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Colombian Bank Efficiency And
The Role Of Market Structure

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Abstract

Colombia's financial system has undertaken major changes during the last decade, with new regulatory regimes being implemented, as well as a significant expansion of financial services. Nevertheless, the recent literature has yet to analyze this new epoch for banking institutions under an efficiency framework. Taking into account the availability of new information and the methodological advances of recent years, our purpose is to study the evolution of bank efficiency during the past few years, as well as to evaluate the influence of some market structure variables on the latter. We find evidence, both under SFA and Order-m, supporting an increase in efficiency over time. Moreover, relating the latter with market structure variables suggests that there is a positive relationship between market power and efficiency; this occurs due to product differentiation, which allows banks to gain in efficiency provided they don't set excessive credit prices. Nonetheless, there is an open debate concerning the behavior of banks with the highest market shares, since the negative relation between market concentration and efficiency advocates for a "quiet life formť", where banks don't have incentives to fully minimize costs. Additional to these results, we provide evidence of potential impacts that mergers and credit specialization may have on efficiency.

JEL classification: *C14, D40, D61, G21*

Keywords: Bank Efficiency, Concentration, Market Power, Stochastic Frontier Analysis, Order-m.

1. Introduction

The Colombian financial system has undergone significant changes during recent years. The decade of the nineties was characterized by the beginning of a "free-market" approach to economic policy which promoted financial liberalization and deep financial reforms (especially in the mortgage market). These factors contributed to significant capital inflows to the economy, which coupled with higher public and private expenditure contributed, all together, to the credit boom that Colombia experienced during the first half of the nineties, and which eventually led to the crisis of the late nineties (Gomez et al. (2013)). Following these events, credit institutions dramatically changed their modus operandi. First, by becoming more conservative with their lending standards and strengthening their capital base in the early 2000's, a time also characterized by a wave of horizontal mergers. In subsequent years, the migration towards a global banking scheme, so as to adapt their business to the innovations and different market competitors, led bank behavior towards more aggressive grounds. During the latter epoch for the financial market, sophisticated products arose along with a significant increase in access to financial services; through mobile banking, the widespread use of credit cards and the surge of microcredit, which allowed a significant augment of first-time financial access to debtors.

Such changes naturally give rise to the question whether the expansion of the financial system has occurred in a healthy way, or on the contrary, that the costs of maintaining such scale of business are disproportional, making the situation for consumers less favorable.

Therein lies the purpose of this paper, and our aim of evaluating the advances of Colombian credit institutions during the last few years, by way of estimating new efficiency measures and relating their evolution to market structure conditions. Studying the behavior of banking efficiency allows one to understand how factors, such as competition, market concentration and market power, affect credit and deposit markets, along with their impacts on interest rate margins.

The performance of the banking system has shown a significant recovery following the crisis of the late nineties, as can be readily verified by observing indices such as return on assets (ROA) and return on capital (ROE), which have exhibited positive values since 2001 (Figure 1, Panel A). This behavior was reinforced with an increase in the loans portfolio (Figure 1, Panel B) as well as investments (Figure 1, Panel C), where the former was accompanied by a reduction in the proportion of non-performing loans (Figure 1, Panel D). Such behavior allows one to envision a more efficient and solid banking system, an intuition that seems to be corroborated by the fall in traditional efficiency indicators, such as the ratio of labor and administrative costs (L&AC) to assets (Figure 1, Panel E), financial expenses to financial income (Figure 1, Panel F) and the intermediation margin. The latter implies that the Colombian banking system has presented a positive evolution together with most traditional indexes for efficiency showing enhancements in this front. However, this recent trend in banking performance has also resulted in a more concentrated market, as evidenced by increments in the Herfindahl-Hirschman Index (HHI) (Figure 1, Panel G).

Following Fernandez (1994), we evaluate how concentration influences interest rates. In his study, the author evaluates the relationship between colombian banks' market shares and credit prices, finding no significant statistical evidence of the latter. However, that study is based on a single estimation for a particular time period, whilst with the information available, we construct a panel for the period 2002-2012, with which we can estimate banks' shares on disbursements and their relationship with interest rates, for each credit type. Using a cubic spline methodology, we obtain a positive relation between market shares in new loans granted and their interest rates for treasury and preferential commercial

FIGURE 1: Evolution of Relevant Financial System Indicators

A. ROA and ROE

B. Amount of Loans

C. Amount of Investments

D. Total Non-Performing Loans

E. L&AC / assets

F. Financial Expenses / Financial Income

G. Intermediation Margin

H. HHI

3
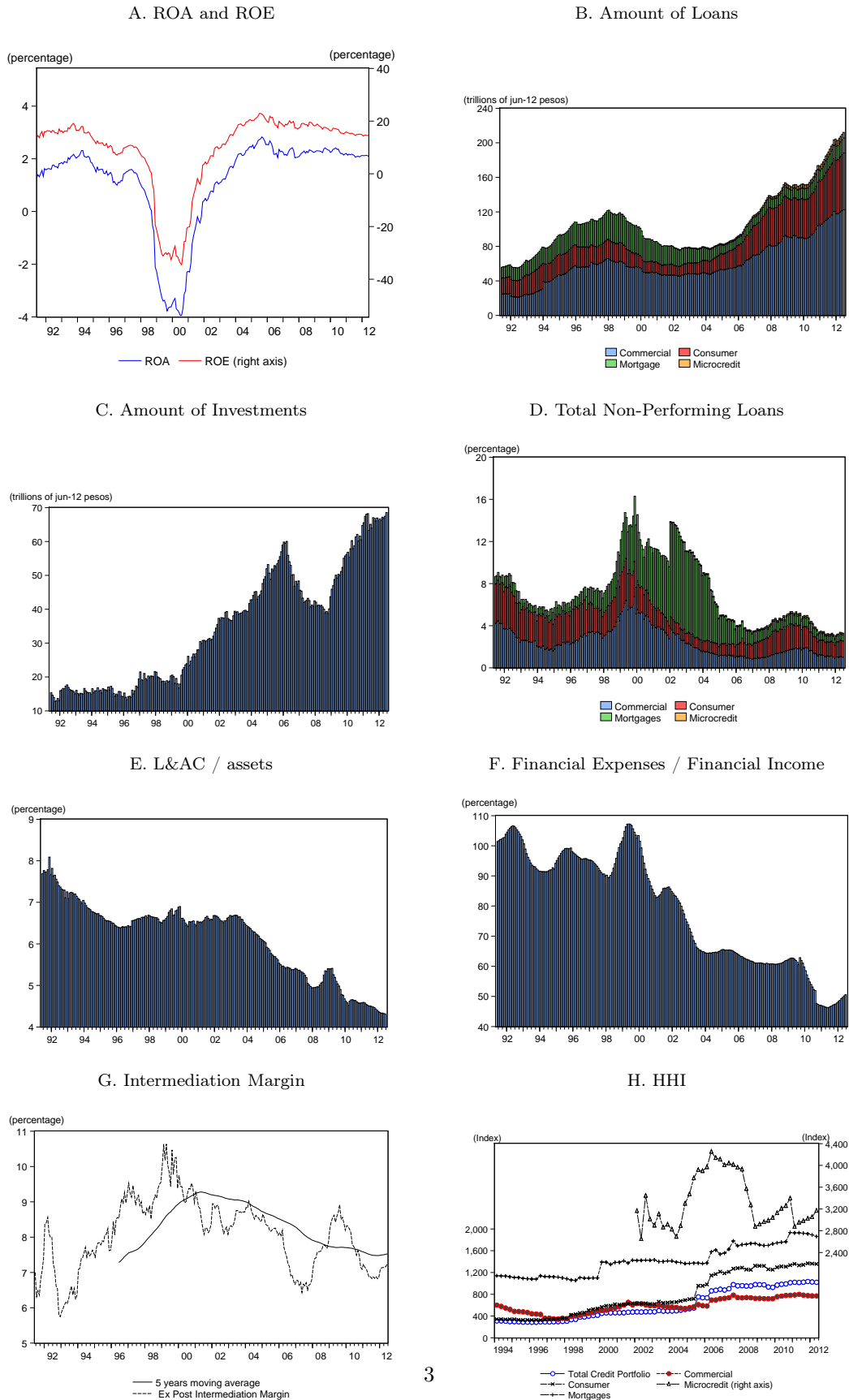
FIGURE 2: Relationship between disbursements and interest rates, by credit type

