Finance*, 23:135–194.

Berger, A. N., DeYoung, R., Genay, H., and Udell, G. (2000). The globalization of financial institutions: evidence from cross border banking performance. *Brookings-Wharton Papers Financial Services*, 3:23–158.

Berger, A. N., Hasan, I., and Zhou, M. (2009). Bank ownership and efficiency in China: what will happen in the world's largest nation? *Journal of Banking and Finance*, 33:113–130.

Berger, A. N. and Humphrey, D. B. (1997). Efficiency of financial institutions: international survey and directions for future research. *European Journal Operational Research*, 98(2):175–212.

Bhatia, V., Basu, S., Mitra, S. K., and Dash, P. (2018). A review of bank efficiency and productivity. *OPSEARCH*, 55:557–600.

Bos, J., Koetter, M., Kolari, J., and Kool, C. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research*, 195:251–261.

Budnevich, C., Franken, H., and Paredes, R. (2010). Economías de escala y economías de ámbito en el sistema bancario chileno. *Working Paper - Central Bank of Chile*, 93.

Caiazza, S., Pozzolo, A. F., and Trovato, G. (2016). Bank efficiency measures, M&A decision and heterogeneity. *Journal of Productivity Analysis*, 46:25–41.

Carreño, J. L., Loyola, G., and Portilla, Y. (2010). Eficiencia bancaria en Chile: un enfoque de frontera de beneficios. *Working Paper - Central Bank of Chile*, 603.

Casu, B., Girardone, C., and Molyneux, P. (2008). Productivity change in European banking: a comparison of parametric and non-parametric approaches. *Journal of Banking and Finance*, 28:2521–2540.

Coelli, T., Gautier, A., Perelman, S., and Saplacan-Pop, R. (2013). Estimating the cost of improving quality in electric distribution: a parametric distance function approach. *Energy Policy*, 53:287–297.

Coelli, T., Rao, D., O'Donnell, C. J., and Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer, Berlin.

Coelli, T., Rao, D. S., and Battese, G. E. (1998). An introduction to efficiency and productivity analysis. *NY: Springer.*

Creel, H. P. and Labondance, F. (2015). Financial stability and economic performance. *Economic Modelling*, 48:25–40.

Cummins, J. and Zi, H. (1998). Comparison of frontier efficiency models: an application to the U.S. life insurance industry. *Journal of Productivity Analysis*, 10:131–152.

Das, A. and Kumbhakar, S. (2012). Productivity and efficiency dynamics in indian banking: An input distance function approach incorporating quality of inputs and outputs. *Journal of Applied Econometrics*, 27:205–234.

Dumitrescu, E. I. and Hurlin, C. (2012). Testing for granger non-causality in heterogeneous panels. *Economic Modelling*, 29:1450–1460.

Ferrier, G. D. and Lovell, C. K. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46:229–245.

Ferro, G. and Mercadier, A. (2016). Technical efficiency in chile´s water and sanitation provides. *Utilities Policy*, 43:97–106.

Fethi, M. D. and Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey. *European Journal of Operational Research*, 204(4):189–198.

Fiordelisi, F., Marquez-Ibañez, D., and Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking and Finance*, 35:1315–1326.

Focarelli, D., Panetta, F., and Salleo, C. (2002). Why do banks merge? *Journal of Money, Credit and Banking*, 34(4):1047–1066.

Färe, R., Grosskopf, S., and Lovell, C. (1994). *Production Frontiers*. Cambridge University Press, Cambridge.

Färe, R. and Primont, D. (1995). *Multi-output Production and Duality: theory and Applications*. Kluwer Academic Press, Boston.

Greene, W. H. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, 126:269–303.

Greenwood, J., Sanchez, J. M., and Wang, C. (2010). Financing development: the role of information costs. *American Economic Review*, 100:1875–1891.

