The Dark Side of Prudential Measures☆

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Resumo

Uma série de mudanças ocorreu no cenário da regulação financeira logo após a grande crise financeira de 2008 e 2009. Globalmente, várias medidas macroprudenciais que buscam limitar o risco sistêmico foram implementeadas e despertaram a atenção para sua eficácia e impactos. Neste artigo, avaliamos o efeito dessas medidas sobre o poder de mercado dos bancos no caso brasileiro, em que houve um processo de grande concentração bancária que coexiste com spreads bancários elevados. Usando uma metodologia inovadora, mostramos que as medidas macroprudenciais tiver um efeito negativo sobre a competição bancária, aumentando o poder de mercado dos bancos. Desta forma, é essencial que os reguladores financeiros considerem esse efeito adverso na elaboração de normas que visem, não apenas a estabilidade financeira, mas também um sistema financeiro mais competitivo.

Palavras-chave: Regulação bancária, Medidas Prudenciais, Poder de mercado, Índice de Lerner, Fronteira Estocástica.

Abstract

In the aftermath of the financial crisis of 2008 and 2009, there is a series of changes in the scenario of financial regulation. Globally, several macroprudential measures that seek to limit systemic risk are currently in use. We evaluated the effect of these measures on the market power of banks in the Brazilian case, in which there was a process of great banking concentration that coexists with high bank spreads. Using an innovative methodology, we show that the effect of macroprudential measures is to reduce bank competition by increasing the market power of banks. It is essential that financial regulators consider this adverse effect in the design of a financial regulation that not only aims at financial stability but also a more competitive banking system.

Keywords: Bank Regulation, Prudential Measures, Market Power, Lerner Index, Stochastic Frontier.

JEL Classification: L13, G18, E58

Área 8 - Microeconomia, Métodos Quantitativos e Finanças

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1. Introduction

The financial crisis that hit the economies of the world from 2007 to 2009 reinvigorated the debate on how to regulate banks and other financial institutions to ensure financial stability. Before the global financial crisis (GFC) financial regulation for banks and other financial intermediaries was focused on instruments aimed at reducing the risk of bankruptcy, i.e., microprudential measures. However, as seen in the GFC, the bankruptcy of a large financial institution (FI) put at risk the solvency of the system as a whole and raised concerns about global financial stability. Since then, systemic risk became the focus of financial regulation - macroprudential measures.

The implementation of this new set of micro and macroprudential measures has raised several challenges for assessing the impact of such measures on banks and the financial system as a whole and spurred a vast literature on the subject. One of the main challenges is to evaluate the effectiveness of macroprudential policies concerning the central objective of increasing resilience. Besides that, to smooth the business cycles of the financial system (Claessens et al., 2013; Claessens & Laeven, 2004; Cerutti et al., 2017; Jiménez et al., 2017; Altunbas et al., 2018; Ely et al., 2019; Klingelhöger & Sun, 2019; Richter et al., 2019).

To the best of our knowledge, we note that most of the research focuses on analyzing the impact of prudential measures (micro and macroprudential) on bank loans, risk-taking behavior of the FI, or transmission of monetary policies, however, not directly on the (in) efficiency of the credit market. There are few exceptions. The first is the work of Cubillas & Suárez (2018) that investigates the negative impact of the GFC on the availability of credit and find that the increase of the banks' market power neutralized this effect. The relevant fact of this study is that this neutralizing effect on the availability of credit, caused by the increase in market power, is more significant in countries with fewer restrictions on the activities of banks, or less power of official supervision of financial institutions.

The second is Ayyagari et al. (2018) combining balance sheet data on 900,000 firms from 48 countries between 2003 and 2011 with detailed data on the use of macroprudential policy instruments. The main result indicate that macroprudential policies are negatively associated with firm financing growth.

In light of this situation, this article, in a pioneering way, investigates the influence of some prudential measures (micro and macroprudential) on the market power of Brazilian banks using a new class of market power estimation models based on border techniques (Stochastic Frontier Analysis - SFA), initially proposed by Kumbhakar et al. (2012).

The central hypothesis formulated in this paper is that prudential rules to which FIs are subject may affect banks market power. According to Claessens & Laeven (2004), any policy that restricts banking activity and makes it challenging to operate has negative impacts on market competition, since it enables large banks to increase their market power. Therefore, a strict prudential regulatory framework could affect concentration indices and influence the market power of FIs since the implementation of Basel I agreements in 1988.

Our main contribution is to demonstrate that tightening on prudential measures has a positive impact on bank mark-ups and, therefore, detrimental effects on competition in the Brazilian banking industry. Although not wholly comparable, intuitively, our results are contrary to those of Cubillas & Suárez (2018). A second empirical verification was to establish a positive relationship between concentration and mark-up, in the same sense established by the traditional structure-conduct-performance paradigm of industrial organization literature.

Another contribution concerns the empirical method. For the first time, we employ SFA models to estimate market power for Brazilian banks on an individual basis. With the estimation of the

Lerner indexes for each bank, it is possible to evaluate the market power according to ownership and to verify that state-owned banks have market power slightly lower than the private banks and foreign banks, respectively. Finally, we also obtain estimates of returns to scale that provides some evidence that Brazil's financial institutions operate with decreasing returns to scale.

We organize the remainder of the paper as follows. In section two, we present related literature. We present the empirical model in section three, while we describe the database and the empirical strategy in section four. In the fifth section, we present our main results, and in the sixth and last section, we present our final considerations.

2. Brief Literature Review

We can divide the literature related to our article into two groups. The first group focuses on the effectiveness of prudential measures, while the second focuses on the traditional literature of industrial organization, more specifically, on the estimation of market power.

Before GFC the focus of financial regulation for banks and other financial intermediaries was on instruments aimed at reducing the risk of bankruptcy, i.e., measures of a microprudential nature and not on the financial system as a whole. However, as seen in the GFC, the bankruptcy of a large FI put at risk the solvency of the system as a whole. When a large FI fails, there is potential for amplification and contagion in the banking system. These effects may lead to cascade failures in the financial system, which can provoke a significant shock that affects the real sector adversely. In order to account for the interconnections that may exist between financial system players, financial regulation changed its focus to curb systemic risk, using macroprudential measures.

The works of Moreno (2011), Galati & Moessner (2013), Lim et al. (2011), Claessens et al. (2013), Claessens (2015) and Freixas et al. (2015) summarize the main prudential instruments (microprudential and macroprudential) implemented by developed and developing countries. Also, they present their meaning and purpose to mitigate the probability of bankruptcy of FIs and the systemic risk arising from the procyclicality and the interconnectivity between FIs.

Among the empirical studies, Lim et al. (2011) analyze the links between macroprudential policies and the development of the credit market and bank leverage. They find evidence suggesting that the presence of policies such as limits on maximum loan value (LTV), limits of indebtedness (DTI), limits of credit growth, capital reserve requirements and dynamic rules of provisioning are associated with reductions in the procyclicality of credit and leverage.