A. Ordinary Commercial Loans

B. Preferential Commercial Loans

C. Treasury Commercial Loans

D. Consumer Loans without credit cards

E. Credit Cards

F. Mortgages

G. Microcredit

4
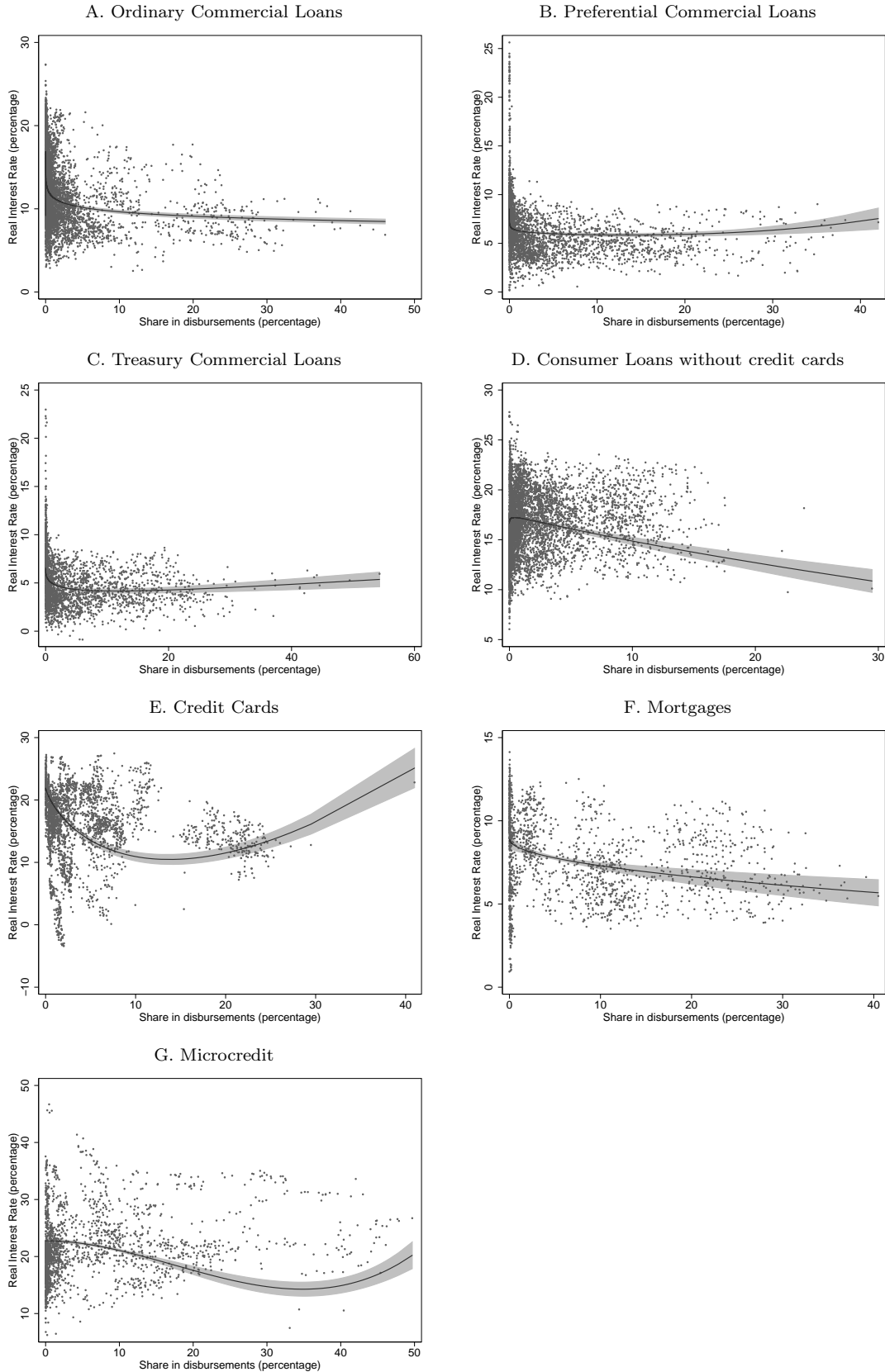
loans, while in credit card loans and microcredit, the relationship is negative for low market shares, but positive on the contrary. Finally, banks with higher disbursement shares on consumer, mortgage and ordinary commercial loans present lower interest rates (Figure 2).

The latter could mean that when banks present an aggressive behavior in disbursements of consumer, mortgage and ordinary commercial loans, they might have been experiencing gains in efficiency, since they offer credit at a lower price. The contrary occurs for the rest of credit modalities, since bigger disbursement shares imply higher interest rates for credit cards, microcredit and treasury and preferential commercial loans. Unfortunately, one cannot ensure that these results are unequivocally driven by efficiency, since banks could simply place higher credit prices due to more market power.

Hence, with the goal of reducing the ambiguity in these, and other, relevant relationships between financial variables, we seek to develop a more accurate efficiency measure for the Colombian banking system. The latter would allow one to evaluate the evolution in recent years of this measure, as well its relationship to other market structure variables. By doing this, we may have some clues regarding the way the financial services expansion has occurred in recent years, especially, if banks have augmented their production levels by gains in efficiency, and if this behavior has been translated to a more favorable situation for consumers.

The methodology used in this document employs two efficiency measures. One is the traditional X-efficiency measure, constructed through stochastic frontier estimates, but we introduce a change in the way products are traditionally considered in the literature: namely, we include the value of the average product, and not the value of the stock, in order to capture differences in the scale of production. The second is a new semi-parametric approach called Order-m, that was used to reinforce the former results. Additionally, we used the most traditional market structure indexes for market power, concentration, firms size and number of mergers to evaluate their relation with changes in efficiency. The main results show a positive trend on efficiency levels for the Colombian banking system during the 2004-2012 period, implying that banks have indeed improved in their efficiency over the years. Moreover, changes in efficiency have a positive relationship with: i) market power for those banks who do not present higher loan interest rates, implying some product differentiation, ii) those who complement deposits services, and iii) banks with commercial loans specialization. Moreover, the results also suggest that there might be economies of scale, because size variables are positive related to efficiency; in this sense, we may conclude that mergers have improved cost structures, augmenting efficiency. However, we are concerned with the relationship between concentration and efficiency, since it turns out to be negative and nowadays, loan concentration is increasing, with its implications over consumer welfare being largely unknown.

The rest of the paper is divided in three more sections, where in section 2 we explain the model used and the methodology to calculate each variable. In section 3 we describe the results obtained. Section 4 presents some conclusions.

2. Empirical Model

In order to analyze the influence of efficiency levels on the financial system's market structure, we construct a model in which we evaluate how strong the relationship between efficiency and variables related to concentration, market power, performance, among others, truly is. Following Berger & Hannan (1993), we can evaluate these relationships estimating equations of the form:

$$eff_{it} = f(\overset{+/-}{HHI_{it}}, \overset{+/-}{Lerner_{it}}, \overset{+}{r_{it}^{dep}}, \overset{-}{r_{it}^{loans}}, \overset{+}{size_{it}}, \overset{+}{esp_{it}}, \overset{+/-}{quality_{it}}, \overset{+}{emp_{it}}, \overset{+}{fus_{it}}) + \epsilon_{it} \qquad (1)$$

where eff_i is an efficiency measure of firm i, HHI is the Herfindahl-Hirschman Index of market concentration for firm i, $Lerner$ is the Lerner Index for market power, r^{dep} is the deposit interest rate and r^{loans} is the loan interest rate; $size$ is the value of total assets of the entity, esp is the distribution of the loans portfolio between credit types, $quality$ is an index for loan portfolio quality, emp is the number of employees and fus is a categorical variable that identifies when the entity has made an acquisition or merger. Finally, ϵ is a mean-zero error term.

The expected signs of some of the coefficients are ambiguous, specifically for concentration and market power, and there is ample theoretical and empirical literature supporting both positive and negative relationships. In particular, we would like to emphasize on the distinct assumptions that traditional industrial organization theory has versus the more "newtŕ approaches. The fact that the latter are recent theories does not mean that they are the ones that dominate current market relationships, nevertheless, their development is quite an important advance in terms of market structure perspective. By including these variables, we aim to establish a starting point from which we may describe how the concentration and market power of the Colombian banking system behaves, especially in terms of efficiency. Thus, in the next paragraphs we illustrate how we may interpret the signs obtained for each market structure variable.

Regarding market concentration, a statistically significant negative relation between eff and HHI will be consistent with the traditional theories, where firms with high market shares do not have incentives to compete or innovate. This could be interpreted in light of a *quiet life* hypothesis, where the market price provides a comfort zone for those with the biggest shares, since owners can earn economic rents without full effort of cost minimization, implying that the more concentrated firms will present lower levels of cost efficiency (Shepherd (1979) and Berger & Hannan (1993)). On the contrary, new theories will support a positive relationship between HHI and eff, since the latter will be consistent with the hypothesis that those banks who can reduce their marginal cost, will capture an additional part of the market, due to an increase in competition. In this way, the reduction on marginal costs will be translated into efficiency gains, at the same time that it is related to greater market concentration (Tirole (1988)).

With respect to market power, defined as the ability to charge prices over the competitive rate, the relation between $Lerner$ and eff could be, on one hand, negative. This is in line with traditional theories, where the less efficient entities are those that cannot compete with the same market price and need to translate their higher production costs to the public. On the other, this relation could also be positive according to newer findings, where the most efficient entities might set a higher price due to the presence of additional factors, such as product differentiation, that may seriously influence this relationship (Clarke et al. (1984)).