Greenwood, J., Sanchez, J. M., and Wang, C. (2016). Quantifying the impact of financial development on economic development. *Review of Economic Dynamics*, 16:194–215.

Isik, I. and Hassan, M. K. (2003). Efficiency, ownership and market structure, corporate control and governance in the Turkish bancking industry. *Journal of Business and Finance Account*, 30(9-10):1363–1421.

Jara, A. and Oda, D. (2015). Agrupación de instituciones bancarias a partir del análisis de cluster: Una aplicación al caso de Chile. *Working Paper - Central Bank of Chile*, 744.

Kick, T. K. and Koetter, M. (2007). Slippery slopes of stress: Ordered failure events in German banking. *Deutsche Bundesbank Discussion Paper Series*, 2(3).

King, R. and Levine, R. (1993a). Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, 108:717–737.

King, R. and Levine, R. (1993b). Finance, entrepreneurship and growth: theory and evidence. *Journal of Monetary Economics*, 32:513–542.

Kumbhakar, S., Wang, H., and Horncastle, A. (2015). *A Practitioner's Guide to Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, England.

Lovell, C., Richardson, S., Travers, P., and Wood, L. (1994). Resources and functionings: a new view of inequality in Australia. In *Models and Measurement of Welfare and Inequality*. Springer-Verlag, Berlin: 787-807.

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18:435–444.

Molinos-Senante, M., Porcher, S., and Maziotis, A. (2017). Impact of regulation on English and Welsh water-only companies: An input distance function approach. *Environmental Science and Pollution Research*, 24(20):16994—17005.

Nigmonov, A. (2010). Bank performance and efficiency in uzbekistan. *, Eurasian Journal of Business and Economics*, 3(5):1–25.

Orea, L. (2002). Parametric decomposition of a generalized malmquist productivity index. *Journal of Productivity Analysis*, 18:5–22.

Rezitis, A. (2008). Efficiency and productivity effects of bank mergers: Evidence from the Greek banking industry. *Economic Modelling*, 25:236–254.

Saal, D., Parker, D., and Weyman-Jones, T. (2007). Determining the contribution of technical efficiency, and scale change to productivity growth in the privatized English and Welsh water and sewerage industry: 1985–2000. *Journal of Productivity Analysis*, 28(1):127–139.

Sealey, C. and Lindley, J. (1977). Inputs, outputs and a theory of production and cost at depository financial institutions. *The Journal of Finance*, 32(September(4)):1251–1266.

Sepúlveda, L. C., Rivas, L., and Domínguez, A. (2019). Eficiencia del sector bancario en Chile ante cambios en las regulaciones de protección al consumidor financiero. *Cuadernos de contabilidad*, 50(20):1–20.

Shephard, R. (1953). *Cost and Production Functions*. Princeton University Press, Princeton, NJ.

Simar, L. and Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science*, 44(1):49–61.

Simar, L. and Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, 27(6):779–802.

Simar, L. and Wilson, P. W. (2007). Estimation and inference in two-stage, semiparametric models of production processes. *Journal of Econometrics*, 136:31–64.

Titko, J., Stankeviciene, J., and Lace, N. (2014). Measuring bank efficiency: Dea application. *Technological and Economic Development of Economy*, 20(4):739–757.

Tone, K. (1997). A slacks-based measure of efficiency in data envelopment analysis. *Research Reports, Graduate School of Policy Science, Saitama University.*

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130:498–509.

Vergara, M. (2006). Technical note for estimating stochastic frontiers: an application to Chilean banking. *Estudios de Administración*, 13(2):47–66.

Wezel, T. (2010). Bank efficiency amid foreign entry: evidence from the Central American region. *IMF Working Paper*, 10.

Wheelock, D. and Wilson, P. (2000). Why do banks disappear? the determinants of U.S. bank failures and acquisitions. *Review of Economics and Statistics*, 82(1):127–138.