Claessens et al. (2013) investigate how the change in the individual balance sheets of banks in 48 countries in the period 2000-2010 responds to specific changes in some macro-legal measures. Among the main results, the authors show that the maximum limits of LTV, DTI, and the maximum limits of foreign currency lending are effective in reducing the growth of bank leverage and the price of assets.

Aiyar et al. (2014) show that, in response to stricter capital requirements (capital requirement), regulated banks reduce borrowing while unregulated banks may even increase. Gropp et al. (2018) study the requirement for higher capital requirements. Its results point to a reduction in credit and a smaller search for capital to meet the new targets. Auer & Ongena (2019) find that an additional capital requirement on real estate loans leads to growth in the retail lending channel.

In addition to this empirical evidence, Cerutti et al. (2017) using an IMF survey covering the use of twelve macroprudential measures in 119 countries over the period 2000-2013 indicate that, in general, emerging countries use intensely such instruments. Also, instruments such as LTV and others that limit the level of indebtedness are associated with the decline in credit growth, especially real estate lending.

Other studies, however, focusing on a few prudential measures and for few countries, also stand out. Igan & Kang (2011) investigate only the effectiveness of LTV and DTI measures in Korea. Wong et al. (2011) also use only the LTV and DTI measures to investigate the behavior of real estate credit and real estate prices in Hong Kong. Camors & Peydro (2014) investigate the effect of capital withdrawal in Uruguay in the year 2008. Aiyar et al. (2014) also investigate the capital requirement for UK banks and confirm a substantial effect on the bank loan. Finally, more recently, Altunbas et al. (2018) direct the investigation of the effectiveness of macroprudential measures for the risk behavior of banks.

Overall, this literature shows that for different countries, samples, and prudential measures, there is a positive effect on systemic risk. Countries that implement these measures can reduce their lending growth to more sustainable levels and improve their financial stability. However, what is the costs of these measures? Is there a trade-off in using such measures? We now discuss the market power and bank competition literature to assess the second strand of the literature that helps us make our connection.

In the competition-related literature in the banking industry, research models and approaches generally have a limitation due to the structure and availability of data. However, the model of Panzar & Rosse (1987) - PR - is a standard method when one wants to evaluate the degree of competition in the industry. Only in Brazil, we can cite the works of Belaisch (2003), Araújo & Jorge Neto (2007), Lucinda (2010), Tabak et al. (2012), Silva, Barbosa et al. (2015), Tabak & Gomes (2015) and Cardoso et al. (2016). In our investigation, we found only two other studies that did not use the PR model. Nakane (2002) uses a structural model as proposed by Bresnahan & Reiss (1991) and Coelho et al. (2013) use a bank entry model developed by Bresnahan (1982). Internationally, the literature is vast, and Bikker et al. (2012) offers a comprehensive survey of the literature developed around the world.

It is important to note that use of the PR model as a measure of market power has some caveats because it does not have a monotonic relationship with the degree of market power (Panzar & Rosse, 1987; Bikker et al., 2012; Cardoso et al., 2016). In addition, their results are obtained under a very restrictive set of assumptions, such as long-term equilibrium. In the same way, the model is quite sensitive to variables and specification used on estimation (Hyde & Perloff, 1995; Bikker et al., 2012). All these issues weaken the evidence of market power found from its results.

Given this context, we will use a new class of models to measure the degree of market power proposed by Kumbhakar et al. (2012) and based on stochastic boundary analysis techniques (SFA). The SFA models have several advantages when compared to the traditional models of literature known as New Industrial Empirical Organization (NEIO) and allow estimating, in a single model, a unified structure, a mark-up measure and an indicator of market power. Also, we can obtain measures of elasticity, return to scale, and efficiency.

Among the main advantages of SFA models, it is possible to emphasize the flexibility and the low requirement of information for estimations of the models. The method also allows estimating market power with or without constant returns to scale and provides an estimate of the degree of market power in the same style as the Lerner index (Lerner, 1934), thereby circumventing the critique of the use of H as a monotonic measure of the degree of competition. Another advantage of the method is that, unlike most NEIO models, this measure of market power is not only an estimate of the average parameter of the competition level of the industry, but the method also allows estimating a measure of the degree of market power per bank and over time. In the same way, it is possible to estimate the returns to the banks' scale. Finally, the SFA technique allows the parameter of market power to be a function of deterministic variables.

One of the pioneering works using SFA techniques in the banking industry is the work of

Coccorese (2014). In this article, the author estimates the Lerner index for each bank individually for a group of countries between 1994 and 2012, with the results being broadly comparable with the traditional NEIO models. More recently, Das & Kumbhakar (2016) have also used this class of models to investigate the market power of Indian banks. We can found others papers that use SFA to estimate market power such as Bairagi & Azzam (2014), Scalco et al. (2017), Lopez et al. (2018) and Kabir & Worthington (2017)

We use this model to evaluate the effect of prudential measures on the bank's market power. Combining an SFA method with data on prudential measures, we can estimate these effects. We use prudential measures as explanatory variables for the market power parameter that we estimate in the SFA.

3. Empirical Method

Our empirical model follows the models proposed by Coccorese (2014) and Das & Kumbhakar (2016). However, we incorporate the possibility that the mark-up has two components, a purely stochastic and a deterministic part. The derivation of the model starts from the equilibrium condition that for a profit-maximizing bank (P) will be greater than or equal to its Marginal Cost (MC):

$$P \geq MC \tag{1}$$

The distance between P and MC determines the degree of market power of the bank. After some simple algebraic manipulations and considering that $MC = \frac{\partial C}{\partial Y}$ we can rewrite eq (1) as

$$\frac{TR}{C} \geq \frac{\partial lnC}{\partial lnY}, \tag{2}$$

where $TR = P \cdot Y$ is the total revenue, and C represent the total cost. The relationship established in equation (2) states that in the same way as price deviates from its marginal cost, the revenue-cost ratio of the bank (TR/C) detracts from its cost-elasticity.

The inequality in equation (2) can be solved by adding a non-negative term u. Thus:

$$RC \equiv \frac{TR}{C} = \frac{\partial lnC}{\partial lnY} + u, \qquad u \geq 0. \tag{3}$$

RC is the observed revenue-cost ratio and $\frac{\partial lnC}{\partial lnY}$ is the cost-elasticity. The non-negative term u represents the mark-up of the bank, however, it can not be calculated using the bank's accounting data because the cost elasticity, unlike RC, must be calculated from a cost function. In addition, the revenue-cost ratio can be affected by other unobserved variables. To accommodate this assumption, we add a random error term i.i.d. v to equation (3):

$$RC = \frac{\partial lnC}{\partial lnY} + u + v. \tag{4}$$

As equation (4) has been defined, we need to specify a cost function to estimate the term u, that is, we are using a dual approach in the context of production theory. Kumbhakar et al. (2012) show, however, that SFA models can use both the dual and primal approaches to estimate market power. In the dual approach the total cost of the bank depends on the output quantity and input prices and the primal approach, we can specify a production function (or an input-distance function), where the output is a function of only input quantities. This flexibility is essential because unlike many examples, in the banking industry, we do not have information available on input prices.