Moreover, we introduce loan and deposit interest rates, each one separately, in order to complement the regression analysis. In particular, by including deposit interest rates, we control for additional deposit services offered by each bank. Since a large revenue associated with this input would likely be evidence that banks provide substantial deposit services, we expect a positive relation between efficiency and deposit rates (Berger & Humphrey (1992)). In addition, following Demsetz (1973), including loan interest rates allows to control for the effect on market prices that a reduction in marginal costs, or increased in competition, may have. In this way, we expect a negative relation between loan rates and efficiency.

Alternatively, we would like to control for the effects of market power over mergers. Recall that one of the negative consequences that market power has is that mergers may be motivated by a desire to set prices that are less favorable to consumers, reducing both consumer and producer surplus. This fact contrasts with the implications from the two Efficient-Structure Hypotheses (ESH) for merger and antitrust policy; ESH imply that mergers may be motivated by efficiency considerations that would increase total surplus because of the more efficient scale of production acquired through the fusion process[1] (Berger (1995)). By using the interaction between the fus variable and $Lerner$, we can test whether mergers were indeed motivated by incentives for higher price-setting (if the sign is negative), or whether the ESH holds true (if positive), meaning that mergers motivated positive changes on bank's cost structures, augmenting efficiency.

Furthermore, we would like to evaluate the influence that bank size has on efficiency. For this, we introduce two variables in the regression: $size$ and emp. We expect a positive relationship between efficiency and both indicators, considering that, in case there exist differences in production costs, there should be a discrepancy between the rate of return earned by large firms and that of small firms, suggesting the presence of economies of scale (Demsetz (1973)).

One additional aspect that is assessed is the relationship between loan quality and efficiency, which is expected to be negative given that failing firms tend to be allocated far from the best practice frontier. The latter is consistent with bank failure viewed as a consequence of originating problematic loans (Berger & DeYoung (1997)). In general, the fact that a credit institution has riskier loans may be explained by diverse factors, such as less risk-averse managers, a gambling-for-survival strategy or the decision to spend fewer resources on monitoring and screening, thus reducing costs. Note that the latter argues in favor of a positive relationship, in the short-run, between efficiency and non-performing loans (**?**). For this reason, the expected sign for $quality$ is uncertain[2].

Finally, we would like to capture differences in efficiency that arise due to the type of business banks are dedicated in. Close to 80% of banking assets are represented by the loan portfolio, so the type of business to be examined will depend on the credit types in which the bank is engaged.

In the next subsections we describe how the variables used in the model are calculated.

2.1. Efficiency Measures

As mentioned above, one of the efficiency measures in this document is the so-called X-efficiency, which is expressed as deviations from the efficient frontier. The latter is defined as the "best-practice" curve, which reflects the optimal combination of inputs (i.e. which minimices costs) to achieve a given level of output. Though ideally one would expect this measure to reflect the minimum technologically achievable costs, this is not possible due to information about firms technology not being known (Berger & Hannan (1993)). However, this won't be a problem for the purpose of our analysis, as we seek to analyze the relationship between relevant market structure variables and the relative levels of efficiency in banks, and are not concerned with the intricacies of absolute efficiencies.

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[1]Berger (1995) explained that the first ESH rests on the premise that firms with superior management or production technologies have lower costs, and therefore higher profits. These firms are also assumed to acquire large market shares that may result in high levels of concentration. Moreover, the second ESH states that firms have essentially equally good management and technology, but some simply produce at more efficient scales than others, and therefore, have lower unit costs and higher unit profits. These firms are assumed to have large market shares that may result in high levels of concentration, again yielding a positive profit-structure relationship as a spurious outcome.

[2]As will be explained below, higher values of $quality$ mean a higher proportion of riskier loans.

Thus, for the purpose of our work, we use a cost frontier function in order to determine how close a bank's cost is relative to the minimum cost that could be achieved if the bank was producing on the efficient frontier. Specifically, a *translog* functional form is chosen with three inputs and two outputs. This form has been widely employed and has proven to allow for the necessary flexibility when estimating the frontier function.

Bauer et al. (1998) evaluate four of the main approaches using the cost efficiency concept to estimate frontier efficiency: Data Envelopment Analysis (DEA), Stochastic Frontier Approach (SFA), Thick Frontier Approach (TFA) and Distribution-Free Approach (DFA). These methods are different from each other in the amount of data needed and the assumptions on efficiency distribution. The results from Bauer et al. (1998) show that parametric methods are generally consistent with one another (SFA, TFA, and DFA); but the parametric and nonparametric methods aren't generally mutually consistent. However, when the parametric measures are compared with other nonfrontier approaches, results are generally highly positively correlated, whereas the DEA measure is much less strongly related to these other indicators of firm performance. As the authors note, this suggests that by using frontier approaches, the regulatory policy conclusions may not be greatly affected with any of the parametric strategies used. Additionally, Berger & Mester (1997) have compared the *translog* to the Alternative Fourier Flexible Form. Despite the latter's added flexibility, the difference in results between both methods appears to be negligible.

In this document we adopt the SFA considering a *translog* functional form. The estimation of cost efficiency is simpler than in other models. The disadvantage of using this parametric approach is having to impose a specific functional form on the frontier efficiencies. Nonetheless, the advantage of this method is that it allows for random error (DEA does not), and so it is less likely to misidentify measurement error, transitory differences in cost, or specification error as inefficiency (Bauer et al. (1998))[3].

Given the above, the frontier cost function for bank k in period t is given by:

$$
\begin{aligned}
\widetilde{c}_{kt}(y,w,z) = {}& \beta_0 + \sum_{i=1}^{2}\beta_i \ln y_{ikt} + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\beta_{ij}\ln y_{ikt}\ln y_{jkt} \\
& + \sum_{i=1}^{3}b_i\ln w_{ikt} + \frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3}b_{ij}\ln w_{ikt}\ln w_{jkt} \\
& + \sum_{i=1}^{3}\sum_{j=1}^{2}d_{ij}\ln w_{ikt}\ln y_{jkt} + U_{kt} + V_{kt}
\end{aligned}
\tag{2}
$$

Where $\widetilde{c}$ represents the value of total costs, y is the value of the products and w of the inputs. U_{kt} and V_{kt} are the inefficiency and random error terms, respectively.

Additionally, following Estrada & Osorio (2004) we incorporate one variable related to financial capital (z) and its interaction with the explanatory variables. This is to capture the effects of financial capital on costs. Thus, the new *translog* function will be:

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[3]Parametric methods differ in the distributional assumptions imposed to best disentangle random error from inefficiency, since neither of them are observed. SFA assumes inefficiencies follow an asymmetric distribution, while random error follows a symmetric one.

$$\widetilde{c}_{kt}(y,w,z) = \beta_0 + \sum_{i=1}^{2} \beta_i \ln y_{ikt} + \frac{1}{2} \sum_{i=1}^{2} \sum_{j=1}^{2} \beta_{ij} \ln y_{ikt} \ln y_{jkt}$$

$$+ \sum_{i=1}^{3} b_i \ln w_{ikt} + \frac{1}{2} \sum_{i=1}^{3} \sum_{j=1}^{3} b_{ij} \ln w_{ikt} \ln w_{jkt}$$

$$+ \sum_{i=1}^{3} \sum_{j=1}^{2} d_{ij} \ln w_{ikt} \ln y_{jkt} \tag{3}$$

$$+ d_0 \ln z_{kt} + \frac{1}{2} d_1 (\ln z_{kt})^2$$

$$+ \sum_{i=1}^{3} e_i \ln w_{ikt} \ln z_{kt} + \sum_{i=1}^{2} f_i \ln y_{ikt} \ln z_{kt} + U_{kt} + V_{kt}$$

An additional modification is that the input variables are included as a ratio, with one of them used as a numéraire (i.e. price of one input is normalized to 1). Note that this imposes homogeneity of degree one in factor prices only. Therefore, only two coefficients (b_i) for w are obtained, while the third can be inferred from the imposed restriction.

The random error term V_{kt} is assumed i.i.d. with $V_{kt} \sim N(0, \sigma_V^2)$ and represents those shocks that are not directly controlled by financial intermediaries and are assumed to be independent of the explanatory variables[4]. Meanwhile, the inefficiency term U_{kt} is i.i.d. with $U_k \sim N(\mu, \sigma_U^2)$ and is independent of V_{kt}. It is drawn from a non-negative distribution truncated in μ instead than at zero[5].

Let $E_{kt} = V_{kt} + U_{kt}$. The specific X-efficiency estimation of bank k at time t is given by the mean of the conditional distribution of U_{kt} given E_{kt}, defined as:

$$\text{EFF}_{kt}(\widetilde{c}) = \text{E}[\exp(U_{kt})|E_{kt}]$$

This measure takes values in the interval $(1, \infty)$. However, for simplicity in interpreting the index, we transform it so that it takes values between 0 and 1, with the fully efficient firm presenting a value of 1. Values below one, indicate that the bank's costs, conditional on its outputs, input prices and capital level, are above the cost that a fully efficient "best-practiceťt́ bank would incur under the same conditions.

$$\text{eff}_{kt}(\widetilde{c}) = 1/EFF_{kt}$$

The period analyzed runs from the first quarter of 2004 to the second quarter of 2012. Despite most of the information being available since 1995, the exercise could only be carried out from 2004 because the number of loans disbursed by each institution is available from this date. Introducing the number of credits into efficiency estimates is new in the banking efficiency literature, and it is the first time that

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[4]See Aigner et al. (1977) and Coelli (1996).