Wheelock, D. and Wilson, P. (2004). Consolidation in US banking: Which banks engage in mergers? *Review of Financial Economics*, 13(1-2):7–39.

Zreika, M. and Elkanj, N. (2011). Banking efficiency in lebanon: an empirical investigation. *Journal of Social Sciences*, 7(2):199–208.

References

Aigner, D., Lovell, K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier function models. *Journal of Economics*, 6:21–37.

Alfaro, R. and Franken, H. (2001). Eficiencia-X en la banca chilena. *Mimeo.*

Arshinova, T. (2014). The banking efficiency measurement using the frontier analysis techniques. *Journal of Applied Mathematics*, 4(3):165–176.

Banker, R., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, (30):1078–1092.

Berger, A. N., Demsetz, R. S., and Strahan, P. E. (1999). The consolidation of the financial services industry: causes consequences and implications for the future. *Journal of Banking and Finance*, 23:135–194.

Berger, A. N., DeYoung, R., Genay, H., and Udell, G. (2000). The globalization of financial institutions: evidence from cross border banking performance. *Brookings-Wharton Papers Financial Services*, 3:23–158.

Berger, A. N., Hasan, I., and Zhou, M. (2009). Bank ownership and efficiency in China: what will happen in the world's largest nation? *Journal of Banking and Finance*, 33:113–130.

Berger, A. N. and Humphrey, D. B. (1997). Efficiency of financial institutions: international survey and directions for future research. *European Journal Operational Research*, 98(2):175–212.

Bhatia, V., Basu, S., Mitra, S. K., and Dash, P. (2018). A review of bank efficiency and productivity. *OPSEARCH*, 55:557–600.

Bos, J., Koetter, M., Kolari, J., and Kool, C. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research*, 195:251–261.

Budnevich, C., Franken, H., and Paredes, R. (2010). Economías de escala y economías de ámbito en el sistema bancario chileno. *Working Paper - Central Bank of Chile*, 93.

Caiazza, S., Pozzolo, A. F., and Trovato, G. (2016). Bank efficiency measures, M&A decision and heterogeneity. *Journal of Productivity Analysis*, 46:25–41.

Carreño, J. L., Loyola, G., and Portilla, Y. (2010). Eficiencia bancaria en Chile: un enfoque de frontera de beneficios. *Working Paper - Central Bank of Chile*, 603.

Casu, B., Girardone, C., and Molyneux, P. (2008). Productivity change in European banking: a comparison of parametric and non-parametric approaches. *Journal of Banking and Finance*, 28:2521–2540.

Coelli, T., Gautier, A., Perelman, S., and Saplacan-Pop, R. (2013). Estimating the cost of improving quality in electric distribution: a parametric distance function approach. *Energy Policy*, 53:287–297.

Coelli, T., Rao, D., O'Donnell, C. J., and Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer, Berlin.

Coelli, T., Rao, D. S., and Battese, G. E. (1998). An introduction to efficiency and productivity analysis. *NY: Springer.*

Creel, H. P. and Labondance, F. (2015). Financial stability and economic performance. *Economic Modelling*, 48:25–40.

Cummins, J. and Zi, H. (1998). Comparison of frontier efficiency models: an application to the U.S. life insurance industry. *Journal of Productivity Analysis*, 10:131–152.

Das, A. and Kumbhakar, S. (2012). Productivity and efficiency dynamics in indian banking: An input distance function approach incorporating quality of inputs and outputs. *Journal of Applied Econometrics*, 27:205–234.

Dumitrescu, E. I. and Hurlin, C. (2012). Testing for granger non-causality in heterogeneous panels. *Economic Modelling*, 29:1450–1460.

Ferrier, G. D. and Lovell, C. K. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46:229–245.

Ferro, G. and Mercadier, A. (2016). Technical efficiency in chile´s water and sanitation provides. *Utilities Policy*, 43:97–106.

Fethi, M. D. and Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey. *European Journal of Operational Research*, 204(4):189–198.

