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The impact of market power at bank level in risk-taking: The Brazilian case

Benjamin Miranda Tabak[1] Guilherme Maia Rodrigues Gomes[2] Maurício da Silva Medeiros Júnior[3]

Abstract

This paper seeks to examine the competitive behavior of the Brazilian banking industry by conducting an individualized analysis to understand how the risk-taking behaviors of banks can be affected by the market power of these banks. Therefore, we compute market power at the bank level and aggregate this variable in a risk-taking model. Our findings suggest that the Brazilian banking industry includes significant heterogeneities in the market power of banks and is characterized by monopolistic competition. Another important result from this study is that market power is positively related to risk-taking behavior. We also verify that the capitalization of banks has an important influence on their market power, which affects risk-taking behaviors. In particular, we find that an increase in capital causes banks with higher market power to behave more conservatively. These results have important implications for the design of appropriate financial regulations.

Keywords: Bank Competition; Risk-taking; Market Power; Emerging Markets.

JEL Classification: D40; G21; G28; G32.

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1 Introduction

Competition is a critically important factor that impacts many different industries, including the banking industry. The competitive behavior of banks is directly related to the financial stability and market consolidation of the banking industry, which are complex issues. The entire development of the financial sector is intrinsically dependent on both the efficiency with which banks produce financial services and the quality of the services provided by those banks. These characteristics are directly influenced by the competition in the market; therefore, as demonstrated by both the empirical and theoretical literature, the competitive behavior of the banks in an economy also determines the access that individuals and firms have to financial services. In effect, all economic growth is affected by the banking industry.

Market competition in the banking industry is interdependent on a variety of other economic variables; therefore, the competitive behavior of the market can be changed by economic fluctuations. However, the relationships among these variables are highly ambiguous; thus, there is currently little understanding of the effects of bank competition on economic activity. Instead, we observe that the theoretical analysis and empirical research that have addressed this issue have yielded diverse results. In a study of the relationship between bank competition and risk-taking, Boyd and Nicol (2005) emphasize that there is no consensus in the literature regarding the interaction between these variables, as different studies have produced conflicting conclusions. Ambiguous findings have also been produced from studies that attempt to address the relationship between competition and market concentration in the banking industry.

Although certain studies have discovered a positive relationship between bank competition and risk-taking (Keeley, 1990), other investigations have actually found a negative relationship between these variables (Boyd and Nicol, 2005). The idea underlying the putative positive relationship between bank competition and risk-taking is essentially that banks can effectively collect monopoly rents and will become relatively conservative as a result. However, the research that has found a negative correlation between bank competition and risk-taking typically explains this correlation by conjecturing that banks with increased market power tend to suffer from moral hazard; as a result, these banks take riskier measures, such as increasing loan rates, that can lead to an increased risk of failure. Boyd and Nicol (2005) conclude that the evidence regarding the theoretical relationship between the risk-taking and competition of banks is best described as mixed.

There is also no consensus relationship between bank competition and concentration. For certain authors, concentration indicators can be a proxy for competition (Bikker and Haaf, 2002), whereas other authors find no evidence that competition and concentration are negatively correlated (Claessens and Laeven, 2004). In an investigation of 23 countries, Bikker and Haaf (2002) conclude that an increase in competition leads to a decrease in concentration; however, Claessens and Laeven (2004) find that there is no evidence to support the notion of interaction between these two variables.

In our attempt to examine the Brazilian bank industry, we estimate the competition in the banking industry by analyzing the market power of each bank. In accordance with Brissimis and Delis (2011), we apply the Panzar and Rosse model created by Rosse and Panzar (1977); Panzar and Rosse (1987) and estimate the market power at the bank level using a local regression methodology (Cleveland, 1979; Cleveland and Devlin, 1988). The methodology that we use is a distinctive feature of this banking competition study as it allows us to examine the heterogeneity presented by the banks that compose the Brazilian banking industry, thereby providing us with a greater understanding of the behavioral changes of these banks.

The results that we obtain from the methodology discussed above provide evidence that there is heterogeneity among the banks of the Brazilian banking industry. In fact, we verify that there are fluctuations in the competitive behavior of Brazilian banks as certain semesters present a higher diversity of H-statistics, indicating that the market power of individual banks is more varied. These periods of high diversity are interspersed among periods of less H-statistic diversity, during which time banks exhibit more homogeneous behaviors and have high H-statistic values. During the periods of lower H-statistic diversity, economic players demonstrate more competitive behavior; these behaviors are consistent with our computations, which demonstrate lower volatility for the average H-statistic during our study period.

We also apply a risk-taking model to analyze the interaction between a banks market power and the risk that a bank assumes. In particular, we incorporate one variable that describes the H-statistic at the bank level and another variable representing the average H-statistic of the economy for a given period into our model. We do not obtain significant information from the average H-statistic of the economy; however, the relationship between market power and risk-taking behavior at the bank level provides interesting details about the competitive behavior of Brazilian banks.

From our analysis, we find evidence that a bank with higher market power in the Brazilian banking industry take more risk than a bank with less market power. Capitalization also impacts risk-taking behavior; thus, we also examine the interaction between capitalization and market power, as well as the impact of capitalization on risk-taking behavior. The broad conclusion that we reach is that an increase in capital can change the risk-taking behaviors of banks. A bank with increasing market power becomes more conservative when its capital increases, while a bank with decreasing market power and increasing capital takes more risk. This result is an extremely important contribution of this study for policy-makers as it allows for the development of new ways to control banks risks, which is an important policy lever for the entire Brazilian economy. As Tabak et al. (2011b) show, this change in risk-taking behavior of banks due to capitalization variation is identified in 10 Latin American countries including Brazil, which reinforces our finding.

This paper is organized into the following sections. In Section 2, we present a literature review of the recent contributions related to market power and risk-taking. In Section 3, we describe the methodology employed to examine the market power at the bank level and the relationship between market power and risk-taking behavior; in particular, within this section, we describe the Panzar and Rosse approach and the local regression methodology in a more detailed manner. Section 4 describes the data obtained from the Central Bank of Brazil that are used in this paper. In Section 5, our results related to market power and its influence on risk-taking behaviors of banks are described and discussed; finally, Section 6 contains our concluding remarks.

2 Literature Review

The recent studies that analyze the competitive behavior of banks employ non-structural approaches that have arisen from the New Empirical Industrial Organization (NEIO) framework. Initially derived from the pioneering contributions of Iwata (1974), the non-structural approaches were reinforced by Rosse and Panzar (1977); Bresnahan (1982); Lau (1982); Bresnahan (1989); Panzar and Rosse (1987); Hall (1988); Roeger (1995). These authors developed three main models to test competition in the banking industry by examining the deviations from competitive pricing that occur.

Studies have been performed that seek to analyze the competitive conditions in the context of particular banking industries. Several authors, such as Yildirim and Philippatos (2007), examine the banking industry of certain Latin American countries, whereas other authors, such as Claessens and Laeven (2004), study the banking industry of certain European countries. Scott and Dunkelberg (2010) examine the recent consolidation of the US banking industry and its effects on small banks. They conclude that increased competition is negatively correlated with deposit concentration in these small banks and that there is a significant positive relationship between bank competition and bank output. Gunji et al. (2009) develop a comparison between bank competition and monetary policy, which they use to demonstrate that bank competition results in smaller monetary policy effects on bank lending.

The investigation of Beck et al. (2004) fundamentally focuses on the relationship between bank concentration and the access of firms to bank finance, using a dataset that encompasses 74 countries. They find a negative impact of bank concentration on access to financing in countries with a precarious level of institutional and economic development. Boyd et al. (2004) study the probability of crisis in competitive and monopolistic banking systems and demonstrate that the nominal interest rate determines whether the probability of a crisis is higher in a competitive banking system or in a monopolistic banking system.

Policies that address bank competition are often extremely complicated due to the necessity of maintaining financial stability. Allen and Gale (2004) examine the impact of bank competition on financial stability and efficiency because increased competition is hypothesized to produce both increased static efficiency and greater financial instability. These authors analyze these interactions using different models; however, their models yield different conclusions because the relationship between competition and stability is complex and highly dependent on the particular situation that is assessed. Chang et al. (2008) examine financial stability in other perspective. They examine the relationship between financial stability and bank concentration. The results suggest that more concentrated banking systems may improve financial stability.