[5]Coelli et al. (1998) argue that the truncated distribution is a generalization of the half-normal distribution. It is obtained by the truncation at zero of the normal distribution with mean, μ, and variance σ^2. If μ is pre-assigned to be zero, then the distribution is the half-normal. The distribution may take a variety of shapes, depending on the size and sign of μ. The estimation of the truncated-normal stochastic frontier involves the estimation of the parameter, μ, together with the other parameters of the model. The log-likelihood function required for the Maximum-Likelihood (ML) estimation of the parameters of the model was first given by Stevenson (1980). Expressions for appropriate predictors of the technical efficiencies of firms were given in Battese & Coelli (1988).

it is used for the Colombian banking system. This feature will allow us to control for the scale of the products, which may significantly vary between entities.

The sample used is comprised of Colombian commercial banks, a group that has represented close to 88% of the total assets of credit institutions during the analyzed period. Hence, their representativeness in providing a general perspective of the Colombian financial system's efficiency is unquestionable. The data used is from the Colombian Financial Superintendency (financial system supervisory authority) and, for each period, we include only those entities with data available for all variables. This leaves us with a non-balanced panel, of 34 periods, 29 banks and 577 observations.

We identify two outputs: i) loans (y_1), defined as the total value of the credit portfolio, and ii) investments (y_2), calculated as the sum of total securities (i.e. equity investments, bonds (private and public) and other investments) held by the bank. As explained before, and in line with Hughes & Mester (1993), we include z as a control variable. The latter includes social capital, earnings, reserves and bank funds with specific destination.

We consider that simply including the total value of loans and investments provides a bias on the efficiency calculation, because these measures do not contemplate the scale of production. For example, some banks can originate a relatively small number of high value loans, and be treated equally to another bank that disburses a large number of loans, but with smaller amounts. To control for this, we use the number of loans outstanding, for each entity, to account for the mean loan value of the entity. Moreover, we divide the value of investments by the number of public debt bonds that each bank possesses[6]. Costs ($\tilde{c}$) and financial capital (z) are divided by the total number of products (loans and investments). In this sense, the efficiency obtained here can be interpreted as the X-efficiency for the average bank product.

Finally, we identify three input prices: i) the price of financial capital (w_1), computed as Interest Expense/(Customer and Short-term Funding + Other Funding); ii) the price of labor (w_2), defined as Personnel Expenses divided by the Number of Employees; and iii) the price of physical capital (w_3), calculated as Administrative Fees over Fixed Assets, where the former includes fees different from personnel fees (i.e. indirect operating costs, depreciation and amortization), while Fixed Assets include own used goods and other assets.

Unfortunately, the number of employees is not available for all banks nor for all periods considered. Therefore, we approximate it as follows: we assume a constant relationship between the number of employees, labor costs and financial capital. For all banks in the Colombian sector for which we have information on the number of employees, we regress the logarithm of the number of employees against the logarithm of both labor costs and financial capital[7].

The main inconvenience that arises with this approach, is that almost certainly the relationship is far from being linear and/or contemporary. Hence, the linearity imposed on the data may be shading the real effects on efficiency, which have to do with the efficiency of the labor factor. Additionally, it imposes a rigid structure of substitution between the labor and capital factors, something which methodologically one would want the data to reveal. This naturally enforces rigidities on the allocative efficiency (as must be known, X-efficiency is comprised of both technical and allocative efficiency), but does not affect technical efficiency.

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[6]Public debt bonds (or TES for their initial in Spanish) represent close to 60% of total bank investments, thus biasing the average investment amount towards a higher value. For this reason, we consider another efficiency measure that only includes average loans as a bank product.

[7]We also estimate the logarithm of the number of employees against the logarithm of assets and other variables. Between all the results, the model explained above presented the best fit.

However, we estimate the efficiency measures using only those firms that have observed data for the number of employees, which gives us an idea on the size of the potential bias incurred when approximating the number of employees with a linear regression. Specifically, we find that the regressions with the "estimatedťť number of employees underestimate bank efficiency levels close to 10%, on average. However, since this bias is only present for banks for which we have no information on the number of employees, it is important to note that this slant should be lower in recent periods as we have more information on the observed number of employees of each bank. Therefore, what we have is a proxy for the price of labor constructed as follows: Personnel Expenses / Estimated or Observed Number of Employees.

In Table 1, we present a brief summary of the main statistics for the variables involved. All quantity variables are expressed in thousands of Colombian Pesos and in real terms (June 2012 prices).

TABLE 1: **Main statistics of variables used in the efficiency estimates**

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Average Total Cost	16,530	2,662	99,258	101	917,855
Average Loan Cost	18,873	2,662	117,446	101	1,144,338
Average Loan	63,866	13,025	356,855	1,568	3,240,964
Average Commercial Loan	236,900	143,122	376,138	10,553	3,441,676
Average Consumer Loan	4,587	3,998	2,798	614	34,600
Average Mortgage	20,349	18,661	20,616	0	197,512
Average Microcredit	16,325	3,945	71,945	0	645,689
Average Investment	62,500,000	52,400,000	50,000,000	1,761,929	390,000,000
w_1	0.055	0.056	0.015	0.004	0.103
w_2^*	130,731	64,540	527,854	9,755	8,469,787
w_2^e	67,226	65,960	14,551	2,532	144,014
w_3	2.98	2.38	2.02	0.34	13.50
Average Total Financial Capital	28,232	2,340	194,833	164	2,298,702
Average Loan Financial Capital	32,770	2,340	233,214	164	2,858,726
Average Total Profits	3,118	477	20,532	1	254,021
Average Loan Profits	3,578	477	24,340	1	319,923

Note: Values are in thousands of Colombian pesos and in real terms (June 2012 prices).
The term *average total* means that the value of the variable is divided by the sum of the number of credits and investments.
Meanwhile, the term *average loan* implies that only the number of loans is used in the denominator.
* Calculated using only those banks with an observed number of employees.
^{e} Calculated using both the estimated and observed number of employees.
Source: Colombian Financial Superintendency; own calculations.

Table 1 contains information for banks from March of 2004 to June of 2012. From a simple inspection of the data, it is easy to verify that the Colombian financial system is comprised of heterogeneous banks, presenting different scales of business. For example, the average cost of a bank product is $16.5 million (m), but the median cost is $2.7 m. In the same way, we observe that the average value for a loan is $63.9 m, but the median is $13 m, with the minimum value being of $1.6 m. These values can be disaggregated according to the different credit modalities. The type of loans that present the highest mean and median value are commercial, which register $237 m and $143 m, respectively. Subsequently come mortgages, where the mean is close to $20.3 m and the median is of $18.7 m. Then come consumer loans, with an average value of $4.6 m, and a median of $4 m. Finally, one has microcredits, which present the highest

relative dispersion of all type of credits, with a mean of \$16 m being four times higher than the median (\$3.9 m).

With regards to the three inputs analyzed, one has that the labor force is the most expensive in the Colombian cost function (w_2), followed by physical capital (w_3). In effect, financial capital (w_1) is the cheapest input, and the one that shows the less variance between entities.

Additionally, for each unit of product (credit and investments), a Colombian bank has, on average, a financial capital of \$28 m and a median value of \$2.3 m as support. Moreover, for each unit of product, banks present mean returns close to \$3.1 m, but with a median revenue of \$0.5 m.

To check the robustness of the X-efficiency results, we also estimate a semi-parametric approach using the same inputs (w_1, w_2 and w_3) and outputs (y_1 and y_2). This measure has the advantage of being less influenced by, and hence more robust to, extreme values and outliers. This indicates that the efficiency measure will not suffer from the curse of dimensionality, since it implies that we do not require large samples to avoid imprecise estimations (Daraio & Simar (2007)).

Under this approach, we use the so-called Order-m approximation (See Cazals et al. (2002)). In this method, firm i is compared with a set m conformed by a random sample of the rest of firms. Among peers, the one that exhibits the minimum input consumption (x_{kj}) serves as a reference to compare against i's input consumption, and ϕ_m is calculated following a four step procedure explained by Tauchmann (2011):

1. From m_i, a sample of m peer firms is randomly drawn with replacement.

2. Pseudo FDH efficiency $\hat{\theta}_{mi}^{\widetilde{FDH}_d}$ is calculated using this artificial reference sample.

$$\hat{\theta}_{mi}^{\widetilde{FDH}_d} = \min_{j \epsilon m_i} \left\{ \max_{k=1,...,K} \left\{ \frac{x_{kj}}{x_{ki}} \right\} \right\} \tag{4}$$

3. Steps 1 and 2 are repeated D times.

4. Order-m efficiency is calculated as the average of pseudo FDH $\hat{\theta}_{mi}^{\widetilde{FDH}_d}$ scores:

$$\phi_i = \frac{1}{D} \sum_{d=1}^{D} \hat{\theta}_{mi}^{\widetilde{FDH}_d} \tag{5}$$

In general, the Order-m expected frontier efficiency can be interpreted as the expected minimum value of input achievable among a fixed number of m firms drawn from the population of firms that produce at least the output y. Recall that $\phi_m(y)$ is not the efficient frontier of the production set, but rather the expected minimum input among a fixed number of m potential competing firms producing more than y.