Thus, like Das & Kumbhakar (2016), we use the primal form as an alternative to the dual form. We start from the specification of a transformation function, defined as $Af(x, Y, T) = 1$, where $f(\cdot)$ is a production function for a given technology, Y is the quantity produced, x is the quantity vector of inputs used, T is a trend variable, capturing technological changes and A is a parameter of neutral technological shift.

Using a set of appropriate identification restrictions (Kumbhakar, 2012) we can derive a function input distance (IDF) from the transformation function, given by $x_J = Ah(\tilde{x}, Y, T)$, or $\ln x_J = Ah(\ln \tilde{x}, \ln Y, T)$, where $\tilde{x}_j = \frac{x_j}{x_J}$, $j = 1, 2, \ldots, J-1$. The IDF uses the normalization that $f(x, Y, T)$ is homogeneous of degree -1 i.e. $\sum_j \frac{\partial lnf}{\partial lnx_j} = -1$.

Assuming that banks minimize the cost subject to technology specified by the production function, the Lagrangian for the minimization can be defined as

$$L = \mathbf{w'x} + \lambda(Af(x, Y, T) - 1), \tag{5}$$

where $\mathbf{w}$ is a vector of input prices and the corresponding first order condition is:

$$w_j = -\lambda A \frac{\partial f(\cdot)}{\partial x_j}, \qquad j = 1, 2, \ldots, J. \tag{6}$$

Multiplying and dividing both sides by x_j and $f(\cdot)$ and rearranging terms, we can rewrite equation (6) as:

$$w_j x_j = -\lambda A f(\cdot) \frac{\partial f(\cdot)}{\partial x_j} \frac{x_j}{f(\cdot)} = -\lambda A f(\cdot) \frac{\partial lnf(\cdot)}{\partial lnx_j}, \qquad j = 1, 2, \ldots, J \tag{7}$$

and if we take the sum of all inputs equation (7) becomes:

$$C \equiv \sum_{j=1}^{J} w_j x_j = -\lambda A f(\cdot) \sum_{j=1}^{J} \frac{\partial lnf(\cdot)}{\partial lnx_j} \Rightarrow -\lambda A = \frac{C}{f(\cdot)} \cdot \frac{1}{\sum_{j=1}^{J} \frac{\partial lnf(\cdot)}{\partial lnx_j}}. \tag{8}$$

From the envelop Theorem, we have that the marginal cost (MC) is $\frac{\partial L}{\partial Y} \equiv MC = \lambda A \frac{\partial f(\cdot)}{\partial Y} = 0$. If we use equation (8) we can express it as:

$$E_C \equiv \frac{\partial C}{\partial y} \frac{Y}{C} \equiv \frac{\partial lnC}{\partial lny} = -\frac{\partial lnf(\cdot)}{\partial lnY} \cdot \frac{1}{\sum_{j=1}^{J} \frac{\partial lnf(\cdot)}{\partial lnx_j}} = \frac{\partial lnf(\cdot)}{\partial lnY} \equiv E_Y \tag{9}$$

Equation 9 states that the Cost Elasticity (E_C) equals Product elasticity (E_Y) which can be calculated from the parameters of the distance input function (IDF). This result is important because it means that we can substitute the term on the right side of the equation (4) by product elasticity, that is,

$$RC = \frac{\partial lnf(\cdot)}{\partial lny} + u + v; \qquad u \geq 0. \tag{10}$$

The advantage of estimating equation (10), rather than equation (4), is that we can estimate mark-ups without the need for input and output prices, that is, we only need the information on revenue and total cost of banks and the respective input quantities.

In order to estimate the mark-up defined in equation (10), we assume that the transformation function takes a form of the translog type and apply the appropriate normalization, as in Kumbhakar (2012), to express the transformation function in the form of an input input function given by:

$$\begin{aligned} lnx_1 = \alpha_0 + \sum_{j=1}^{J-1} \alpha_j ln\tilde{x}_j + \frac{1}{2} \sum_{j=1}^{J-1} \sum_{k=2}^{J} \alpha_{jk} ln\tilde{x}_j ln\tilde{x}_k \\ + \alpha_Y lnY + \frac{1}{2}\alpha_{YY}(lnY)^2 + \sum_{j=1}^{J-1} \alpha_{jY} ln\tilde{x}_j lnY + + \alpha_T T + \frac{1}{2}\alpha_{TT}T^2 \\ + \sum_{j=1}^{J-1} \alpha_{jT} ln\tilde{x}_j T + \alpha_{YT} T lnY, \end{aligned} \tag{11}$$

from which, we can derive the product-elasticity as

$$E_Y \equiv \frac{\partial lnx_1}{\partial lnY} = \alpha_Y + \alpha_{YY} lnY + \sum_{j=1}^{J-1} \alpha_{jY} ln\tilde{x}_j + \alpha_{YT} T, \tag{12}$$

where $\tilde{x}_j = \frac{x_j}{x_J}, j = 1, 2, \ldots, J-1$.

Replacing equation (12) in equation (10) we define our empirical equation as:

$$RC = \alpha_Y + \alpha_{YY} lnY + \sum_{j=1}^{J-1} \alpha_{jY} \ln x_j + \alpha_{YT} T + u + v. \tag{13}$$

As highlighted by Kumbhakar et al. (2012), once that we are interested in estimating the individual mark-up of each bank, we need to focus only on (13) without the need to estimate the full distance input function, defined by (11). Besides, since the compound error term ($\varepsilon = u+v$) is the same in the SFA models, we use the Maximum Likelihood method to estimate the model (14). For this, it is necessary to assume a hypothesis about the distribution of the two components.

We follow the literature and assume that the random error component v is independent and identically distributed with a normal distribution, zero mean and constant variance, that is, $v \sim N(0, \sigma_v^2)$. On the other hand, for the nonnegative component, u, representing the banks' mark-up, we extend the models of by Coccorese (2014) and Das & Kumbhakar (2016) and separating the deviation from the competitive frontier in a deterministic part, which is a function of a vector of explanatory variables **Z'**, of the purely stochastic part.

Following the SFA literature, we estimate the deterministic component of mark-up simultaneously with the parameters of the (13), in the same way as Lopez et al. (2018). This procedure reduces possibility of bias of the estimates when the stochastic term includes determinants of deviations. Thus, the mark-up (u) in (13) can be represented by

$$u = \mathbf{Z'}\delta + \omega \tag{14}$$

where ω is the stochastic component of mark-up and is defined by a truncated normal distribution with zero mean and constant variance, σ_ω^2, such that $\omega \geq$ **-**$\mathbf{Z'}\delta$. Therefore the mark-up (u) follows a distribution $u \sim N^+(\mathbf{Z'}\delta, \sigma_\omega^2)$.