Demirg-Kunt et al. (2004) analyze the impacts that bank regulations, market structure and national institutions have on the costs of intermediation that are experienced by banks in 72 countries. These authors discover evidence that regulatory measures in a banking system cannot be viewed in isolation, as there is a direct relationship between bank regulations and the national institutions that defend the more general issues of private property and free competition. Therefore, although they conclude that bank concentration is positively related to costs of intermediation, Demirg-Kunt et al. (2004) conclude that other variables must also be taken into account to accurately evaluate the impact of bank regulations on bank concentration.

Fernández de Guevara et al. (2007) perform an analysis of the level of competition and its inequalities among the European banking industry for the period 1993-2001. They find an increase in market power and also an increase in inequality among banks. Carbó et al. (2009) study the banking market competition taking into account the influence of cross-country differences in the traditional indicators of bank pricing power of the European banking market. Assessing the competitive conditions of 14 European banking markets, they observe that the banking market competition in the European countries analyzed may well be stronger than the results obtained through the competitive indicators usually applied in the literature. We present a summary of other contributions to the literature related to banking competition in Table 1.

Place Table 1 About Here.

Most authors employ non-structural approaches to assess competition in the banking industry. Molyneux et al. (1994) observe that in the period between 1986 and 1989, the banking industry in Italy operated as a monopoly, whereas the banking industries of France, Germany, Spain and the UK operated in monopolistic competition. Molyneux et al. (1996) verify that the Japanese banking industry was a monopoly for the period from 1986 to 1988. Vesala (1995) identifies a state of monopolistic competition for the Finnish banking industry for all but two years of the period from 1985 to 1992.

Alternative measures of bank competition exist in addition to the non-structural approaches discussed above. Bolt and Humphrey (2010) employ a frontier efficiency analysis to produce an indicator of bank competition; in this study, the frontier is defined by how well banking costs explain variations in the loan-deposit rate spread and non-interest activity revenues. These authors choose to estimate the bank competition using frontier efficiency instead of the H-statistic because the input costs and the output prices that they study are not always strongly correlated either within or across countries. The results of this frontier efficiency analysis reveal a slight difference in the status of bank competition among the various different environments found within the European banking industry.

There are few studies similar to that of Nakane (2001), which evaluates the competition in the Brazilian banking industry using the methods of Bresnahan (1982); Lau (1982). Tabak et al. (2011a) study the relationship between bank performance and risk in the Brazilian banking industry, whereas Tecles and Tabak (2010) seek to understand bank efficiency in the Brazilian case. We could obtain important findings about the Brazilian banking industry and its changes by jointly examining contributions related to different variables of interest. However, the contributions to the field of NEIO literature that address Brazilian banking industry are still scarce.

Studies exist that focus their analysis on measuring the market power of each bank, and the findings of these studies are of interest for their contributions to understanding the heterogeneities in banks market power. Agoraki et al. (2011); Delis and Tsionas (2009); Delis (2012) study bank competition at the bank level using the Lerner index, a recent innovation in the bank competition literature. Research regarding risk-taking has also been analyzed from a local perspective. Delis and Kouretas (2011) employ local regression to analyze the countries of the euro area. They conclude that interest rates have a greater influence on banks with higher off-balance-sheet items than on banks with higher equity capital.

Agoraki et al. (2011) examine the market power of banks in the Central and Eastern European regions and conclude that banks with increased market power tend to assume lower credit risks and have a lower probability of default. These authors also observe that there are countries, such as Greece, in which banks possess highly concentrated market power. Delis and Tsionas (2009) compute bank efficiency and the market power of individual banks jointly and conclude both that certain banks do not engage in competitive behavior and that individual bank efficiency and market power are negatively correlated. Delis (2012) examines banking competition at the bank level and demonstrates that financial reforms that seek to improve banking competition and the efficiency of banking markets require a certain level of institutional maturity to be effective.

Brissimis and Delis (2011) use the Panzar and Rosse model and the local regression methodology to examine the market power of individual banks. This approach differs from the methodology used in Agoraki et al. (2011); Delis and Tsionas (2009); Delis (2012) because these latter studies use the Lerner index to compute the market power at the bank level. The work of Brissimis and Delis (2011) study 20 European countries and conclude that certain nations, such as Croatia, Estonia and Slovakia, contain a few banks that individually possess very high market power. These countries therefore have a monopolistic banking industry.

3 Methodology

3.1 Market power at the bank level

As we seek to evaluate the competitive conditions of the Brazilian banking industry at the individual bank level, we choose to employ the Panzar and Rosse model. This model involves a non-structural measure of competition known as the H-statistic, which was developed by Rosse and Panzar (1977); Panzar and Rosse (1987). The H-statistic is the sum of the input prices elasticities of the reduced-form revenue equation, which reveals the market competition conditions of the banking industry. The input prices elasticities capture the relation between the revenue and the input prices. Thus, we can use these elasticities to examine how changes in revenue occur when input prices vary, and the estimate of the sum of these elasticities can serve as a proxy for the competitive behavior within the banking market. The H-statistic is therefore defined by the following equation:

$$H = \sum_{k=1}^{m} \frac{\partial R_i^*}{\partial w_{ki}} \times \frac{w_{ki}}{R_i^*} \tag{1}$$

where R_i is the revenue of bank i, w_{ki} is the input price for bank i, and ∂R_i^* and ∂w_{ki} are the variations in revenue and input prices, respectively. The variables marked with an asterisk are the equilibrium values for these variables (Panzar and Rosse, 1987; Shaffer and DiSalvo, 1994; Vesala, 1995; Bikker and Haaf, 2002).

The magnitude of the H-statistic provides information about the competitive behavior of the market in question (Panzar and Rosse, 1987). As described in Table 2, if $H \leq 0$, then the market is a monopoly or a short-run conjectural variation oligopoly because an increase in input prices increases the marginal costs of the bank, which leads to a reduction in equilibrium output level and total revenue (Panzar and Rosse, 1987; Vesala, 1995; Shaffer, 1983). If the H-statistic value is between zero and unity, i.e., $0 < H < 1$, then the market possesses a monopolistic competition structure. Under these circumstances, the income increases less than proportionally to factor prices variations because the demand is inelastic (Panzar and Rosse, 1987). Finally, for perfect competition, the H-statistic is equal to unity, i.e., $H = 1$. In this case, a raise in input prices causes the exit of certain banks from the market; this phenomenon occurs because an increase in the average and marginal costs of banks will not cause changes in the optimum output levels of individual banks, since the demand is perfectly elastic. The resulting reduction in the number of banks in the industry leads to an increase in both demand and output prices; consequently, revenue and costs rise equally, and the industry remains in a long-run equilibrium (Panzar and Rosse, 1987).

Place Table 2 About Here.

The estimation of the H-statistic, however, requires caution. The test must be performed on observations that represent a long-run equilibrium. An equilibrium test, therefore, must be conducted to investigate the sample. This test can be executed by employing the predictor variables initially used to estimate the H-statistic and the response variable of the rate of return. If $H = 0$, the risk-adjusted rates of return across banks will equalize, indicating that the observations in question represent a long-run equilibrium Molyneux et al. (1994); De Bandt and Davis (2000); Bikker and Haaf (2002).

The Panzar and Rosse approach is based on a reduced-form revenue equation that relates gross revenue to input prices and other control variables. This equation has been widely applied in the existing literature to examine the competitive conditions of bank samples (Shaffer, 1985; Molyneux et al., 1994; De Bandt and Davis, 2000; Bikker and Haaf, 2002; Bikker and Spierdijk, 2008; Rezitis, 2010). Given a production function with n inputs and a single output, we use the following reduced-form revenue equation for i banks during t periods to obtain estimates of the market power of the banks that operate in the Brazilian banking industry:

$$\begin{aligned} \ln TR_{it} &= \alpha + \beta \ln w_{1,it} + \gamma \ln w_{2,it} + \delta \ln w_{3,it} + \\ &\quad \xi \ln Q/ASSETS_{it} + \eta \ln L/ASSETS_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

The following model is used to perform the equilibrium test:

$$\begin{aligned} \ln ROA_{it} &= \alpha + \beta \ln w_{1,it} + \gamma \ln w_{2,it} + \delta \ln w_{3,it} + \\ &\quad \xi \ln Q/ASSETS_{it} + \eta \ln L/ASSETS_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where TR is the total revenue and ROA is the net profit divided by equity. The three input prices are described as w_1, w_2 and w_3: where w_1 is calculated as interest expenses divided by total deposits, w_2 is calculated as overheads minus personnel expenses divided by fixed assets and w_3 is calculated as personnel expenses divided by total assets. In the expression above, w_1, w_2 and w_3, which are proxies for the deposit interest rate, the price of physical capital and the price of labor, respectively (Panzar and Rosse, 1987; Molyneux et al., 1994; Bikker et al., 2009; Brissimis and Delis, 2011). The variables $Q/ASSETS$ and $L/ASSETS$ represent bank-specific characteristics; in particular, $Q/ASSETS$ is equity divided by total assets, and $L/ASSETS$ is total loans divided by total assets.