In this sense, Order-m efficiency gives us an indication of how efficient a bank is when compared to m of its peers, where the latter are chosen arbitrarily by the researcher. For example, an Order-m efficiency value of 0.7 means that the bank uses 30% more inputs than the expected value of the minimum input level of the other m firms that produce a level of output $\geq y$ (Cazals et al. (2002)).

It is worth noting that due to random re-sampling, in each replication D, each firm may or may not be available as its own peer. For this reason, Order-m efficiency scores may exceed a value of one, meaning that Order-m allows for super-efficient firms that are located beyond the estimated production possibility frontier (Tauchmann (2011)).

By using both X-efficiency, obtained by SFA, and Order-m efficiency, we can enhance the results of this research. If the efficiencies resulting from these two different methods yield similar qualitative findings in their relationship with the market structure variables, then the results would be considerably enhanced in terms of confidence (Bauer et al. (1998)).

2.2. Market Structure Variables

Again, the purpose of this paper is to examine the relation between efficiency and relevant market structure variables through the following equation:

$$eff_{it} = f(\overset{+/-}{HHI_{it}}, \overset{+/-}{Lerner_{it}}, \overset{+}{r_{it}^{dep}}, \overset{-}{r_{it}^{loans}}, \overset{+}{size_{it}}, \overset{+/-}{esp_{it}}, \overset{+/-}{quality_{it}}, \overset{+}{emp_{it}}, \overset{+}{fus_{it}}) + \epsilon_{it} \tag{6}$$

Table 2 presents the main descriptives statistics for the variables used in the model.

The Herfindahl-Hirschman Index (HHI) captures the degree of concentration, and is calculated as the sum of the squared loan market shares of all firms operating in the market. Regarding the value obtained for this index for the entire banking system in Colombia, we observe that there is indeed a low levels of concentration in the local credit market; the mean and median for this index is 855.4 and 935.5, respectively for the 2004-2012 period. However, the maximum value of this index reveals that, during certain periods, there have been significant increases in loan concentration. We identify those events as occurring during the first and second quarters of 2008, and in recent periods following 2011.

One important statistical aspect for our purposes is to obtain unbiased estimators. For this reason, we would like to introduce variability in the index for the estimation exercises, and we do so by making it relative to each bank, as proposed by Berger & Hannan (1993). Specifically, we multiply total HHI each period by the proportion of loans each bank has in the market[8]. By doing so, we capture, not only market concentration, but a relative measure regarding the contribution of every bank to the concentration level.

To measure market power we use the Lerner index, defined as the difference between loan and deposit interest rates, divided by the latter. r^{loans} and r^{dep} are calculated as a weighted sum of the rates charged on the different products offered by each bank. The values calculated for $Lerner$ indicate that the average firm maintains a loan interest rate 52.9% above the deposit rate. It is worth noting that this index has a large variance, since we can have an entity with a Lerner Index of 78%, and another of 15%. These results imply that, on average, Colombian banks charge customers a loan rate that is 1.5 times their funding cost, while a small group charge even higher, displaying considerable market power.

When we analyze interest rates, deposit's are more stable, presenting a mean and median of 6.7%, with a standard deviation of 2%, while loans rates are 15.2% on average but with a standard deviation of 4.5%. The latter suggests that the deposit market is more competitive than that of credit, which is in line with the findings highlighted on the Special Report on concentration and competition in the financial system on the Financial Stability Report of the Central Bank of Colombia.

To account for differences in efficiency due to distinct banks size, we also include the logarithm of the amount of total assets. On average, a Colombian bank holds an asset base of COP\$11.4 trillion (t), but the distribution has a standard deviation of COP\$7.8 t. This reflects the level of heterogeneity in bank size, where the smallest represents 0.8% of the biggest bank's assets. This discrepancy motivates

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[8]In Berger & Hannan (1993), the bank's HHI was weighted by the proportion of the bank's deposits relative to the market.

Table 2: **Main statistics of market structure variables**

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
HHI Total System	845.4	935.5	202.0	496.2	1,118.0
HHI Weighted	50.6	12.5	95.5	0.0	489.0
Lerner Index (%)	52.9	52.5	11.9	15.0	78.0
Credit Rate (%)	14.6	14.4	4.1	6.4	27.5
Deposit Rate (%)	6.7	6.8	2.0	2.2	11.8
Assets*	11.4	7.8	11.1	0.5	64.1
Prop. Consumer Loans (%)	31.3	27.3	20.4	0.0	94.0
Prop. Commercial Loans (%)	56.9	54.7	21.3	3.5	100.0
Prop. Mortgages (%)	8.8	0.9	14.7	0.0	76.6
Prop. Microcredits (%)	3.0	0.0	11.2	0.0	96.5
Loan Portfolio Quality (%)	9.1	8.2	4.7	2.1	37.5
Number of Employees	3,683.7	2,755.5	3,691.1	11.0	18,001.0
Number of Fusions or Merges	1.7	1.0	1.5	5.0	0.0

*Assets are expressed in trillions of Colombian pesos and in real terms (December 2012 prices).
Source: Colombia Financial Superintendency; own calculations.

us to investigate up until which scale we actually observe significant differences in efficiency. To do so, we introduce dummy variables that identify bank clusters, constructed considering the value of assets. The estimation yields the groups presented in Table , where the banks with the lowest level of assets are group No. 1 (Tiny), followed by No. 2 (Small) and No. 3 (Medium). Banks with the highest value of assets are in group No. 4 (Large), which is the least representative (in number of banks) of the sample.

Table 3: **Bank Clusters, by assets**

Number of Cluster	Distribution of Banks (%)	Mean of Assets*	Definition
1	30.1	1.6	Tiny
2	41.3	7.3	Small
3	17.8	15.6	Medium
4	10.8	35.7	Large

*Trillion of Pesos (December 2012 prices).
Source: own calculations.

Additionally, even though regulation allows for universal banking, some of the banks analyzed are clearly specialized in a specific segment of the credit market. For this reason, we incorporate the *esp* variable, which is a dummy that represents clusters that depend on the share in the credit portfolio of the different loan modalities, such as consumer, commercial, mortgage and/or microcredit.

On average, commercial credit contributes with the 56.9% of banks' loan portfolio, consumer with 31.3%, mortgages with 8.8% and the other 3% is microcredit. Nonetheless, there are intermediaries that are fully concentrated in commercial loans, and most are in consumer or microcredit, while the highest value for mortgages on an individual bank is 76.6%. In general, these extremes are rare, and so it is important to consider the different type of banks based on combinations of shares of the different credit modalities.

For this purpose, we characterize 4 groups through cluster analysis depending on the participation of the different credit modalities. Results are shown in Table 4.

TABLE 4: **Bank Clusters, by credit specialization**

Number of Cluster	Distribution of Banks (%)	Proportion of credit modality to total loans				Definition
		Commercial	Consumer	Mortgages	Microcredit	
1	8	96.6	3.3	0	0	Commercial
2	30.1	36.7	26.4	23.9	13	All type of credits
3	37.5	73.2	17.8	2.7	6.3	Mainly commercial with consumer
4	24.4	36.4	61.4	1.8	0.5	Mainly consumer with commercial

Source: own calculations.

From the analysis, we identify the following: Cluster 1 is comprised of those banks specialized in commercial loans, while Cluster 2 groups those who grant all the different modalities. Additionally, Cluster 3 refers to those entities whose activities are concentrated mainly on commercial credit, but with a significant share of consumer loans. Finally, Cluster 4 comprises banks that are concentrated in consumer credit, but with a significant participation of commercial loans as well.

In dealing with the query related with the relationship between efficiency and loan quality, we include the *quality* variable as the ratio between risky loans and the total loan portfolio. A higher value of this variable should be interpreted as an increase in credit risk; in this sense, we can think of this ratio as a *poor quality* index. On average, for the period between 2004-2012, 9.1% of banks' credit portfolio was labeled as risky, though heterogeniety is again high, with A particular bank registering an index of 2.1% and another of 37.5%. Nevertheless, it is worth noting that values over 25% are present in very few banks and for short periods of time.

Furthermore, we include the number of employees in the estimation (emp) with the purpose of examining whether an increment in the banking labor force, another size measure, has been translated into higher efficiency levels. On average, a Colombian bank operates with 3.684 employees; the bank with the largest labor force has had 18.001, while the smallest had 11[9].

Finally, with the purpose of evaluating the impact of market power on mergers we include a categorical variable that identifies when an entity has gone through a fusion process (i.e. acquisition or merger) (fus). On average, each bank has presented 1.5 fusions, while the firm with the most frequency has had 5 acquisitions or merges. Also, we observe banks with 0 fusion procedures.

In the next section, we present the results for both efficiency and the relationship of the latter with the relevant market structure variables.