Fiordelisi, F., Marquez-Ibañez, D., and Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking and Finance*, 35:1315–1326.

Focarelli, D., Panetta, F., and Salleo, C. (2002). Why do banks merge? *Journal of Money, Credit and Banking*, 34(4):1047–1066.

Färe, R., Grosskopf, S., and Lovell, C. (1994). *Production Frontiers*. Cambridge University Press, Cambridge.

Färe, R. and Primont, D. (1995). *Multi-output Production and Duality: theory and Applications.* Kluwer Academic Press, Boston.

Greene, W. H. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, 126:269–303.

Greenwood, J., Sanchez, J. M., and Wang, C. (2010). Financing development: the role of information costs. *American Economic Review*, 100:1875–1891.

Greenwood, J., Sanchez, J. M., and Wang, C. (2016). Quantifying the impact of financial development on economic development. *Review of Economic Dynamics*, 16:194–215.

Isik, I. and Hassan, M. K. (2003). Efficiency, ownership and market structure, corporate control and governance in the Turkish bancking industry. *Journal of Business and Finance Account*, 30(9-10):1363–1421.

Jara, A. and Oda, D. (2015). Agrupación de instituciones bancarias a partir del análisis de cluster: Una aplicación al caso de Chile. *Working Paper - Central Bank of Chile*, 744.

Kick, T. K. and Koetter, M. (2007). Slippery slopes of stress: Ordered failure events in German banking. *Deutsche Bundesbank Discussion Paper Series*, 2(3).

King, R. and Levine, R. (1993a). Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, 108:717–737.

King, R. and Levine, R. (1993b). Finance, entrepreneurship and growth: theory and evidence. *Journal of Monetary Economics*, 32:513–542.

Kumbhakar, S., Wang, H., and Horncastle, A. (2015). *A Practitioner's Guide to Stochastic Frontier Analysis*. Cambridge University Press, Cambridge, England.

Lovell, C., Richardson, S., Travers, P., and Wood, L. (1994). Resources and functionings: a new view of inequality in Australia. In *Models and Measurement of Welfare and Inequality*. Springer-Verlag, Berlin: 787-807.

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18:435–444.

Molinos-Senante, M., Porcher, S., and Maziotis, A. (2017). Impact of regulation on English and Welsh water-only companies: An input distance function approach. *Environmental Science and Pollution Research*, 24(20):16994—17005.

Nigmonov, A. (2010). Bank performance and efficiency in uzbekistan. *, Eurasian Journal of Business and Economics*, 3(5):1–25.

Orea, L. (2002). Parametric decomposition of a generalized malmquist productivity index. *Journal of Productivity Analysis*, 18:5–22.

Rezitis, A. (2008). Efficiency and productivity effects of bank mergers: Evidence from the Greek banking industry. *Economic Modelling*, 25:236–254.

Saal, D., Parker, D., and Weyman-Jones, T. (2007). Determining the contribution of technical efficiency, and scale change to productivity growth in the privatized English and Welsh water and sewerage industry: 1985–2000. *Journal of Productivity Analysis*, 28(1):127–139.

Sealey, C. and Lindley, J. (1977). Inputs, outputs and a theory of production and cost at depository financial institutions. *The Journal of Finance*, 32(September(4)):1251–1266.

Sepúlveda, L. C., Rivas, L., and Domínguez, A. (2019). Eficiencia del sector bancario en Chile ante cambios en las regulaciones de protección al consumidor financiero. *Cuadernos de contabilidad*, 50(20):1–20.

Shephard, R. (1953). *Cost and Production Functions*. Princeton University Press, Princeton, NJ.

Simar, L. and Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science*, 44(1):49–61.

Simar, L. and Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, 27(6):779–802.

Simar, L. and Wilson, P. W. (2007). Estimation and inference in two-stage, semiparametric models of production processes. *Journal of Econometrics*, 136:31–64.