Initially, we compute a fixed-effects panel to obtain an estimate for the H-statistic. For our reduced-form revenue equation, the H-statistic is calculated as $H = \beta + \gamma + \delta$. We estimate the parameters in this equation in sequence, using a robust fixed-effects panel to verify the robustness of our sample. To perform the equilibrium test, we also employ the same two procedures. We find that our observations represent a long-run equilibrium, as we cannot reject the null hypotheses ($H = 0$) in either case.[4]

As our fundamental interest lies in determining the market power of each bank that operates in Brazil, we employ a non-parametric estimation technique known as local regression (Cleveland, 1979; Cleveland and Devlin, 1988; Simonoff, 1996; Loader, 1999). This technique is employed because the estimation of the reduced-form revenue equation by conventional econometric techniques provides information regarding the competitive behavior of the entire banking industry.

The local regression is described by $y_i = \mu(x_i) + \varepsilon_i$, where x_i are the observations of n predictor variables related to i banks, y_i is the response variable, the function $\mu(x_i)$ is unknown and ε_i is an error term, which we assume to be independent and identically distributed with a mean equal to 0 and a variance equal to σ_i for each cross-section (Cleveland and Loader, 1996; Simonoff, 1996; Loader, 1999).

Because $\mu(x_i)$ has no strong global assumptions, we assume that the unknown function is locally well fitted. Therefore, $\mu(x_i)$ is locally approximated by a member of a simple class of parametric functions; the extant literature typically uses the polynomial approximation for this purpose. Either a linear or a quadratic polynomial is more frequently used to locally approximate $\mu(x_i)$ because polynomials of higher degrees are harder to compute and can cause overfitting. Therefore, for our observations, we use a linear polynomial to fit $\mu(x_i)$.

We locally fit $\mu(x_i)$ by defining a fitting point x, which we use to determine a neighborhood that is based on the design of the data space and to delimit by the independent variables. To compute the $\mu(x_i)$ approximation, we determine a bandwidth $h(x)$ and a smoothing window $(x - h(x), x + h(x))$. We perform the approximation of $\mu(x_i)$ using only the observations within the interval determined by the bandwidth.[5]

With the bandwidth and the fitting method determined, we must define the weight function, which is known as the Kernel. We use the Kernel smoother if no parametric model can describe the function of

[4] We also perform the equilibrium test using ROE. Our results from this analysis confirm that the observations used in this study represent a long-run equilibrium.

[5] The bandwidth that we choose to apply in the local regression is equal to 0.6 because the standard literature use this bandwidth value to compute the local regression.

the observations because the Kernel can be used to estimate the coefficients, accounting for the distances between the fitting point and the other observations presented inside the neighborhood of that point. The most recommended weight function is a triweight function, as suggested by Simonoff (1996). Therefore, we use the following weight function:

$$w_i = \frac{32}{5}\left(1 - \left(\frac{d_i}{d_q}\right)^3\right)^3 \tag{4}$$

where q denotes the number of points in the local neighborhoods, and d_1, d_2,..., d_q denote the distances in increasing order of the points closest to the fitting point. The largest weight is assigned to the smallest d_i; therefore, in the local regression, w_i decreases as the distance from x increases.

The weight function is directly dependent on the distance between the fitting point and the observations that are inside of a certain smoothing window. There are various methods for calculating this distance; in this study, we consider the distance to be the Euclidean distance, calculated using the mean of each independent variable of the model. For each bank, we run a local regression using a least-squares criterion (Cleveland and Loader, 1996) that accounts for the bandwidth, the polynomial fitting, our criterion to estimate the distance between the banks and the Kernel[6]. We obtain a regression for each bank in which we employ a fixed-effects regression. Notably, our local regression results in coefficients for each regression providing information that relates to each bank.

Therefore, the local regression method allows us to understand how the revenue of a certain bank reacts to a variation in either the input prices or certain bank-specific characteristics. The H-statistic is $H_i = \beta_i + \gamma_i + \delta_i$, where the subscript i denotes an individual bank. The H_i calculated by the local regression, therefore, represents the market power for each individual bank, not the competitive behavior of the banking industry.

3.2 The relationship between risk-taking and market power at the bank level

As we seek to analyze the interaction between market power and risk-taking, we employ a model that describes the variables that influence risk-taking behaviors the most. We draw inspiration from the model implemented by Delis and Kouretas (2011), as we examine the relationships among risk-taking, a set of bank-level control variables, the market power at the bank level and the competitive behavior of the Brazilian banking industry. The specific model that we employ is described as follows for i banks and t periods:

$$\begin{aligned} \ln RISK_{it} \quad = \quad & \alpha + \beta_1 \ln h_{i,t-1} + \beta_2 \ln Q/ASSETS_{i,t-1} + \beta_3 \ln h_{i,t-1} * dummy \\ & + \beta_4 \ln PROF_{i,t-1} + \beta_5 \ln SIZE_{i,t-1} + \beta_6 \ln EFF_{i,t-1} \\ & + \beta_7 \ln OBS_{i,t-1} + \beta_8 \ln H_{i,t-1} + u_{i,t-1} \end{aligned} \tag{5}$$

where r_{it} is a risk variable for bank i during period t, i.e., a proxy for risk-taking. We use risk assets, non-performing loans and the Z-score as risk variables. Risk assets are calculated as the ratio of risk assets to total assets ($Risk_{it}$), and non-performing loans (NPL) are calculated as the ratio of non-performing loans to total loans[7]. The Z-score measures the number of ROA standard deviations that the bank's ROA plus its leverage would have to be reduced by before the bank becomes insolvent; thus, the Z-score is inversely proportional to a bank's probability of default. The Z-score can be computed as $\frac{ROA+CapitalRatio}{\sigma_{ROA}}$, where ROA is net profit divided by average total assets. The NPL that we use as a dependent variable is defined as the ratio of the sum of loans with risk levels of E, F, G and H to total loans.

The set of bank-level control variables consists of factors that represent capitalization, profitability, size and efficiency. Off-balance-sheet items constitute another bank-level control variable that is used in the risk-taking model applied by Delis and Kouretas (2011). However, we do not use this variable in our model because our dataset does not readily provide us with the means to identify and remove off-balance-sheet

[6]In an attempt to identify the effect over time for the variables. We also estimate the local regression by accounting for interactions between variables and time dummy variables.

[7]We add 1 to the values of risk assets and NPL (dependent variables) to correct our sample for null values.

items from the data as a whole. For this study, the control variables are calculated as follows: capitalization is defined as the ratio of equity capital to the lagged total assets ($Q/ASSET_{i,t-1}$); profitability is the ratio of profits before tax to the lagged total assets ($PROF_{i,t-1}$); size is the natural logarithm of real total assets ($SIZE_{i,t-1}$); and efficiency is the ratio of total revenue to the lagged total expenses ($EFF_{i,t-1}$).

We also introduce an interaction to examine the risk-taking of banks in the Brazilian banking industry in a more detailed way. In particular, we add the independent variable $\ln(h)_{i,t-1} * dummy$ to our model, which represents the interaction between the market power of each bank and a dummy variable that indicates the variation in the variable $Q/ASSETS_{i,t-1}$; this dummy variable is equal to 1 for an increase in capital and 0 otherwise. In the risk-taking model, instead of using a set of regulatory, macroeconomic and structural control variables, we control for time-fixed effects.[8]

We estimate the risk-taking model using a fixed-effects panel; as verification of the models robustness, this panel considers both an OLS standard deviation and a robust standard deviation.[9] However, we also perform an all-encompassing analysis because we seek to investigate far more than merely the interactions between risk-taking behavior and bank control variables. In particular, we would like to examine the effect of bank competition on risk-taking behaviors and the impact that market power at the firm level can produce on risk-taking tendencies.