3. Estimation results

3.1. Efficiency

The results for the X-efficiency measure through SFA are presented in Figure 3. There we can observe two alternative measures, one that considers loans as the only product, and another which also includes investments. The latter presents higher efficiency levels in the entire sample period considered, though it is worth noting that the evolution and trends are very similar. The gap between both measures could be

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[9]This information is for observed employee data only (i.e. excludes estimated number of employees).

explained by the fact that we cannot explicitly separate costs between loans and investment production. Consequently, the model is minimizing the cost of a production supposedly based only on credits, but using total banks costs, which include loans and investments. In this sense, if we estimate X-efficiency only with loans, we are underestimating the results.

Having said that, we intuit that the credit market is the most significant segment of the asset side of Colombian banks, not only because they represent 88% of the latter, but because we observe similar trends and patterns on the X-efficiency measures including and excluding investments (the line simply shows a parallel shift). This could mean that bank investments in Colombia are a complementary product that boosts the scale of the banking business. It is worth noting that the biggest difference between these two measures is observed in the period comprised between the latter part of 2008 and the beginnings of 2010, when public bonds showed particularly high yields due to the increment on interest rates by the Central Bank and hightened uncertainity caused by the external macro environment.

Moreover, during the period analyzed (2004-2012) we note that there is a positive trend of the X-efficiency level. However, there is also an evident valley that coincides with the dates following the macro-prudential measures imposed on the Colombian financial system to slow credit growth[10]. During this time, credit growth decreased significantly, eventually reaching negative rates. The release of this efficiency valley occurs at the beginning of 2011, when credit growth showed signs of renewed strength. The most recent data show that Colombian banks continue gaining in efficiency, though at a lower pace.

FIGURE 3: Average Banking X-Efficiency through time
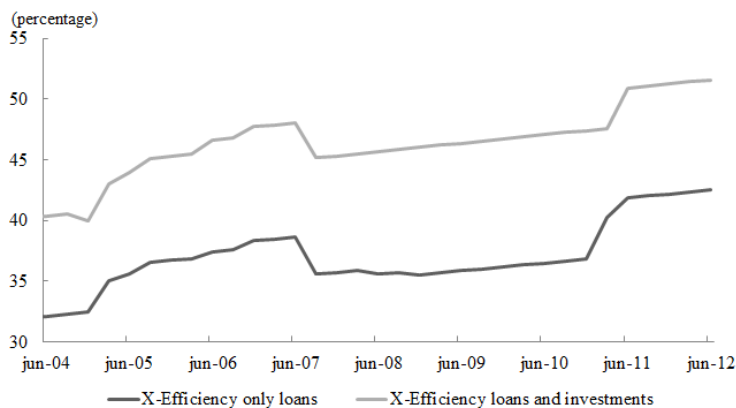
Source: own calculations.

The average efficiency level (including investments) for the sample period is 46.3%, and the value for June of 2012 is 51.6%. While this indicator is biased downward in around 10% for those firms were the number of employees is not observed, when we examine bank efficiency levels in other countries, we conclude that our result is not too low. Indeed, a quick overview of the literature concerned with estimating bank efficiency reveals that the banking systems in Austria, France, and Italy are similar, in terms of efficiency levels, to Colombia's; while banks in Belgium, Luxembourg, UK, Malaysia, Brazil and Chile, are below its level. On the other hand, the banking systems in Germany, Denmark, Philippines and some South-Eastern Europe countries present a higher efficiency level of operations (Table 5).

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[10]The measure was imposed on May of 2007.

TABLE 5: **Bank efficiency in other countries**

Country	Year	Efficiency	Methodology	Source
Austria	2008	0.5952		
Belgium	2008	0.443		
Denmark	2008	0.9999		
France	2008	0.5244	Fourier-flexible and translog form	*Apergis& Alevizopoulou* (2011)
Germany	2008	0.6316		
Italy	2008	0.6052		
Luxembourg	2008	0.2882		
UK	2008	0.458		
Albania	2007	0.7222	SFA with translog	*Fanget al.* (2011)
Bulgaria	2008	0.7277		
Croatia	2008	0.7417		
Macedonia	2008	0.6787		
Romania	2008	0.7429		
Serbia	2008	0.6945		
Philippines	2006	0.8474	SFA with translog	*Manlagnit* (2011)
Malaysia	1999	0.327	DEA and intermediation approach	*Sufian* (2009)
Brazil	2007	0.402	DEA in costs evolution	*Staubet al.* (2009)
Chile	2007	0.36	Free Distribution Approach on Benefits	*Carrenoet al.* (2010)

Subsequently, we estimate the semi-parametric approach and find efficiency levels that exhibit a similar behavior to those calculated parametrically. This provides a sound test on the robustness of our results, since Order-m efficiency, contrary to the SFA method, is not imposing a particular functional form. Moreover, Order-m efficiency levels result from comparing the quantity of inputs used, given a level of production, to the expected minimum input consumption among a fixed number of m potential competing firms that produce at least the same level of output.

These two different efficiency measures should not be contrasted, but rather complemented with each other. In particular, Order-m computes efficiency by comparison, while X-efficiency does so by estimating an optimal stochastic frontier. For this reason, we are not surprised by the fact that we find a higher efficiency average for Colombian banks each year by using the Order-m approximation; the mean for the 2004-2012 period is 69%, while the result for June of 2012 is 96.2%. On interpreting this result, recall that the sample of m firms is chosen randomly from banks of past, present and future periods, resulting in a comparison of each bank with peers from different time periods. This last statement suggests that bank efficiency has improved over time, and if we observe Figure 4, this seems to occur specially since the second half of 2010.

By comparing changes in the efficiency indices against the credit cycle, we confirm that there is a similar behavior between both series. This means that when the local economy has experienced rapid credit growth, this have been accompanied by increments in banks efficiency. Indeed, the most recent acceleration on credit growth (2011) was met by an increase of 4 percentage points (pp) in the average X-efficiency measure as well as a significant increase in Order-M efficiency, of around 12 pp. A similar situation occurred in 2005, when the credit growth rate presented a noteworthy augment. Thus, the question that

FIGURE 4: Average Banking Order-M Efficiency through time
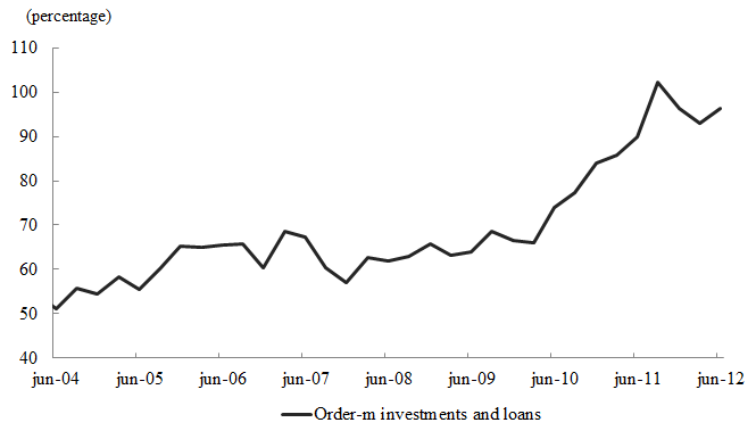
Note: this efficiency measure may present values over 100% since its methodology is by comparison. This is different from a stochastic frontier measure, where the efficiencies are equal or below 100%.
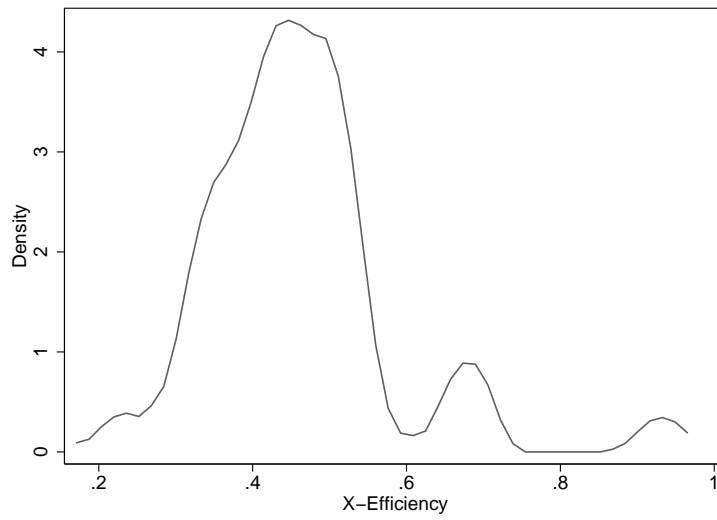Source: own calculations.

remains is why in recent periods, when the credit growth rate has eased off, the efficiency levels continue showing increments. To shed some light on this issue, we consider that some particular circumstances in the financial system have reinforced efficiency, such as the technological revolution on financial services (e.g. mobile banking) and the increase in the bancarization levels of the population, which translates in transactions being done at a lower cost, and at a higher frequency.

One relevant aspect mentioned by Bauer et al. (1998) is that two efficiency measures show consistency conditions if they have a similar distribution and rank the entities approximately in the same order, among other aspects.