Titko, J., Stankeviciene, J., and Lace, N. (2014). Measuring bank efficiency: Dea application. *Technological and Economic Development of Economy*, 20(4):739–757.

Tone, K. (1997). A slacks-based measure of efficiency in data envelopment analysis. *Research Reports, Graduate School of Policy Science, Saitama University.*

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130:498–509.

Vergara, M. (2006). Technical note for estimating stochastic frontiers: an application to Chilean banking. *Estudios de Administración*, 13(2):47–66.

Wezel, T. (2010). Bank efficiency amid foreign entry: evidence from the Central American region. *IMF Working Paper*, 10.

Wheelock, D. and Wilson, P. (2000). Why do banks disappear? the determinants of U.S. bank failures and acquisitions. *Review of Economics and Statistics*, 82(1):127–138.

Wheelock, D. and Wilson, P. (2004). Consolidation in US banking: Which banks engage in mergers? *Review of Financial Economics*, 13(1-2):7–39.

Zreika, M. and Elkanj, N. (2011). Banking efficiency in lebanon: an empirical investigation. *Journal of Social Sciences*, 7(2):199–208.

Appendix

A Classification of local banks in clusters

Table A reproduces banks clustered according to Jara and Oda (2015). Note that in the case of Consumption cluster, there is both a size (these are the smallest banks) and commercial strategy differentiation as these banks specialize in consumption segment assembling credit over a strong retail commerce activity.

Table 7: Chilean banks according to industry clusters.

Big	**Medium**	**Consumption**
BCI	BBVA	Conosur
Edwards	BICE	Falabella
Chile	Citibank	Paris
Estado	Corpbanca	Ripley
Santander	Itau	
Santiago	Desarrollo	
	Scotiabank	
	Internacional	
	Rabobank	
	Security	

B Efficiency at cluster level using SBM

As in SFA and DEA, overall inputs efficiency using SBM in Figure 7 sustains the tonic of Big banks at the top of the scores followed by Medium size and finally Consumption banks. There is a recent convergence in input efficiency between the most efficient groups while we obtain an increasing inefficiency on inputs at the Consumption cluster. Using cluster averages, the gap between Big and Consumption banks reached 70% in 2019.

Figure 7: Cluster average efficiency with SBM during 2000-2019.

C Evolution of sight deposits by cluster

During 2000-2020, the share of sight deposits on total deposits doubled for Big banks, increased by almost 75% for Medium banks and more than ten fold for Consumption banks (Figure 8).

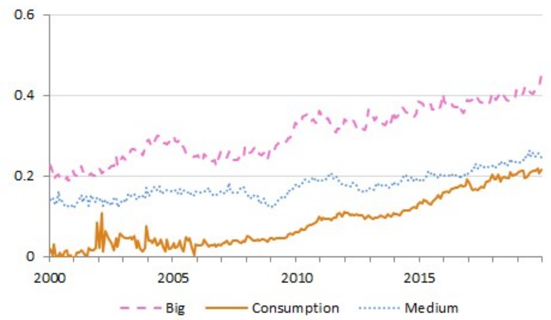

Figure 8: Sight deposits as a share of total deposits, cluster average.

D Evolution of provisions and ROE by cluster

ROE in 2000-2019 broken down at cluster level, shows that in 2002 Consumption banks achieved market levels. Furthermore, after 2015, even with an important excess capital when compared to other clusters, this group persistently managed to locate at the top of the industry (Figure 9). This riskier profile is compensated with a provisions rate above that of system average (Figure 10).