For this purpose, we incorporate into our model both the independent variable $h_{i,t-1}$, the lagged H-statistic at the bank level, which is the market power at the bank level that we obtained through local regression and the Panzar and Rosse approach, and the independent variable $H_{i,t-1}$, the lagged H-statistic for the Brazil banking industry as a whole. We use two different methods to compute this overall H-statistic. In one approach, we calculate the value of the overall H-statistic to be the average of the H-statistics obtained for each bank through local regression for each period; in the other approach, we determine this variable based on the model developed by Bikker and Haaf (2002), which multiplies the elasticities used to compute the H-statistic by values generated by a continuous time-curve model ($e_{\varepsilon TIME}$).

4 Data Sampling

The present study uses an unbalanced dataset of Brazilian commercial banks, individual banks and conglomerates that spans the period from 2001 to 2011. We perform the market power analysis using two semiannual datasets released by the Central Bank of Brazil, namely, the TOP 50 dataset and the COSIF dataset. The TOP 50 dataset is related to 76 commercial banks that operate in the Brazilian banking industry and contains 1092 observations[10]. The COSIF dataset includes information about 139 commercial banks that operate in the Brazilian banking industry; these banks are described in 2230 observations[11]. Certain banks were excluded from the empirical analysis because the majority of the required data for these banks was missing in both datasets.

Banking conglomerates are more completely described in the TOP 50 dataset than they are in the COSIF dataset. However, the TOP 50 dataset does not include all of the variables that our analysis requires; thus, we use the COSIF dataset to complement the TOP 50 dataset, thereby obtaining all of the necessary information. In particular, the NPL variable used in our risk-taking model is not incorporated into the TOP 50 dataset, and therefore, values for this variable are obtained using the COSIF dataset. For the other employed variables, we preferentially use bank- and conglomerate-level data from the TOP 50 dataset, if possible. To create the conglomerate observations that we extract from the COSIF dataset, we merge the data from all of the banks that are controlled by the same institution[12]. The TOP 50 dataset already contains conglomerate-level information, and thus, we are not required to merge values for this dataset.

The sample that we obtained from the COSIF dataset represented commercial banks that operate in the Brazilian financial system, as these banks are required to publish information that is of interest to the Central Bank of Brazil. The Central Bank sends a spreadsheet of information requests to each registered commercial

[8]We add 1 to each bank's ratio of profits before tax to total assets to address negative profits in our sample; this addition is necessary because we apply a logarithmic function to this ratio as part of the calculation of variables.

[9]The results obtained from the robust fixed-effects panel are extremely similar to the ones obtained through the fixed-effects panel for OLS standard deviation, which indicates that our risk-taking model may be robust.

[10]The TOP 50 data are available at http://www4.bcb.gov.br/top50/port/top50.asp.

[11]The COSIF data are available at http://www4.bcb.gov.br/fis/cosif/balancetes.asp.

[12]This information is available at http://www4.bcb.gov.br/fis/cosif/principal.asp.

bank that operates in Brazil. The commercial banks are obligated to provide all of the information that is requested by the Central Bank and are subject to sanctions if they do not comply. The integrity of these communications between the Central Bank and commercial banks of Brazil is a critical aspect of building a solid and stable financial environment. The TOP 50 dataset is derived from the COSIF dataset; thus, the methodology underlying the TOP50 dataset is the same as the processes that are used to construct the COSIF dataset.

5 Empirical Results

5.1 Market power at the bank level

The results generated by the local regression method for Eq. (2) are illustrated in Table 3; as our analysis generates a separate coefficient for each bank, we chose to only present the average coefficients of each variable that we predict. In Table 4, we provide, for each time period of our sample, the mean H-statistic, as well as the standard deviation, minimum and maximum for the H-statistic. Figure 1 indicates the time variation of both the average H-statistic obtained through local regression and the H-statistic predicted by the fixed-effects panel regression. We use this result to justify the application of local regression as a technique for examining the competitive behavior both at the bank level and at the level of the Brazilian banking industry as a whole.

Place Tables 3 and 4 About Here.

Place Figure 1 About Here.

Figure 2 presents the variation of the average H-statistic over time, Figure 3 depicts the 25th percentile and 75th percentile of the average H-statistic, and Figure 4 illustrates the kurtosis of the H-statistic. We represent the skewness of the variation in the average H-statistic with respect to time in Figure 5. Figure 6 illustrates the standard deviation of the average H-statistic, and Figure 7 displays the distribution of H-statistics for each period, accounting for the market power of each bank for the period in question.[13]

Place Figures 2, 3, 4, 5, 6 and 7 About Here.

One important observation from our empirical analysis is that the average H-statistic is positive over the 2001-2011 time period, as is the average H-statistic that we obtain for each individual period that we examine. The consistency of the local regression is determined by estimating the H-statistic using a fixed-effects panel regression. In our case, we verified that the result from the fixed-effects panel regression is both highly significant and remarkably similar to the result obtained using local regression (Brissimis and Delis, 2011). We correlate the H-statistics obtained using these two methods to assess the similarity between these two predictions. However, the fixed-effects panel regression method does not produce H-statistics that can specifically be related to each bank and period; instead, this method only produces an H-statistic that is generally descriptive of the economy as a whole.

Therefore, to compare the H-statistic obtained through these two methodologies, we initially compute the H-statistic using panel regression and then multiply the prices at a particular time by the temporal dummy variables to estimate the H-statistic value for a given period. We subsequently perform the same procedure using local regression and assess the variation of the calculated H-statistics over time. Because the local regression estimates are for each individual bank, we use the local regression results to compute an average H-statistic for the period as a whole; from these calculations, we conclude that the time variations identified by these two methods are remarkably similar.

We use a correlation test to confirm that the time variations of these two H-statistics are correlated[14]. We also visually observe that both H-statistics display similar behavior during the period addressed by our analysis, as can be observed from Figure 1. Despite this similarity, we note that the competitive behavior of the banking industry in this period is better modeled by the local regression methodology than by the

[13] We analyzed Figure 4, Figure 5 and Figure 6 to verify that our H-statistic results are not adversely affected by outliers and misspecifications.

[14] The p-value for our Pearson Correlation Test is 0.1249

fixed-effects panel regression because the former method comprehensively computes the average H-statistic of the banking industry from the market power prediction for each bank.

Figure 7 presents the distribution of H-statistics for each semester. The market power heterogeneity between banks is significant for all periods. The results also show the presence of cyclic behavior in banks' market power. Initially, we observe a concentration of market power at the bank level, i.e., there are various banks that possess similar levels of market power. In particular, in June 2001, the concentration of banks' market power is notable, although we then observe a more diluted behavior in subsequent semesters. The minimum H-statistic is lower and the maximum H-statistic is higher in December 2001 than in June 2001. This behavior is verified in all periods because semesters during which certain banks have very high market power and other banks have extremely low market power are consistently followed by periods in which banks evince broadly similar competitive behaviors.

Table 4 also presents the fluctuation of the average H-statistic that we verified in Figure 2. In June 2001, the average H-statistic was 0.11558, whereas in June 2011, the average H-statistic was 0.16968. As these two values are similar, we could initially conjecture that for this period, the competitive behavior of the Brazilian banking industry did not significantly change; however, we observe in Figure 2 that the fluctuations in the H-statistic were very intensive during the examined period, contradicting this hypothesis. The market power estimated by the average H-statistic achieved its maximum in June 2009, when the H-statistic was 0.44015, and an environment of monopolistic competition was observed in the Brazilian banking industry; the average H-statistic was at its minimum in December 2005, when the value of this statistic was -0.06753 and the Brazilian banking industry evinces monopolistic behavior.

Through Table 4, we can observe that negative average H-statistics only occurred during three semesters. In all semesters, the H-statistic minimum is negative and the maximum H-statistic is a highly positive value. As shown in Table 5, the lowest maximum H-statistic is 0.52552, which occurred in June 2003. Thus, we can conclude that although each period had a positive average H-statistic, the sample always contains banks with high market power, which have negative H-statistic values, and banks with low market power, which have positive H-statistic value.

The Global Financial Crisis led to a significant increase in the average H-statistic until June 2010 because the average June 2008 H-statistic of 0.15423 increased to 0.39339 by June 2010, reaching its maximum value of 0.44015 in June 2009[15]. Therefore, we can conclude that the crisis increased competition in the Brazilian banking industry. We find banks with high market power in June 2008 because the minimum H-statistic at that time was -0.88404. However, the minimum H-statistic in June 2010 was only -0.14252; thus, we can conclude that the market power of the most powerful banks had decreased during the intervening time, leading to more competitive behavior in the banking industry.