Combining equations (13) and (14), the model we estimate is as follows:

$$RC = \alpha_Y + \alpha_{YY} lnY + \sum_{j=1}^{J-1} \alpha_{jY} \ln x_j + \alpha_{YT} T + \mathbf{Z'}\delta + \omega_{it} + v. \tag{15}$$

In order to verify the impact of prudential measures on the degree of competition, we have included the measures Cerutti et al. (2016) as determinants of mark-up, in addition to a measure of concentration, represented by the HHI, calculated from the total assets of the banks.

To measure the degree of power of each bank, we use the traditional measure defined by Lerner (1934),

$$L = \frac{P - MC}{P}, \tag{16}$$

if $L = 0$, $P = MC$ and for any value $L > 0$, $P > MC$. In the limit, $L = 1$.

The connection between the SFA model (equation 15) and the Lerner index, is done rearranging the equation (4). Omitting the error term (v) for simplification we can rewrite equation 4 as:

$$\frac{P \cdot Y}{C} \frac{\partial lnY}{\partial lnC} - 1 = u \frac{\partial lnY}{\partial lnC}. \tag{17}$$

Considering that $\frac{\partial lnY}{\partial lnC} = (\frac{\partial Y}{\partial C})(\frac{C}{Y})$, we have :

$$\frac{P - MC}{MC} = \frac{u}{E_C}. \tag{18}$$

Equation (18) corresponds to an alternative definition of mark-up, called θ, where the distance between price and marginal cost is expressed as a fraction of the latter. In addition, since the function input distance is dual the cost function, we can substitute E_C for E_Y in equation (18) and, after estimating equation (15) and obtain estimates of the mark-up ($\hat{u}$), the estimation of market power can be obtained by replacing the values estimated in equation (18) as follow:

$$\theta \equiv \frac{P - MC}{MC} = \frac{\hat{u}}{\hat{\alpha}_Y + \hat{\alpha}_{YY} lnY + \sum_{j=1}^{J-1} \hat{\alpha}_{jY} \ln \tilde{x}_j + \hat{\alpha}_{YT} T}. \tag{19}$$

This estimate can be used to obtain the traditional measure of Lerner index, as in equation (15), employing the following formula:

$$L = \frac{\hat{\theta}}{1 + \hat{\theta}}. \tag{20}$$

Finally, we can use the estimates of equation 15 to obtain other characteristics of technology, such as the return to scale and the scale bias. Formally, $E_C = \frac{\partial lnC}{\partial lnY} = (\frac{\partial C}{\partial Y})(Y/C) = MC/AC$, where AC represents the average cost. This means that the return to scale is inversely related to cost elasticity, that is, $RTS = \frac{1}{E_C}$. If $E_C = 1$ we will have constant returns to scale, if $E_C < 1$ we will have increasing returns (economies of scale) and if ($E_C > 1$) we will have decreasing returns (diseconomies of scale). Again, using the duality condition between IDF and the cost function, we can use the estimates of equation (15) to calculate the return to scale and scale bias. Respectively:

$$RTS = \frac{1}{\hat{\alpha}_Y + \hat{\alpha}_{YY} lnY + \sum_{j=1}^{J-1} \hat{\alpha}_{jY} \ln \tilde{x}_j + \hat{\alpha}_{YT} T} \tag{21}$$

and

$$Scale\ Bias = \hat{\alpha}_{YT}. \tag{22}$$

If the scale bias parameter ($\hat{\alpha}_{YT}$) is statistically significant and greater than zero, this suggests that technological change is reducing economies of scale over time.

4. Database and empirical approach

The database used can be divided into two parts. The first part includes the information of all FI authorized to operate in Brazil by the Brazilian Central Bank (BCB). This information is available on the BCB's website through the IF.data system and contains detailed information on the balance sheet, income statement, and credit portfolio of all IFs. In addition, data are available on an individual basis, as well as on financial conglomerates and prudential conglomerates. For this work, we use the concept of financial conglomerates. In December 2018, there was information on a total of 2,753 IFs between commercial banks, or multiple banks with and without commercial portfolios, credit cooperatives, development banks, among others, arranged quarterly, since the first quarter of 2000.

The second database was obtained from Cerutti et al. (2016). They collect data about change and intensity in the use of a set of prudential instruments classified as micro-prudential and macro-prudential for 64 countries with a quarterly period covering the period between the first quarter of 2000 and the fourth quarter of 2014. The original instruments of the database are the capital requirement, capital buffer, interbank exposure limit, concentration limit, maximum loan amount, commonly known as Loan-to-value, and reserve requirement and the information on intensity and change in prudential measures is collected as follows by the researchers: if the financial regulator tightens the instrument in question in a specific quarter, the index assumes a value of $+1$. On the other hand, if the same instrument undergoes relaxation or loosening, the value of -1. Finally, the index receives a value of zero if there was no change in the prudential instrument in that quarter[1].

Not all the instruments available on the original basis were used because some measures were not implemented by the BCB. Examples are the capital buffer for real estate credit, the concentration limit of banks to sectors or borrowers, and the limit on interbank exposure. Moreover, due to the low variability in most measures and the semi-annual structure of the database obtained in the BCB, we chose to use the cumulative indexes of variation. According to Cerutti et al. (2016), the purpose of this cumulative index is to capture the level of tightness or looseness over a given period. Finally, to capture an overall measure of prudential instruments, we aggregate all variations of prudential instruments into a single aggregate instrument called cumulative prudential. Table A.5, attached, illustrates the change and the intensity of the prudential instruments implemented by Brazil, according to the data collected by Cerutti et al. (2016).

Our sample was restricted only to commercial banks or multiple banks with commercial portfolios and savings banks. Banks with loan portfolio equal zero and did not contain information for at least three consecutive years were excluded. In the same way we excluded banks with observations that fell bellow 1st percentile of the sample for each one of variables used in the model, or above 99th percentile only for the dependent variable $RC = TR/C$. Furthermore a further reason to use semi-annual data is because inconsistencies we have found in some quarterly accounting data. Therefore, our data correspond to June and December base dates. After applying all these criteria, our sample was restricted to a panel with only 83 banks, between the first half of 2000

[1]For more details on how the base was built, see Cerutti et al. (2016)

and the second half of 2014, totaling 1,818 observations. In terms of representativeness our sample corresponded to 79.4% of the total assets and 81.7% of the credit portfolio of the entire SFN in December 2014[2].

Our empirical strategy consists in estimating the equation (15) by Maximum Likelihood in a two-stage procedure, wherein the first stage we obtain the estimates of the parameters of the equation and in the second stage, we calculate the estimates of $\hat{u}_{it}$, using the conditional mean estimator of Jondrow et al. (1982). After obtaining the estimates of $\hat{u}$ and $\widehat{RC} \equiv \hat{E}_Y$, we use equation (19) to calculate the estimated values of θ, which are used to calculate e the Lerner Index (L), according to equation (20).