Despite having considered that the distributions of parametric and semi-parametric measures should not be strictly compared because of the ex-ante divergence on the distributional assumptions, we would like to show that there are a few similarities between both indexes. The efficiency distributions are shown in Graphs 5 and 6 for the X-efficiency and Order-m, respectively. With respect to the X-efficiency, most banks lie between 30% and 55%, with some observations in the range 64% - 74%, and just a few greater than 90%. In terms of Order-m measures, we find that most banks range below 60%, but there are a few that could be categorized as super-efficient. In a nutshell, we find that most banks lie below 60% on their efficiency levels, while there are some that present significant (high) values.

Analyzing the results on the average efficiency level for each entity, we distinguish who have been the more efficient banks, and how far they are from the others (Graphs 7 and 8). When comparing the outcome of X-efficiency and Order-m efficiency, in the former we observe two banks with levels over 90% (No. 1 and No. 2), and three more above 60% (No. 3, 4 and 5). On the other hand, in the Order-m results there are four firms with efficiency values higher than 100% (No. 1, 2, 4 and 21) and an additional three above 90% (No. 3, 18 and 19). These outcomes more or less place the same entities as the most efficient (No. 1, 2, 3 and 4). Additionally, the Order-m approximation gives us two more entities that have a significant level of production relative to the inputs used by their peers. This seems to imply that the X-efficiency measure is consistent, insofar as its results are in line with those obtained from the Order-m estimations.

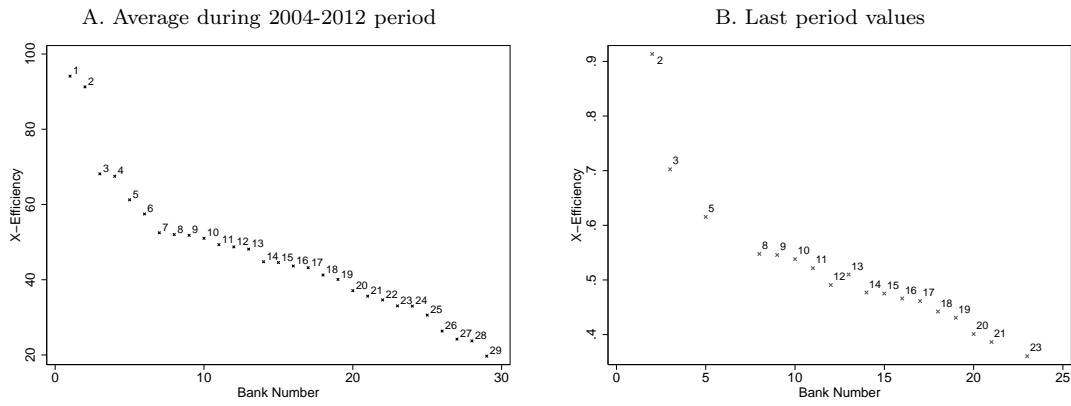FIGURE 5: Kernel Density on X-Efficiency

Source: own calculations.

FIGURE 6: Kernel Density on Order-M Efficiency
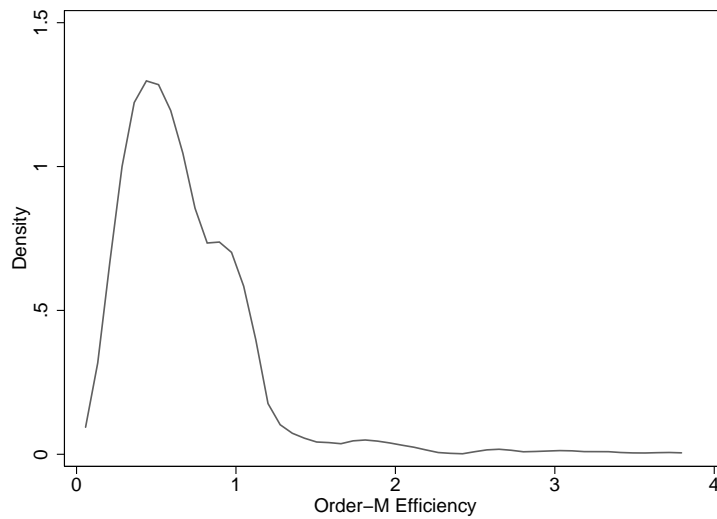
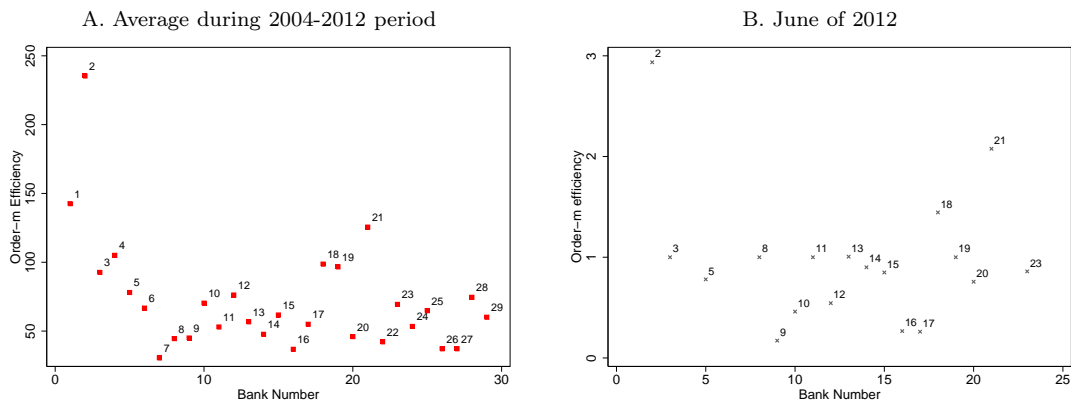Source: own calculations.

Bearing this consistency in mind, in what follows we estimate the relation between certain market structure variables and the X-efficiency levels.

FIGURE 7: X-Efficiency

A. Average during 2004-2012 period

B. Last period values

Source: own calculations.

FIGURE 8: Order-m Efficiency

A. Average during 2004-2012 period

B. June of 2012

Source: own calculations.

3.2. Bank efficiency and the relationship with market structure variables

In Table 6 the results from the regression analysis are presented, were we model the X-efficiency measure[11] as a function of concentration, market power, interest rates, banks size, loan specialization, number of employees and fusions.

It is worth noting that by using this approach there exists a concern of "reverse causation", since we are assuming that changes in bank concentration, market power, interest rates and asset value can affect efficiency, but shifts on the efficiency level could also have an impact on these variables. Therefore, we consider that $ln(HHIpart)$, $Lerner$, r_i^{dep}, r_i^{loans} and $on(assets)$ are endogenous variables[12]. Hence, a bias may exist if we run the regressions by ordinary least-squares (OLS). To correct this issue, we ran the estimations using the two-stage least squares (2SLS) methodology, where the instrumental variables were lags of the same endogenous variables.

The results shown in Columns 1 to 7 regarding market concentration provide evidence of a significant negative relation between $ln(HHIpart)$ and efficiency, as expected by the traditional perspective. This implies that Colombian banks that report the highest levels of market share, behave in the form of a *quiet life*; they present lower cost efficiency levels since they are already in a comfort zone, where they can earn economic profits without the full effort of cost minimization.

Moreover, concerning the relationship between efficiency and market power, we find a positive and significant coefficient for $Lerner$, also found in Columns 1 to 7. As explained above, this could imply that some Colombian banks have market power as the result of a certain degree of product differentiation or economies of scale, which allows them to produce more efficiently while at the same time setting a higher price for their products relative to the cost of their inputs.

Analyzing the results for loan interest rates, we obtain a negative and significant coefficient (Columns 1 to 7, except 3). This means, *ceteris paribus* (specially the Lerner Index), that those banks that set lower credit rates are the most efficient, as they may have a production technology which allows them to enjoy diminished marginal costs and increased efficiency. Analogously, this also implies that banks with higher loans rates are the less efficient, and are transferring their higher production costs to debtors.

If we segment those banks that have a greater degree of market power and additionally present the largest absolute loan rates (which is done with the interaction between $Lerner$ and loans rate found in Column 3), we obtain a negative relation with efficiency. The latter means that those banks with high market power will be more efficient provided they face reduced marginal costs, for instance due to product differentiation, that are effectively translated to lower credit prices. Otherwise, those banks with high market power will be less efficient, since their costs are higher.

In addition, in Column 2 we interact $ln(HHIpart)$ with $Lerner$, since the traditional theory contemplates that concentration may be related to more market power. However, the coefficient for the interaction is not significant, suggesting, everything else being equal, that those banks that increase their market share and at the same time gain market power, not necessarily experience an increase in efficiency. This may be also explained from the perspective of the *quiet life* hypothesis, where gains in efficiency are explained by a reduction in marginal costs which is not done by those firms with the biggest share and market power, since they already earn profits without the full effort of cost minimization, by simply placing higher credit prices.

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[11] The same regression models were estimated using the Order-M efficiencies and are available upon request. Results are qualitatively identical.

[12] The Hausman tests for endogeneity were done to prove these assumptions.