However, the behavior identified in the crisis period is followed by a subsequent reduction in the competitiveness of the Brazilian banking industry. In Table 4, we observe a reduction in the average H-statistic after June 2010; moreover, banks with greater market power have also risen since June 2010 because the minimum H-statistic has fallen from -0.14252 to -0.46279. We also observe fluctuations in market power throughout the crisis period; nonetheless, the Global Financial Crisis, on the whole, produced a significant increase in the average H-statistic, implying that this crisis increased the competitiveness in Brazilian banking industry.

5.2 The relationship between risk-taking and market power at the bank level

We also compute models for the risk-taking behavior of the Brazilian banking industry using all of the dependent variables discussed in the Subsection 3.2, as well as two different types of average H-statistic. The three different proxies used for risk-taking were the Z-score, risk assets and NPL. Table 5 provides the results of these models. We also perform a robust fixed-effects panel for all of the models, however, we only present the results of the fixed-effects panel with OLS standard deviation in Table 5 because the results obtained from the robust fixed-effects panel are remarkably similar to those produced by the panel that used the OLS standard deviation.

Place Table 5 About Here.

[15]The Global Financial Crisis started with the collapse of the subprime market in the USA in 2007.

Initially, we compute the Z-score model, as described in Table 5, and determine that only the variable of bank size is not statistically significant. We observe that greater profitability results in an increase in risk-taking behaviors and that increased efficiency produces a reduction in risk-taking behaviors; these observations constitute important results as they demonstrate that efficiency and profitability are not necessarily related. Profitability and efficiency have opposite effects on the risk assumed by banks, and both variables are statistically significant.

Using the risk assets model, which is presented in Table 5, we find that the market power at the bank level, the interaction between the H-statistic of each bank and the capital dummy variable, the banks profitability and the banks size are not statistically significants. However, the banks efficiency is statistically significant and positively related to its risk. Thus, we conclude that banks with higher efficiency assume more risk, which is the inverse of the result found by the Z-score model. Capitalization ($Q/ASSETS$) is also significant in this model; in particular, an increase in the banks capital appears to produce a reduction in the risk assumed by that bank, a result that is in accordance with the findings of the Z-score model.

The model that uses NPL as the dependent variable has more insignificant coefficients than the other two risk models; in addition, the NPL model also produces inconsistent estimates as many of its parameters have values and standard deviations close to 0, as illustrated in Table 5. Although the Z-score model has an R_2 lower than the R_2 presented by the risk assets and NPL models, we choose to rely on the Z-score model for the purposes of this study. Because the variables that are integrated into this model are more accurately estimated than the variables that are used by the risk assets and NPL models, the Z-score model should prove more appropriate both for predicting risk-taking behavior and for describing the relationship between risk-taking and the other analyzed factors.

We compute the average H-statistic using the methodology described in Bikker and Haaf (2002) for all models. We also estimate this variable as the average of the H-statistics obtained for each bank through local regression for each period. For the Z-score model, the H-statistic related to the Brazilian banking industry is significant; however, this variable does not provide any additional meaningful information to the model. Instead, the increase in the H-statistic over time merely justifies its significance. We also compute the mean of the H-statistic obtained through local regression; this variable is not significant for the Z-score model, but it is significant for the risk assets model[16]. Given that we chose to use the Z-score model, we decided to exclude this variable from our model, as it is not statistically significant.

Using the Z-score model, it can be observed that banks with higher market power take more risk. Therefore, banks with decreased market power reduce their risky behaviors. According to Boyd and Nicol (2005), a bank can assume more risk if there is an increase in its market power because greater market power allows the bank in question to charge higher loan rates and increase their rents in the loan markets. Moral hazard effects can cause this bank to engage in riskier but more lucrative loans, causing its probability of bankruptcy to increase. In this situation, as borrowers interest costs are high, these borrowers are also assuming more risk and are subject to greater moral hazard effects than they would experience in a more competitive banking environment.

Capitalization is another important variable for banks and is negatively correlated with risk-taking behavior. However, in our attempt to understand the entire impact of market power in risk-taking, we must perform a very delicate assessment because capitalization and market power are directly related in our model. In our analysis, we include an examination of the interaction between the market power of each bank and a dummy variable representing capital variation for that bank, and we find that the effect of the H-statistic at an individual bank level is dependent on whether the bank experiences a capital increase.

If a capital increase does not occur ($dummy = 0$), then an increase in $\ln h_{i,t-1}$ leads the bank to assume less risk, i.e., a reduction of market power implies a decrease in risk-taking, as β_1 is positive. Conversely, an increase in a banks market power will tend to produce an increase in the risk assumed by that bank. However, if a capital increase does occur, given that β_3 is negative and $|\beta_1| < |\beta_3|$, a reduction in market power implies that increased risk-taking will result. The converse holds for an increase in market power. This interpretation can be easily reached through the examination of the following equation.[17]

[16]However, even for the risk assets model, which produces inaccurate estimates, the value of this mean H-statistic is nearly 0.

[17]As we chose to employ the Z-score model, the parameters that we used in this analysis are described in the first column of Table 5.

$$\frac{\partial \ln RISK_{it}}{\partial \ln h_{i,t-1}} = \beta_1 + \beta_3 \times dummy \tag{6}$$

where $RISK_{it}$ is the dependent variable analyzed (risk-taking), $h_{i,t-1}$ is the market power at the bank level and $dummy$ is the capital variation dummy variable, which assumes a value of 1 for an increase in capital. From the first column of Table 5, we observe that β_1 is positive, β_3 is negative and $|\beta_1| < |\beta_3|$.

From Table 5, we observe that β_2 is positive; thus, capitalization is negatively related to risk-taking, since our proxy for risk-taking is the Z-score. This can be an explanation for the changes in risk-taking behaviors of banks when their capital increases. There is a positive relationship between market power and risk-taking when banks do not have a capital increase. However, we find a negative relationship between these two variables when banks experience a capital increase. An examination of Eq. (6) reveals that banks with an increase in market power increase their risk for $dummy = 0$; however, banks assume less risk if they have both an increase in market power and an increase in capital. We also note that banks with greater market power adjust for risk more quickly than banks with lower market power; therefore, a faster reduction in risk levels upon capital increases and market power increases will be observed for banks with greater market power than for banks with less market power.

For each of our models, we perform Wald tests in which the null hypothesis states that the sum of the coefficients related to $h_{i,t-1}$ and $\ln(h)_{i,t-1} * dummy$ is 0. We cannot reject the null hypotheses for all of the models. As we have already chosen not to employ the NPL and risk assets models, we only consider the Wald test results that are related to the Z-score model. Although the interaction $\ln(h)_{i,t-1} * dummy$ and the variable $\ln(h)_{i,t-1}$ are significant at the 5% and 10% levels of statistical significance, respectively, the Wald test does not provide results indicating that market power directly impacts the risk taken by banks. However, the significance of these variables demonstrates that the risk assumed by banks is related to their market power and their power to control prices.

6 Conclusion

This paper applies a new method for measuring the market power at an individual level for the Brazilian banking industry. In particular, we incorporate an econometric framework based on Brissimis and Delis (2011) into the methodology that we use to analyze the competitive behavior of this industry. Thus, we assess this industry using both the Panzar and Rosse model, which is described by Rosse and Panzar (1977); Panzar and Rosse (1987), and a non-parametric estimation technique known as local regression (Cleveland, 1979; Cleveland and Devlin, 1988; Simonoff, 1996; Loader, 1999). This approach provides information related to the market power that each bank possesses in its industry and allows for the individual estimation of each coefficient that composes the Panzar and Rosse model. We apply this methodology to assess the banks that participated in the Brazilian banking industry during the 2001-2011 time period.

As recent literature has raised questions regarding the relationship between market power and risk-taking in the banking industry, this paper examines the states of competitive behavior of Brazilian banks during the time period in question and the effect of market power at the bank level in the risk-taking tendencies of a bank. We also analyze the implications of risk-based changes in banks' behavior with regard to market power and the Brazilian economy. This analysis provides valuable information addressing how banks determine whether it is advisable to assume greater risk and how banks with greater market power can influence the performance of the economy as a whole.