We estimated six models wif different sets of deterministic variables (prudential measures) to control the parameter of market power (u_{it}). In the first model, we did not add any controls. In the second we include only the *HHI*. In the third specification, we include the *capital buffer* and *capital requirement*. The fourth model uses only the *loan-to-value*. In the fifth model, we include *reserve requirements* in both *foreign* and *local currency* and in the last model, we include the cumulative *prudential measure* which is the sum of the changes in all other prudential measures.

We summarize the description of the variables that we will use in the estimation of equation (15) and how we calculate them in Table 1. All variables included in equation (15), except for trend, prudential variables an HHI are in the logarithms form.

Table 1: *Variables used to IDF estimatation*

Variabel	Description	Source
Basic variables		
TR	Total Revenue = Gross Insterest Income (a) + Banking Service Fee Income (d1) + Banking Fee Income (d2) + Other Operating Income (d7)	Inc. stat./IF.Data
TC	Total Cost = Interest Expenses (b) + Personnel Expenses (d3) + Administrative Expenses (d4) + Tax Expenses (d5) + Other Operating Expenses (d8)	Inc. stat./IF.Data
Y	Loan, Lease and Other Credit Operations by Risk Level	Summary/IF.Data
x_1	Personnel Expenses (d3)	Inc. stat./IF.Data
x_2	Funding (e)	Liabilities/IF.Data
x_3	Equity (j)	Liabilities/IF.Data
Model variabels		
$lnRC$	Log of Revenue-Cost ratio	
lnY	Log of total loan	
$ln\tilde{x}_1$	Log of personnel expenses and equity ratio (x_1/x_3)	
$ln\tilde{x}_2$	Log of funding and equity ratio (x_2/x_3)	
T	Time	
Prudential variables - Deterministic mark-up parameters		
HHI_t	$HHI_t = \sum S_{it}^2$ where $S_i t^2$ is market share of total asset of bank i on time t	Inc. stat./IF.Data
cb	cumulative change of capital buffer	Cerutti et al. (2016)
cr	cumulative change of capital requirement	Cerutti et al. (2016)
ltv	cumulative change of loan-to-value	Cerutti et al. (2016)
$rr\_foreign$	cumulative change of reserve requirement (foreign currency)	Cerutti et al. (2016)
rr_local	cumulative change of reserve requirement (domestic currency)	Cerutti et al. (2016)

[2]For a more detailed description of our data base we invite to consult the WP available at: http://www.face.ufg.br/arquivos/midias/TD_078.pdf.

5. Empirical Results

We present the results of the models in Table 2. Initially, focusing on the interpretation of the parameters of the input-distance function, we verified that the size of the FI credit portfolio (lnY) has a negative sign, but it was significant only for models 1, 4 and 5. This result implies that the larger the portfolio size, the lower the revenue-cost ratio of the FI.

The coefficients of Staff costs ($ln\tilde{x}_1$) and volume of funding ($ln\tilde{x}_2$) were also negative and significant in all models. Thus the higher the staff costs, and the higher the funding volume, the lower the cost-to-cost ratio of the FIs. The trend variable, as established by equation 22, represents the scale bias and the negative sign would indicate that technological change would increase economies of scale, over time, however, no estimate was significant.

5.1. Impact of Prudential Measures on Mark-up

The evaluation of the variables that determine the mark-up parameter ($\hat{u}$) shows that all of them are statistically significant and positive. The SFA model is not linear in these parameters. Therefore, the value of the coefficients does not represent the effect of the magnitude of changes in the variables on the mark-up (their elasticities). However, we can estimate their marginal effects. We present them for each variable in Figure 1.

The positive sign of HHI in model 2 means that the more concentrated the banking industry is, the higher the market power of FIs. This result is in line with that established by the traditional structure-conduct-performance paradigm. However, is important highlight the increase in the concentration index coincides with the tightening of the prudential measures stemming from the GFC. In this sense, we can not say whether this is the real effect of the increase in market concentration on the market power of FIs, or whether it is affected by the tightening of prudential measures.

If we focus on prudential instruments, the results for capital buffers and the capital requirement (model 3) indicate that a tightening in these variables - whose purpose is to increase banks' capital reserve during positive shocks in the economy - has a detrimental effect on competition market since they raise the IF mark-ups. This effect happens because this prudential measure influences the smoothing of the credit supply cycle.

The same results are present for the loan-to-value variable (model 4). In general, this measure sets limits on the leverage of mortgages and other securities, and a tightening in ltv is effective in controlling possible booms in the real estate market by reducing real estate prices and ultimately reducing the excess volatility of the economy (Zhang & Zoli, 2016; Ely et al., 2019). According to the result found, the higher the limits, the greater the market power of the FIs.

With respect to reserve requirements both in foreign and local currency - credit limits directly in foreign currency and domestic currency, respectively - the results (model 5) also demonstrate a detrimental effect on competition since the tightening in such measures also implies an increase mark-up of IFs. In the model 6, where we introduce the aggregate prudential measure, the result found is similar to the others, that is, the higher the tightness (in general) in the prudential measures of the financial system, the higher the market power of FIs.

Unfortunately, since prudential variables represent only a measure of tightening or loosening of prudential policy and not its magnitude, we can not accurately assess the impact of these variables on the mark-up. The marginal effects represented in Figure 1 give us only an idea of how such variables affected the estimated mark-ups. However, in general, we can say that the positive signs of the estimates mean that the higher the tightness in these prudential policies, the greater the

Table 2: *Results of IDF estimation*

Parameters	Variables	Estimates					
		Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Input Distance Function Parameters							
α_{YY}	lnY	-0.013***	-0.003	-0.004	-0.012***	-0.011***	-0.005
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{1Y}	$ln\tilde{x}_1$	-0.096***	-0.095***	-0.094***	-0.094***	-0.096***	-0.090***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
α_{2Y}	$ln\tilde{x}_2$	-0.019**	-0.022**	-0.022**	-0.019**	-0.020**	-0.021**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
α_{YT}	T	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_Y	const.	1.153***	1.010***	1.035***	1.134***	1.129***	1.057***
		(0.05)	(0.07)	(0.05)	(0.05)	(0.05)	(0.06)
Deterministic Mark-up parameters							
δ_1	HHI		764.157***				
			(122.70)				
δ_1	Capital Buffer			7.586***			
				(0.65)			
δ_2	Capital Req.			4.696***			
				(1.60)			
δ_1	Loan-to-value				38.511***		
					(6.71)		
δ_1	Res.R.(foreign)					10.730**	
						(4.33)	
δ_2	Res.R.(local)					2.869**	
						(1.26)	
δ_1	Cum. Prud.						3.237***
							(0.20)
δ_0	const.	-106.01***	-101.94***	-53.06***	-98.66***	-85.77***	-49.93***
		(0.32)	(20.64)	(3.16)	(0.79)	(1.19)	(1.22)
Distribution of u and v							
σ_u^2		2.840***	1.418***	1.620***	2.643***	2.441***	1.593***
σ_v^2		0.118***	0.121***	0.120***	0.118***	0.118***	0.120***
λ		24.02***	11.72***	13.54***	22.33***	20.65***	13.25***
Log. Lik.		887.404	922.033	918.606	896.019	891.991	907.817
EstimatesEstimates of Mark-up ($\hat{u}$)							
Avg.		0.075	0.065	0.068	0.074	0.075	0.069
1st quartile		0.052	0.038	0.051	0.051	0.051	0.044
Median		0.062	0.048	0.060	0.060	0.061	0.054
3st quartile		0.080	0.074	0.079	0.079	0.079	0.075
std-dev		0.053	0.054	0.053	0.053	0.054	0.054

Note: * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$

mark-up and, consequently, the higher the market power of the FIs. Therefore, we find a perverse effect on industry competition and probably a loss of borrowers welfare.