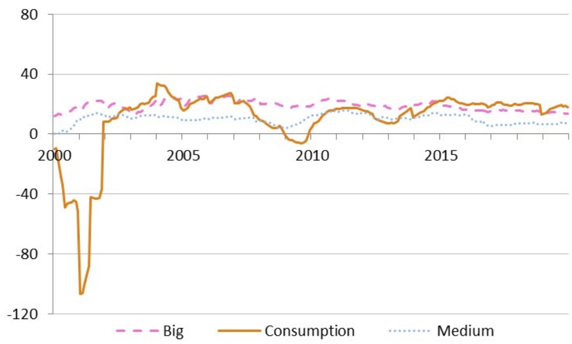

Figure 9: Return on equity, cluster average.

E Efficiency ROE and market share, monthly data

In this section, we include our results for Granger causality tests using monthly data of market share (on assets) and the return on equity (dividends are paid once a year). The goal is to test whether efficiency gains are directed towards an increase in market share or to the accumulation of utilities. We used the Non Granger Causality test for up to 7 lags (maximum available according to sample).[23] Note that the lag time limit restricts us to test at most medium term relations, not long term plans.

Focusing on DEA results, summarized in Table 8, we find that efficiency dynamics Granger cause the return on equity but not otherwise. This means that efficiency gains or losses impact on results

[23] All variables are stationary according to panel data Fisher-type test based on Augmented Dickey Fuller.

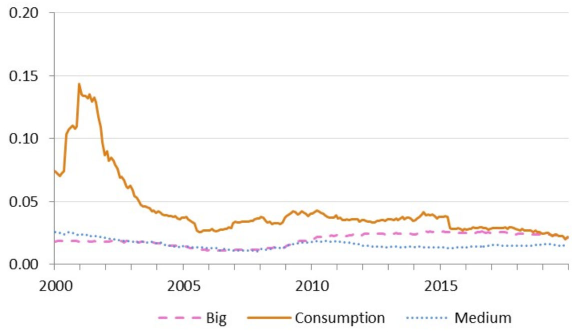

Figure 10: Ratio provisions to assets, cluster average.

up to seven months afterwards. However, changes in the return on equity does not precede efficiency in the medium term. Maybe long term policies of efficiency gains take place in the long term but our test cannot capture them due to the size of the panel.

In addition, efficiency only translates into market share changes with a lag of three months. This means that pass through to prices, and then to market share, takes on average a quarter. On the other hand, it does not surprises us the observed causality from market share to efficiency as it is calculated as the portion of assets which are a component of efficiency estimate.

From a general perspective, results differ according the estimated efficiency series applied. In particular, SFA efficiency yields bidirectional causality relations in all variables while DEA efficiency renders unidirectional causality relations.

Table 8: Panel Granger Non-Causality test, $\tilde{Z}$ values. Monthly data.

E2.a Test using DEA efficiency measure

max	**x**	roe	ef_{DEA}	$mktsh$	ef_{DEA}
lags	**y**	ef_{DEA}	roe	ef_{DEA}	$mktsh$
1		1.5226	7.7342***	2.9686***	-0.174
2		1.1979	7.5348***	2.9604***	1.5097
3		1.5738	6.3546***	2.8197***	2.7788***
4		1.2482	5.9646***	1.8921**	1.4016
5		0.7784	4.4897***	1.0963	0.5343
6		0.3838	2.7089***	0.3265	0.1665

E2.b Test using SFA efficiency measure

max	**x**	roe	ef_{SFA}	$mktsh$	ef_{SFA}
lags	**y**	ef_{SFA}	roe	ef_{SFA}	$mktsh$
1		3.0542***	6.4882***	5.6045***	3.2891***
2		5.9765***	4.3632***	11.250***	
3		4.3320***	4.6481***	6.3885***	9.3000***
4		10.650***	4.1248***	7.8388***	8.1300***
5		9.8847***	2.8708***	6.2827***	8.0473***
6		6.6788***	2.3482**	3.9061***	6.5972***

H_0 : x does not Granger cause y. H_1 : Granger Causality for at least one individual. $^{***} : p < 0.01, ^{**} : p < 0.05, ^{*} : p < 0.1$.