Our findings suggest that there is a significant heterogeneity in the market power of the sampled banks. We also observe that the Brazilian banking industry functions under conditions of monopolistic competition. This observation is reinforced by the finding that under the current economic conditions, the banking industry often features several banks with high market power and a large majority of banks with relatively little market power. Our sample also demonstrates fluctuations in the concentration of bank market power, as indicated by variations in the distribution of H-statistic estimates among different banks.

In particular, we observe that at times, banks display similar competitive behaviors and market powers. We then verify that during other periods, banks present a wide range of different competitive behaviors and market powers. These two types of periods occur sequentially as a situation in which all banks present more competitive behavior is followed by a period in which a few banks possess higher market power while the majority of banks have low market power; these latter conditions are indicated by a reduction in the average H-statistic, as shown in Table 4.

This cyclic fluctuation occurs during the entire period addressed by our analysis. Notably, we continue to observe this fluctuation in the competitive behavior of banks even during the period of the Global Financial Crisis. The crisis increased the competition in the Brazilian banking market; however, this crisis was followed by a reduction in the average H-statistic of the banking industry. In June 2009, the average H-statistic was 0.44015, which marked a dramatic increase from H-statistic values in June 2007, demonstrating the effect of the crisis. Subsequently, however, this June 2009 state of the industry was replaced by conditions of decreased competitiveness. Therefore, we can verify that the fluctuating behavior of banks continued during the Global Financial Crisis period. The post-crisis effect simply accentuated the reduction in the market power of banks and only postponed but did not prevent the normal cyclic fluctuations in banking industry behavior.

The fundamental objective of this paper is to understand the impact of market power on risk-taking behavior because the literature does not present conclusive results regarding this topic. Therefore, based on Delis and Kouretas (2011), we construct a risk-taking model for the Brazilian banking industry that incorporates variables such as market power at the bank level and the average H-statistic of the Brazilian economy for a particular time period. Although the latter variable did not produce significant results, we found that the market power at the bank level and its interaction with bank capitalization effects produced valuable information for policy-makers. We demonstrate that banks with increasing market power engage in riskier behavior than banks with decreasing market power. However, banks' decisions regarding risk are also significantly influenced by changes in their capitalization because increased capitalization consistently reduces the risk taken by banks.

Our findings suggest that Brazilian banks do not evince conservative behavior; instead, banks with greater market power increase their risk to increase collected rents. However, if a bank with increased market power becomes more capitalized, then we observe a change in its behavior, as the bank becomes more conservative and reduces its risk. Conversely, banks with decreased market power and increased capitalization assume more risk. This effect of capitalization on banks' decision is in accordance with the results of Tabak et al. (2011b), which show the presence of this risk-taking behavior of banks in 10 Latin American countries including Brazil. The study performed by Tabak et al. (2011b) enhances our findings, linking them with the current discussion on financial regulation and financial stability.

Banks with higher market power will often assume more risk in an attempt to obtain increased rents. However, an increase in capital for a bank leads to the growth of the banks charter value, as well as the consequent possibility that risky behavior will result in increased losses to this charter value. Thus, banks with monopoly rents are not conservative in the Brazilian banking industry until they achieve sufficiently high charter values, at which point the potential losses from risky actions become too exorbitant to justify the assumption of greater risks. These conclusions provide vital information for managers and policy-makers, as an increased knowledge of the relationships among bank market power, the capitalization of banks and banks risk-taking behavior can improve the effectiveness of governmental regulation in the economy and thereby prevent the collapse of the Brazilian financial system.

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Table 1: Summary of the contributions related to banking competition

Authors	Country	Period	Independents Variables	Empirical findings
Agoraki et al. (2011)	13 Central Eastern European (CEE) countries	1998-2005	Regulatory measures	Increased market power and higher activity restrictions lead to a reduction in credit risk and risk of default.
Beck et al. (2006)	69 countries	1980-1997	Bank concentration and crisis	Crisis are less likely in economies with more concentrated banking systems even after controlling for some variables.
Casu and Girardone (2009)	France, Germany, Italy, Spain and the United Kingdom	2000-2005	Efficiency	An increase in market power increases bank efficiency, whereas the causality running from efficiency to competition is weak.
Coccorese (2005)	Italy	1988-2000	Banking concentration	Competition and concentration are not negatively related.
Degryse and Ongena (2007)	Belgium	1995-1997	Bank orientation(the choice of relationship-based lending versus transactional banking)	Bank branches engage in more bank-firm relationships when the inter-bank competition is increased.
Jeon et al. (2011)	7 Asian and 19 Latin American countries	1997-2008	Foreign bank penetration	Foreign bank penetration is positively related to competition.
Jimnez et al. (2007)	Spain	1988-2003	Ratio of non-performing commercial loans (NPL), the measure of bank risk	An increase in market power decreases the bank risk (NPL ratios).
Keeley (1990)	US	1970-1986	Default risk, asset risk and bank capital	Banks with higher market power hold more capital relative to assets and have a small default risk.
Manlagñit (2011)	Philippines	1990-2006	Banking liberalization	The purpose of banking liberalization in increase the competitiveness and the efficiency of domestic banks works considerably well.
Maudos and Solís (2011)	Mexico	1993-2005	Deregulation, liberalization and consolidation of banking industry	The effectiveness of the measures employed that aim to increase the competition in the Mexican banking industry is dubious.
Olivero et al. (2011)	10 Asian and 10 Latin American countries	1996-2006	Monetary policy	Increased banking competition reduces the effectiveness of monetary policy.
Park (2009)	Korea	1992-2004	Banking concentration	Increased concentration has not lessened competition.
Uchida and Tsutsui (2005)	Japan	1974-2000	Competition in banking sector	Competition had improved, especially, in the 1970s and in the first half of the 1980s.
Yeyati and Micco (2007)	8 Latin American countries	1993-2002	Foreign banks penetration	There are positive relation between market bank stability and foreign penetration.
Yildirim and Philippatos (2007)	11 Latin American countries	1993-2000	Consolidation of bank industry	Banking competition is not related to banking concentration; the reduction of the banking competition in some countries may be justify by increased consolidation.
Zhao et al. (2010)	India	1992-2004	Regulation of banks' activities	Deregulation improves banks' performance and banking competition.

Table 2: Discriminatory power of H-statistics

Estimated values of H	Competitive environment	Especification
$H \leq 0$	Monopolistic market or Conjectural variation short-run oligopoly	Each bank operates independently as under monopoly profit maximization conditions or perfect cartel.
$0 < H < 1$	Monopolistic competition	There are product differentiation and banks produce more than in monopoly, however the price is less than would be in this scenario.
$H = 1$	Natural monopoly in perfectly contestable market or Perfect competition	Free entry equilibrium with full efficient capacity utilization.

Source Bikker and Haaf (2002); Rezitis (2010).

Table 3: Descriptive statistics

Name	Mean	Std.	Minimum	Maximum
$\ln TR$	13.0039	2.0376	7.6783	18.067
$\ln w1$	-2.4223	0.63415	-8.6141	-0.0154
$\ln w2$	-5.3325	1.46607	-13.9572	-2.3897
$\ln w3$	4.1013	0.88562	0.3676	10.289
$\ln Q/ASSETS$	-2.0466	0.56704	-4.6506	-0.1126
$\ln L/ASSETS$	-0.9547	0.62247	-4.8995	0.7642

The table reports the descriptive statistics of average coefficients, where Std. means standard deviation. Primarily, we predict the parameters for each bank, then we compute the mean of these parameters to find the summary statistics for each variable.