Our results are in accordance with the evidence that the increase in prudential rigor has negative impacts, mainly on the supply of credit (Lim et al., 2011; Claessens, 2015; Aiyar et al., 2014; Gropp et al., 2018; Cerutti et al., 2017). Ceteris paribus the increase of IF mark-ups would be a fully expected effect. As highlighted by Claessens & Laeven (2004), any policy that restricts the activity of banks and hinders their operation has negative impacts on market competition.

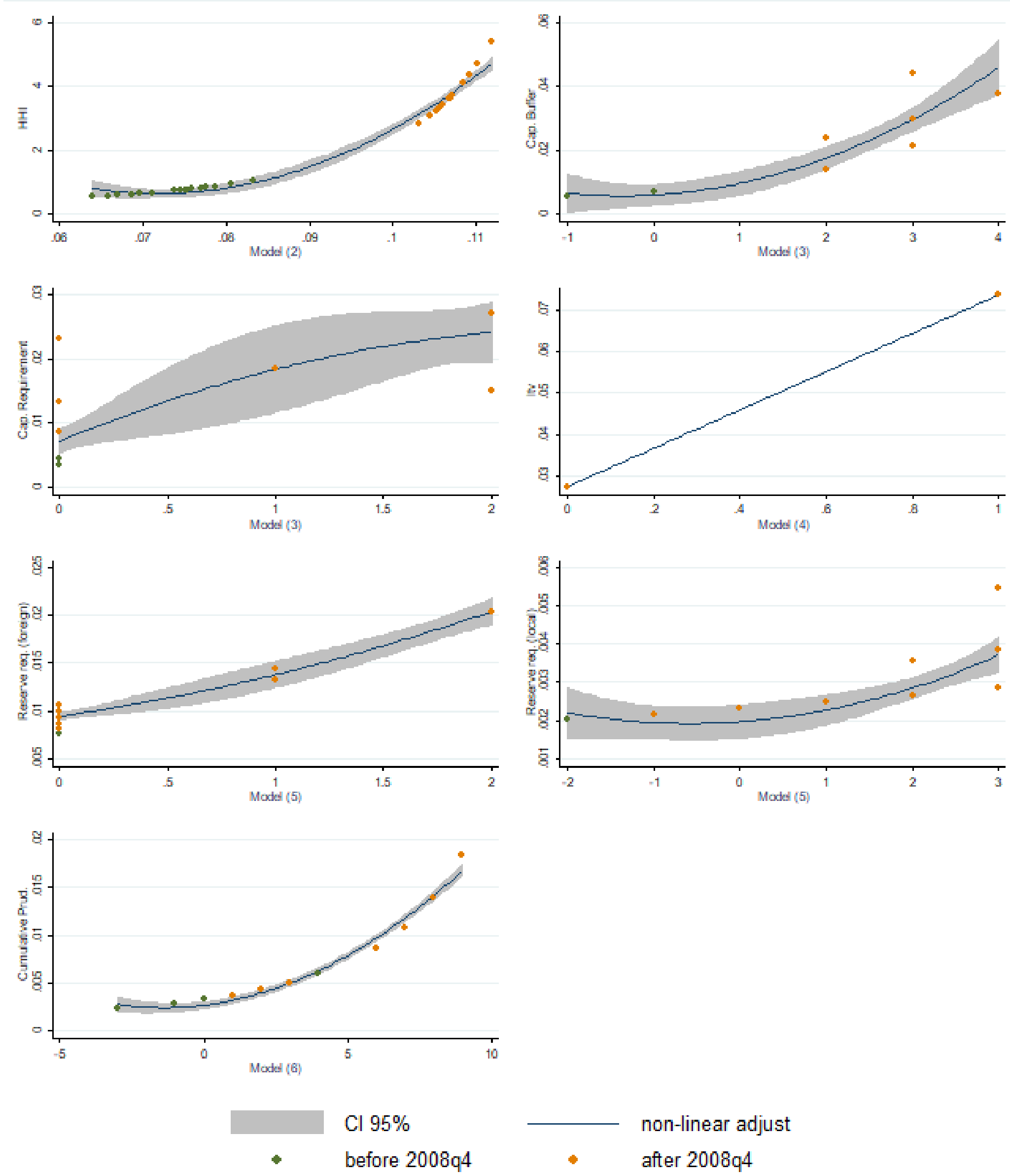

Figure 1: *Marginal effects of HHI and prudential instruments (Capital Buffer, Capital Requirement, LTV, Reserve Requirement (Foreign), Reserve Requirement (domestic) and Cumulative prud.) on the mark-up u component.*

5.2. Estimation of Lerner indices

Regarding the mark-up estimation, the values reported at the bottom of Table 2 correspond to the distance between the observed revenue-cost ratio and its competitive boundary, that is, the component $\hat{u}$.

To interpret the mark-up, however, we will focus the discussion on the estimates of Lerner index (equation 20) because they have a more unambiguous economic meaning. We summarize the results of Lerner index for general estimates, by type of control and for each model in Table 3 and the Figure 2 shows their frequency distributions [3].