If we further interact the Lerner Index with the mergers and acquisitions variable, to evaluate the influence of market power over fusions, we obtain a non significant coefficient, as show in Column 4. Nevertheless, when we test the significance of the fusions variable in the same Column 4, we find a meaningful (positive) coefficient, verifying the two efficient-structure hypotheses. In this order of ideas, when a merger or acquisition process has been undertaken in the Colombian banking sector, it has generally been translated into a gain in efficiency.

Another aspect that is evaluated is the influence of additional deposit services over efficiency, assuming we can capture such added value through superior deposit rates. Under this assumption, the coefficients in Columns 1 to 7, excepting 3, show a positive relation between r_i^{dep} and efficiency, implying that banks which offer more services relating to their deposit accounts are more efficient.

Moreover, with the aim of testing differences in efficiency due to bank size, we introduce the logarithm of asset value. The coefficient, found in Columns 1 to 5, reveals a positive and significant relation between the size and efficiency of banks, which could be evidence of the presence of economies of scale. Additionally, in order to explore how strong this connection is when considering different levels of banking size, we incorporate dummy variables that identify if the bank is classified as tiny, small, medium or large. In Column 6 we present the results for every size-group, with tiny as the benchmark. First, we observe a positive coefficient for all sizes. In addition, we find that the coefficient becomes higher as we advance from small to medium, and then to large size. This means that the bigger the bank is, the larger the marginal impact on efficiency due to possible economies of scale.

An additional measure of banks size could be the number of employees, since it should be proportional, not only to the value of assets, but also to the size of the bank's business. In Column 7 we introduce the logarithm of the observed number of employees. We find that those with a larger number of employees present higher levels of efficiency. This also suggests economies of scale.

As noted above, even when the regulatory framework allows banks to operate under a universal banking business, there is, currently, a certain degree of market specialization. This raises the question as to whether field banks operate in a more efficient level. To capture this, we first include the proportion of credits that are granted in each modality to total loans, leaving that of mortgages as the base. Results can be observed in Columns 1 to 7, excluding 5. As can be seen, we find that an increase of every type of loan in the credit portfolio, compared to mortgages, increments the efficiency level of banks. When we distinguish the coefficients between the different modalities, we observe that the greatest increment on efficiency occurs when the bank is augmenting its portion of microcredits.

An alternative regression was designed to allow for different combinations between credit types. Considering a cluster analysis based on the different share modalities on the loans portfolio, we obtain 4 groups of banks as explained in Table 4. The result is shown in Column 5, where the base is chosen as those banks that are in the group of every type of loan (Group 2). We observe that specializing only augments efficiency if the loans are commercial (*esp* No. 1). Otherwise, granting all types of loans yields more efficient outcomes than those of the other specializations studied here.

Concerning the impact of loan quality, we obtain no significance in the coefficients. This implies that seems to be no relation between the level of cost efficiency of a bank and the soundness of its risk evaluation.

TABLE 6: **Relationship between bank efficiency (in logs) and market structure variables (2SLS)**

Dependent: X-efficiency							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$ln(HHIpart)$	−0.016***	−0.016***	−0.016***	−0.017***	−0.016***	−0.007***	−0.008***
	(0.0007)	(0.001)	(0.0007)	(0.0007)	(0.0007)	(0.001)	(0.001)
$Lerner$	0.100***	0.099***	0.100***	0.101***	0.095***	0.141***	0.126***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.018)	(0.020)
$ln(HHIpart) \times Lerner$		0.0003					
		(0.001)					
r^{loans}	−0.003***	−0.003***	0.003***	−0.004***	−0.003***	−0.005***	−0.005***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0006)
$r^{loans} \times Lerner$			−0.006***				
			(0.0006)				
r^{dep}	0.006***	0.006***		0.006***	0.006***	0.008***	0.007***
	(0.0006)	(0.0006)		(0.0006)	(0.0006)	(0.001)	(0.001)
$ln(assets)$	0.045***	0.045***	0.045***	0.042***	0.049***		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Large						0.060***	0.052***
						(0.003)	(0.004)
Medium						0.033***	0.032***
						(0.002)	(0.004)
Small						0.015***	0.017***
						(0.002)	(0.003)
esp No. 1					0.009***		
					(0.002)		
esp No. 3					0.001		
					(0.001)		
esp No. 4					−0.003*		
					(0.001)		
Consumer share	0.019***	0.020***	0.019***	0.023***		0.080***	0.070***
	(0.004)	(0.004)	(0.004)	(0.004)		(0.008)	(0.023)
Commercial share	0.022***	0.022***	0.022***	0.020***		0.021**	0.047**
	(0.004)	(0.004)	(0.004)	(0.004)		(0.007)	(0.021)
Microcredits share	0.049***	0.049***	0.049***	0.058***		0.051*	0.101**
	(0.013)	(0.013)	(0.013)	(0.013)		(0.025)	(0.037)
$quality$	−0.005	−0.005	−0.005	−0.002		0.015	−0.001
	(0.007)	(0.007)	(0.007)	(0.007)		(0.016)	(0.024)
lnemp							0.004***
							(0.0007)
fus				0.004***			
				(0.001)			
$Lerner \times fus$				−0.0003			
				(0.001)			
Constant	−0.594***	−0.594***	−0.594***	−0.510***	−0.631***	0.367***	0.367***
	(0.022)	(0.022)	(0.022)	(0.024)	(0.022)	(0.012)	(0.012)
R squared (within)	0.9103	0.9103	0.9103	0.9181	0.9125	0.7239	0.6162
Observations	569	569	569	569	569	545	396

Note: *** represents significance at 1% level, ** at 5%, and * at 10%. Error standards are in parenthesis.
Source: own calculations.

4. Concluding remarks

In this document we examine how certain market structure variables are related to cost efficiency for Colombian banks. Even when bank efficiency has not been studied for some time in Colombia, we consider that the financial system has gone through significant changes that highlight the importance for studies on efficiency to be revived. In particular, we estimate cost efficiency by the traditional SFA, but making a meaningful change on the way products are considered; loans and investments were considered by their mean unit value, and not by total stock. In this way, we expect our measure to be less narrow, as we control for differences in business scale. Moreover, the results obtained with the traditional SFA method were tested for consistency with a new semi-parametric approach: Order-m.

The results show that the Colombian banking system has increased its efficiency through the 2004-2012 period. However, we find a valley where efficiency levels staggered after the macroprudential measure imposed to reduce the rate of credit growth in 2007, since it translated in an increase on production costs. That fall in efficiency is recovered once credit starts rising again in 2011. Currently, even when the growth rate of credit has been sluggish, bank efficiency is still augmenting. This could be explained by other factors, such as the technological revolution on financial services and an increase in bancarization, which have led to lower transaction costs and higher frequency.

As of June of 2012, Colombia's bank X-efficiency level was around 60.3%. Comparing this situation with other countries, we find that efficiency in Colombia is not necessarily low, as other documents report that the banking systems from Austria, France, and Italy have levels of efficiency similar to ours, while banks from Belgium, Luxembourg, UK, Malaysia and some Latinamerican countries (Brazil and Chile), are actually below. Conversely, banks from Germany, Denmark, Philippines and some South-Eastern Europe countries present higher levels.

The relation between efficiency and the relevant market structure variables was established through 2SLS regressions in order to control for endogeneity. The results suggest that the Colombian banking system is characterized by a form of *quiet life*, since concentration is negatively related to efficiency; meaning that entities that exhibit the highest concentration are the less efficient, because they do not have the incentives to make the full effort of minimize costs, as they already have a significant market share which allows them to gain economic profits.

Regarding market power as the ability to charge a credit price beyond deposit rates, we find a positive relation with efficiency, implying that entities with high market power are possibly those who present some product differentiation, since they can charge a relatively high rate, while at the same time exhibiting efficiency gains. However, this relation is not always positive, because if we segment those banks that have the greatest market power and present the largest absolute loans rate, efficiency actually falls. This implies that, even when market power is potentially related to product differentiation, banks that set lower interest rates are the ones that show increased efficiency.

Another subject studied regarding market power was its relation to concentration and its influence on mergers. Both interactions turn out to be statistically non significant. However, when analyzing fusions independently, we obtain a positive relation with efficiency. Additional aspects, such as the size of the banks and the amount of workers, are positively related to greater efficiency levels, possibly signaling the existence of economies of scale in the banking sector. In addition, we find that specializing on a specific loan type only augments efficiency if it is commercial, otherwise its better to diversify and grant every credit modality. Finally, we do not find a significant relation between the risky portfolio and efficiency.

In terms of general policy, we find evidence to support that the expansion of financial services has been produced in positive terms. First, the wave of horizontal mergers from recent years has been accompanied by internal changes, with entities apparently experiencing cost structure adjustments hat have led to gains in efficiency; and even when some firms present significant market power, this fact has not influenced, at least in a negative way, the efficiency levels of the market. Additionally, we expect that in coming years universal banking will continue to expand, enhancing the results of greater efficiency on firms that grant all type of loan modalities. One last aspect to mention is that we would like to call attention on the relevance of closely monitoring market concentration levels, since these have increased in recent years, and exhibit a negative relation with market efficiency.

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