Table 4: Descriptive statistics of H-statistics for period

Date	Mean	Std.	Minimum	Maximum
June 2001	0.11558	0.21101	-0.28659	0.5836
December 2001	0.04427	0.45756	-0.53432	1.0001
June 2002	0.23775	0.24105	-0.17656	0.76053
December 2002	0.35369	0.2403	-0.37407	0.97471
June 2003	0.21679	0.17861	-0.21691	0.52552
December 2003	-0.00289	0.25587	-0.72941	0.91771
June 2004	0.13285	0.28534	-0.25056	0.96659
December 2004	0.13549	0.24582	-0.38002	0.83148
June 2005	0.05726	0.21422	-0.23375	0.85838
December 2005	-0.06753	0.32272	-0.93518	0.65123
June 2006	0.00526	0.28956	-0.4032	0.73767
December 2006	0.12669	0.25619	-0.30125	0.77385
June 2007	-0.01338	0.28844	-0.50103	0.70606
December 2007	0.17228	0.21209	-0.26015	0.79259
June 2008	0.15423	0.27344	-0.88404	0.70413
December 2008	0.31023	0.24253	-0.09882	0.84599
June 2009	0.44015	0.37472	-0.34019	1.42629
December 2009	0.29313	0.35876	-0.56448	1.16697
June 2010	0.39229	0.26666	-0.14252	1.25965
December 2010	0.18733	0.32508	-0.46279	1.05465
June 2011	0.16968	0.36464	-0.46933	1.09708

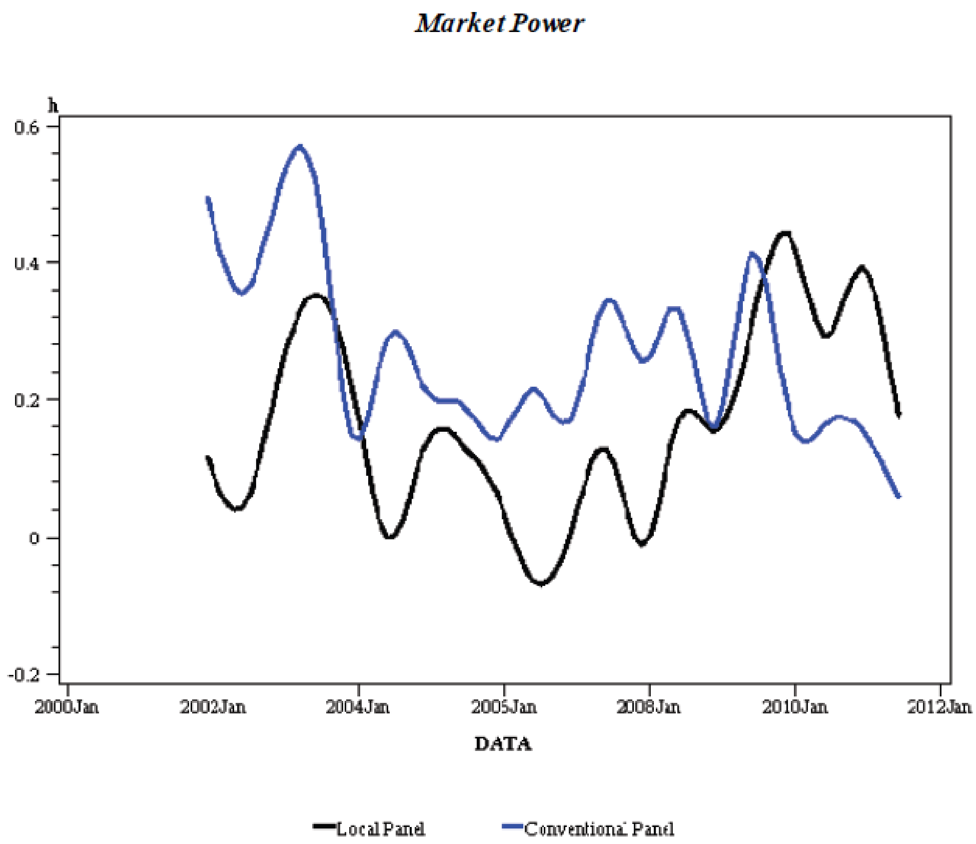
The table describes the summary statistics for H-statistics in each period presented in the sample, where Std. means standard deviation.

Table 5: Risk-taking panel description models

	Z-score	$Risk_{it}$	NPL
Intercept	1.50***	0.56***	0.31***
	(0.34)	(0.03)	(0.06)
$\ln h_{i,t-1}$	0.06*	0.00	-0.00
	(0.03)	(0.00)	(0.01)
$\ln Q/ASSETS_{i,t-1}$	0.17***	-0.01***	0.02***
	(0.03)	(0.00)	(0.01)
$\ln h_{i,t-1} * dummy$	-0.11**	0.00	0.01
	(0.05)	(0.01)	(0.01)
$\ln PROF_{i,t-1}$	-1.44***	-0.05	-0.07
	(0.36)	(0.04)	(0.08)
$\ln SIZE_{i,t-1}$	-0.00	0.00	-0.01**
	(0.02)	(0.00)	(0.00)
$\ln EFF_{i,t-1}$	0.17***	0.02***	-0.07***
	(0.06)	(0.01)	(0.01)
Time FE	YES	YES	YES
Cross section FE	YES	YES	YES
R-Square	0.61	0.71	0.64
Wald	0.97	0.54	0.02
p-value	0.32	0.46	0.89

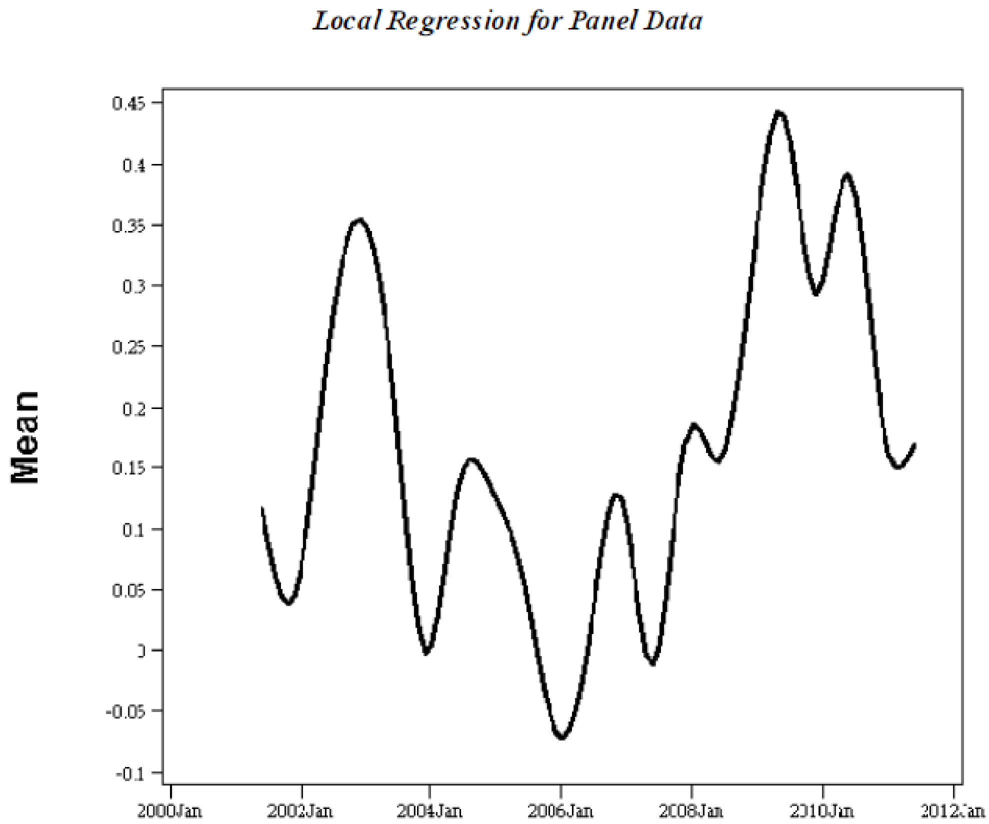
The table reports coefficients and standard deviation (in parentheses). First column describes the Z-score estimates, the second presents the risk assets ($Risk_{it}$) estimates and the third column report the NPL estimates. The variables presented are the H-statistic of each bank lagged ($h_{i,t-1}$), the banks' capital lagged ($Q/ASSETS_{i,t-1}$), the interaction between the H-statistic at bank-level lagged and the dummy of capital variation ($\ln h_{i,t-1} * dummy$), which is 1 for an increase in $Q/ASSETS_{i,t-1}$, the banks' profitability lagged ($PROF_{i,t-1}$), size of banks indicated by the logarithm of its total assets lagged ($SIZE_{i,t-1}$) and $EFF_{i,t-1}$ is the banks' efficiency lagged. The independent variable $H_{i,t-1}$ it is not described in the table because it is not significant for all models and does not present valuable information. The table also reports a Wald test that we perform to study the significance of the market power, where we test the significance of the sum of $h_{i,t-1}$ and its interaction coefficients.
*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.