[3] We should emphasize that these estimates are individuals, that is, we obtain the estimates for each FI and at each period, t. You can find a complete description of estimates in the WP available at:

Table 3: Estimates of Lerner index general and by type of control

	Estimates					
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Mark-up (L): general						
Average	0.058	0.051	0.053	0.057	0.058	0.053
std-dev	0.032	0.034	0.034	0.032	0.032	0.033
1st quartile	0.043	0.031	0.034	0.041	0.042	0.036
Median	0.051	0.039	0.044	0.050	0.050	0.045
3st quartile	0.063	0.060	0.059	0.063	0.063	0.060
Mark-up (L): State-owned banks						
Average	0.057	0.047	0.049	0.056	0.056	0.050
std-dev	0.018	0.017	0.017	0.018	0.016	0.016
1st quartile	0.047	0.035	0.038	0.045	0.046	0.040
Median	0.054	0.041	0.046	0.053	0.053	0.046
3st quartile	0.064	0.056	0.056	0.064	0.063	0.057
Mark-up (L): National banks						
Average	0.057	0.052	0.054	0.057	0.057	0.054
std-dev	0.034	0.038	0.038	0.035	0.035	0.037
1st quartile	0.041	0.030	0.033	0.040	0.041	0.035
Median	0.050	0.038	0.043	0.048	0.049	0.044
3st quartile	0.061	0.061	0.060	0.061	0.062	0.060
Mark-up (L): Foreign banks						
Average	0.061	0.050	0.053	0.059	0.060	0.054
std-dev	0.034	0.033	0.032	0.034	0.034	0.032
1st quartile	0.042	0.031	0.034	0.041	0.042	0.036
Median	0.052	0.040	0.044	0.051	0.051	0.045
3st quartile	0.068	0.059	0.060	0.066	0.066	0.061

For all six models, all mark-up estimates were within the theoretical range of 0 and 1, with the minimum value being 0.009 (model 2) and the maximum value 0.362 (model 3). In general, the estimated average value was between 0.051 (model 2) and 0.058 (models 1 and 5), which means that, on average, Brazilian banks have a mark-up between 5.1% and 5.8%. These values are slightly different when we separate the estimates by type of control.

In the case of state-owned banks, the average mark-up was between 0.047 (model 2) and 0.057 (model 1). These values are lower, in all the estimated models, to the values of (privates) national banks (0.052-0.057) and foreign banks (0.050-0.061). However, the medians of estimated values for state-owned banks were higher than the national and foreign private banks in all models.

For comparison purposes, these values are considerably lower than the value (0.16) estimated for Brazil in Coccorese (2014). However we believe that this difference is due to the model and sample used. Coccorese (2014) has estimated the dual version of model (equation 4) and, as highlighted by Kumbhakar et al. (2012), the use of accounting information to calculate input prices can generate problems when they are endogenous. Regarding the sample, Coccorese (2014) also used a different period from ours (1994 to 2012) and a more significant number of FIs in the sample (189, against 83 used by us). The main difference here is in the number of IF - 106 in total. In this respect, it is essential to note that these FIs constitute small FIs and in the second half of 2014 they held only

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http://www.face.ufg.br/arquivos/midias/TD_078.pdf

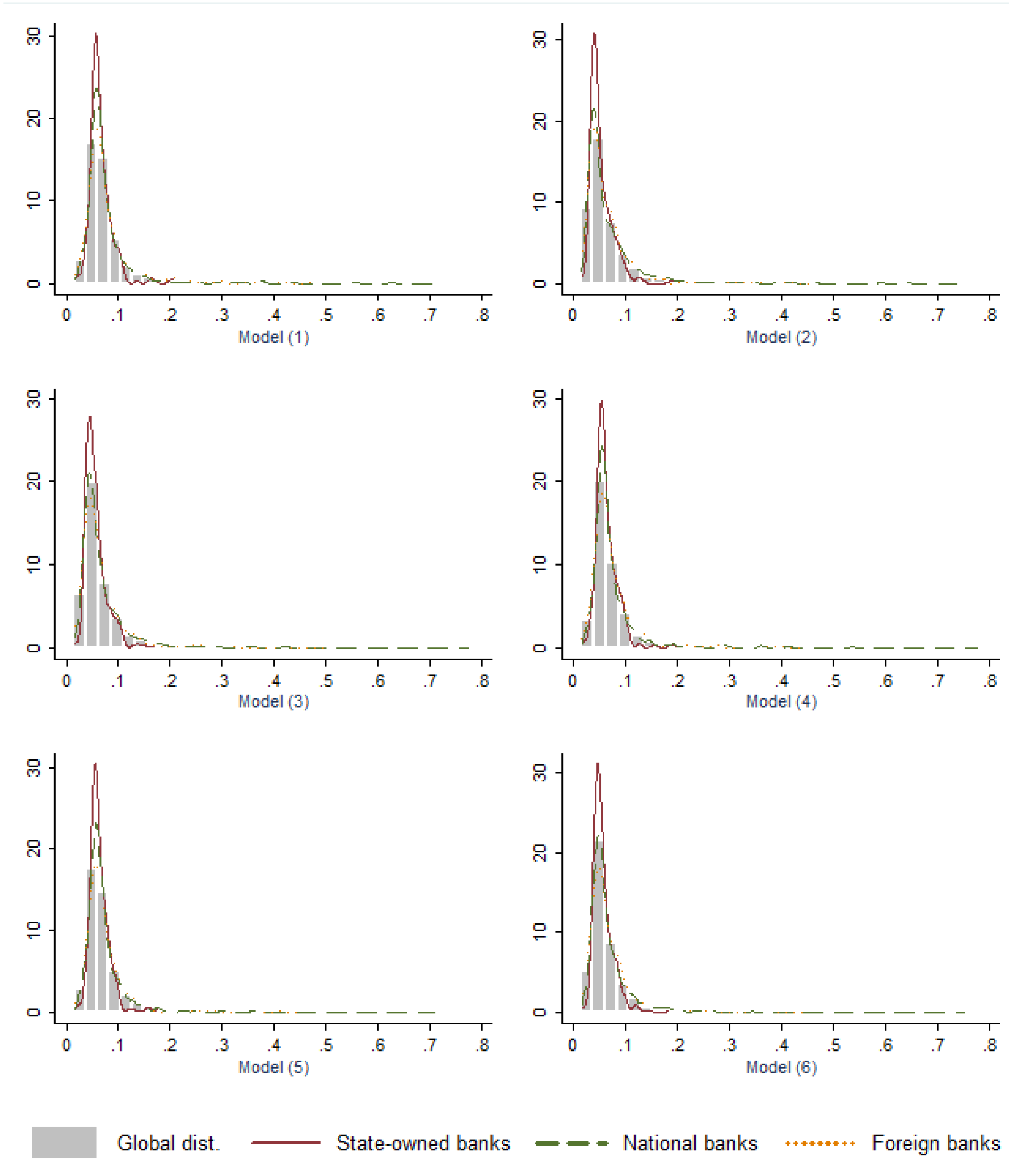

Figure 2: *Frequency distribution of Lerner indexes for each model and density estimation Kernel by type of control.*

3.7% of total SFN assets and 2.4% of the total credit portfolio.

We tried to replicated the Coccorese' sample but in preliminary tests we have found great difficulties in the models estimations, in particular, at convergence of likelihood function. We observed these small IFs had, in several situations, extremely high values for the revenue-cost ratio, or excessively low for the inputs used (personnel expenses and funding), as well as other problems such as launch errors (positive values in variables of expenditure, for example) and missings. For these reasons, and considering that such IFs represented only a small fraction of Brazilian credit market, we decided to exclude them from the sample. However, it is worth highlight as they are small FIs the vast majority operate in particular segments of the credit market and probably assume a more risk-taking behavior. Considering that they will work with a segment of credit claimants with "worse scores" than borrowers using large FIs we expect that the mark-up of these IFs will be higher.

Regardless of this, our results seem to adhere well to reality, because if we look at Figure 3, we note that the Lerner indices show a significant increase from the second semester of 2008. These results are in agreement with the results of Cubillas & Suárez (2018). Besides, in Figure 4, Lerner indexes are separated by type of control, and we can observe that, with some exceptions, the market power has always been lower for state-owned banks, especially considering the period after the GFC.

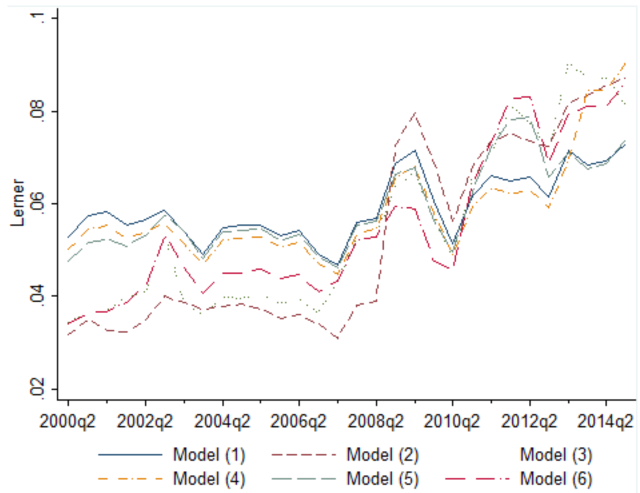

Figure 3: *Average Lerner indices for each model between 2000q2 and 2014q4.*

5.3. Estimation of Returns to Scale

Finally, Table 4 and Figure 5 summarize the estimates of returns to scale. We highlight that the average of the returns to the scale of the Brazilian FIs is very close if we comparer the six estimated models (between 0.848 and 0.851). Although the values are close to unity, in all IFs we reject the hypotheses of constant returns to the scale, that is, RTS = 1, therefore IFs have diseconomies of scale.

Table 4: *Estimates of returns to scale by control type and general*

Model	State-owned banks	National banks	Foreign banks	General	std-dev.	Min.	Max.,
1	0.944	0.824	0.842	0.848	0.073	0.665	1.124
2	0.940	0.829	0.843	0.851	0.066	0.690	1.073
3	0.938	0.827	0.842	0.849	0.066	0.689	1.076
4	0.941	0.824	0.842	0.848	0.071	0.671	1.111
5	0.942	0.824	0.841	0.848	0.072	0.669	1.113
6	0.937	0.829	0.844	0.850	0.065	0.692	1.073

When we separate estimates by type of control, the estimates of state-owned banks (0.937-0.944) are higher than national (0.824-0.829) and foreign banks (0.841-0.844). This result means that the scale problem is a problem common to all FIs in Brazil. Moreover state-owned banks runs closer to the constant return region than national and foreign banks.

Figure 4: *Average Lerner indices estimated for public, private national and private foreign banks between 2000q2 and 2014q4.*

6. Final Considerations

Considering that the banking industry underwent a significant restructuring in recent years, caused by several mergers and acquisitions in the sector, as well as by a severe financial crisis started in mid 2007 and potentialized in 2008, understand the behavior of market power and as a (partial) set of prudential instruments influencing this dynamic has become paramount. Thus, in an innovative way this paper proposed the use of stochastic frontier analysis techniques to measure market power for the Brazilian banking industry and to test if such prudential measures had an impact on the competitive dynamics of sector.

The estimated average Lerner index was between 5.1% and 5.8% for Brazilian FIs. However, when controlled by the type of control, we find that state-owned banks have slightly lower estimates than national and foreign banks, respectively. Also, estimates of returns to scale allow us to infer

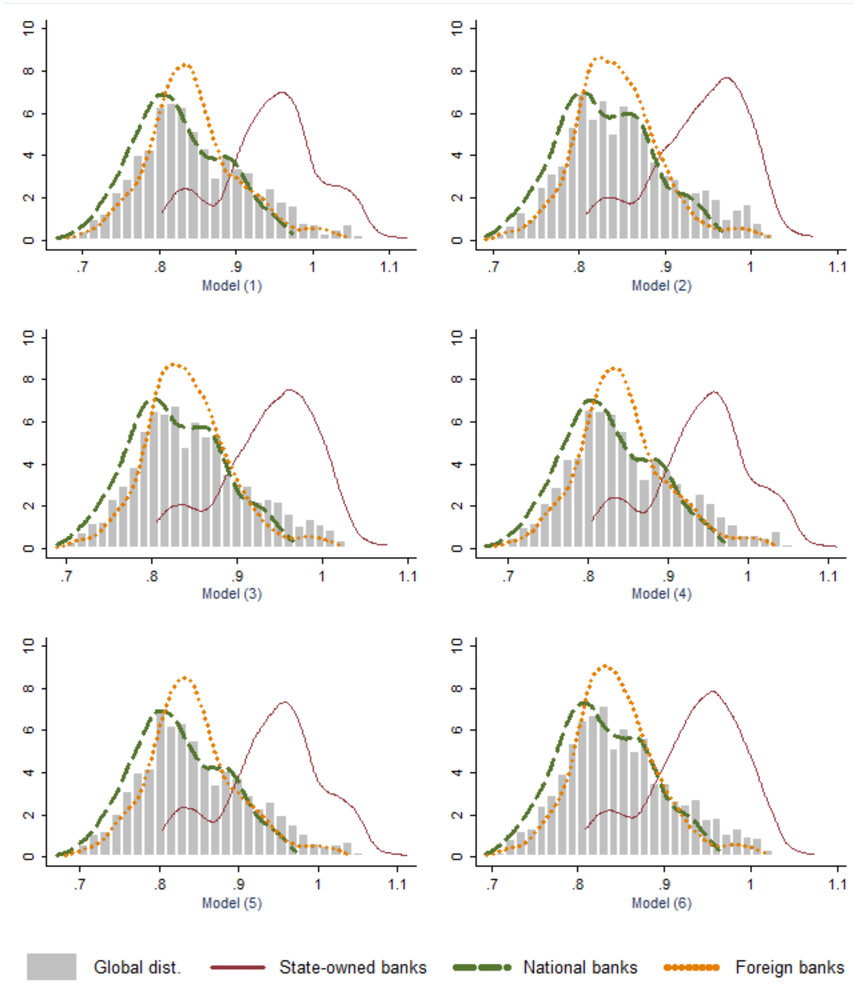

Figure 5: *Frequency distribution of the returns to scale indexes for each model and density estimation Kernel by type of control.*

that FIs operate with diseconomies of scale.

Concerning the impact of prudential measures on the market power of FIs, our results generally suggest that tightening of prudential measures have a positive impact on bank mark-up and, consequently, have detrimental effects on competition in industry banking. Finally, in future research, it will be possible to better understand the influence of some prudential measures in the banking market, through the study by type of segment or line of credit.

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