Figure 1: Difference between the H-statistics' prediction



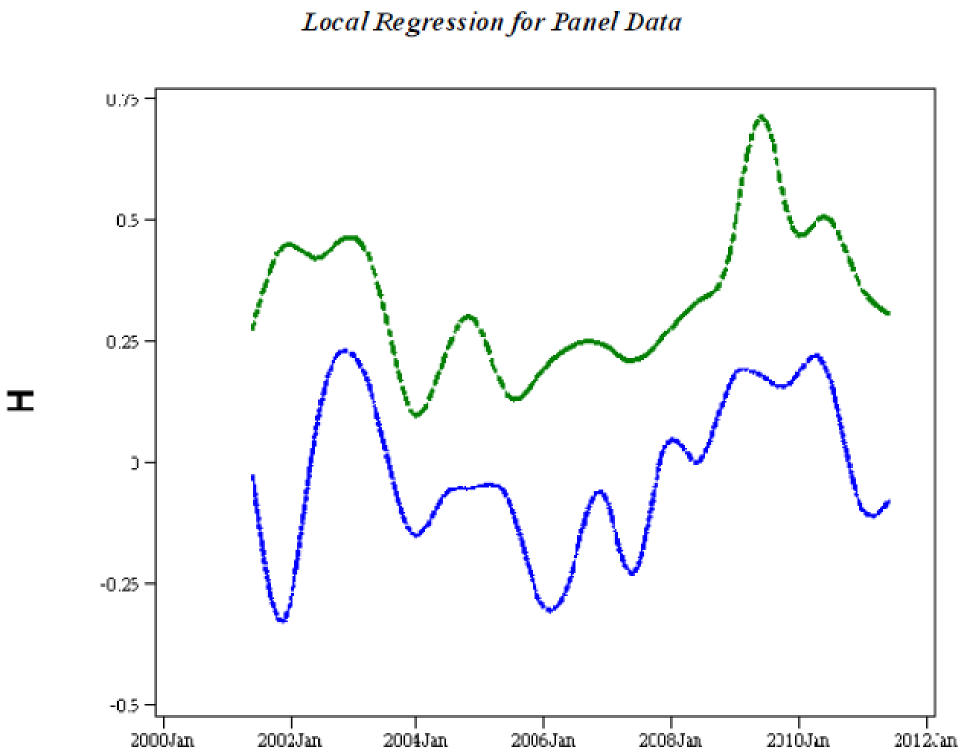
The figure reports the time variation of H-statistic obtained through two different methodologies for each period, the local regression and the fixed-effects panel regression. We obtain the average H-statistic for each period using local regression by computing the mean of the banks' H-statistic for period.

Figure 2: Average H-statistic in time



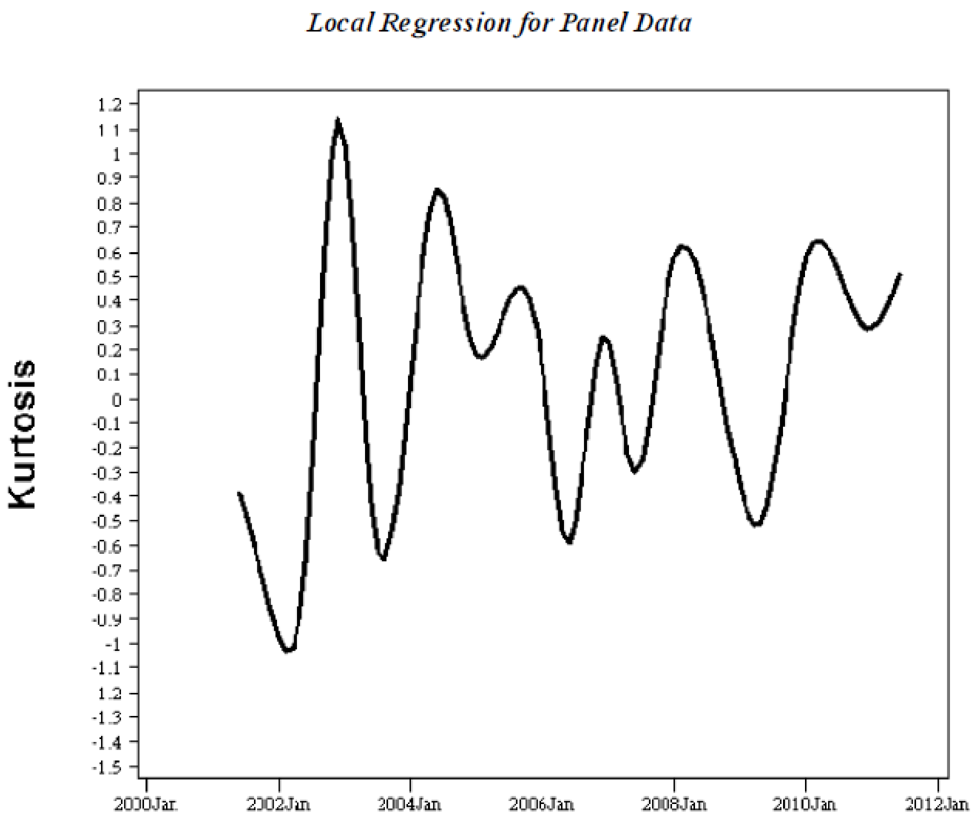
The figure reports the average H-statistic in time. We obtain this average H-statistic computing the mean of the banks' H-statistic for period.

Figure 3: Average H-statistic percentile 25 and 75 in time



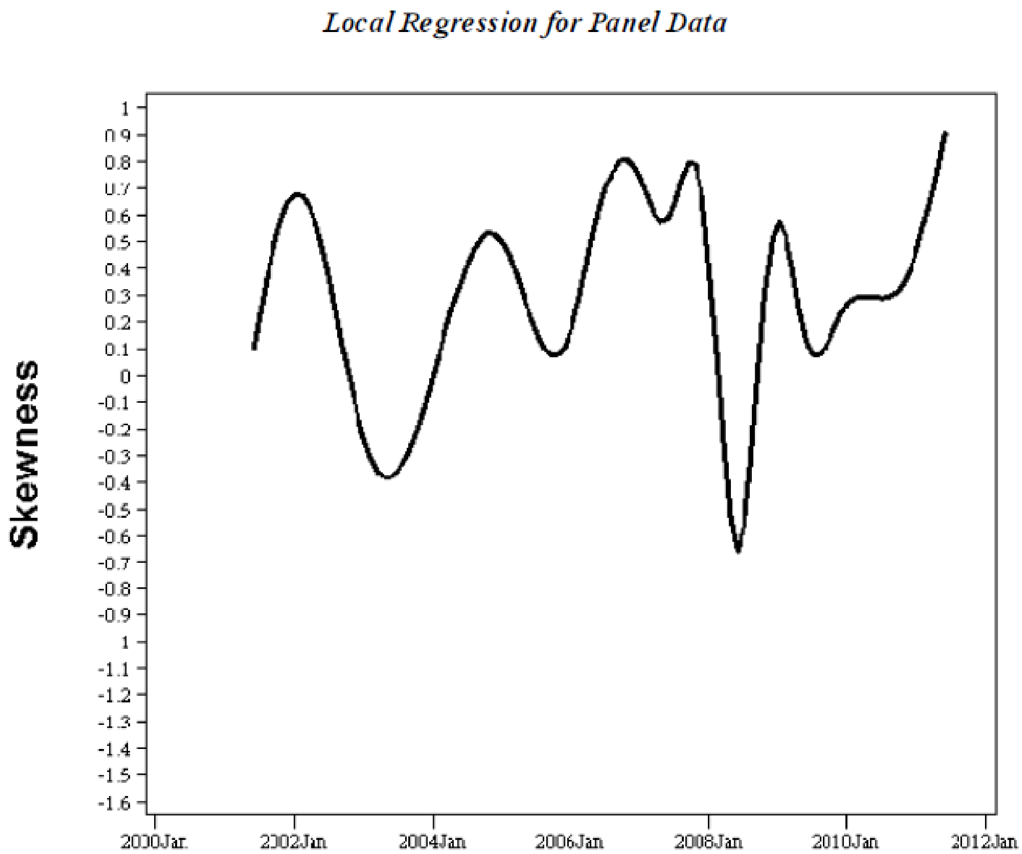
The figure reports the average H-statistic percentile 25 and 75 in time. We obtain this average H-statistic computing the mean of the banks' H-statistic for period.

Figure 4: Average H-statistic kurtosis in time



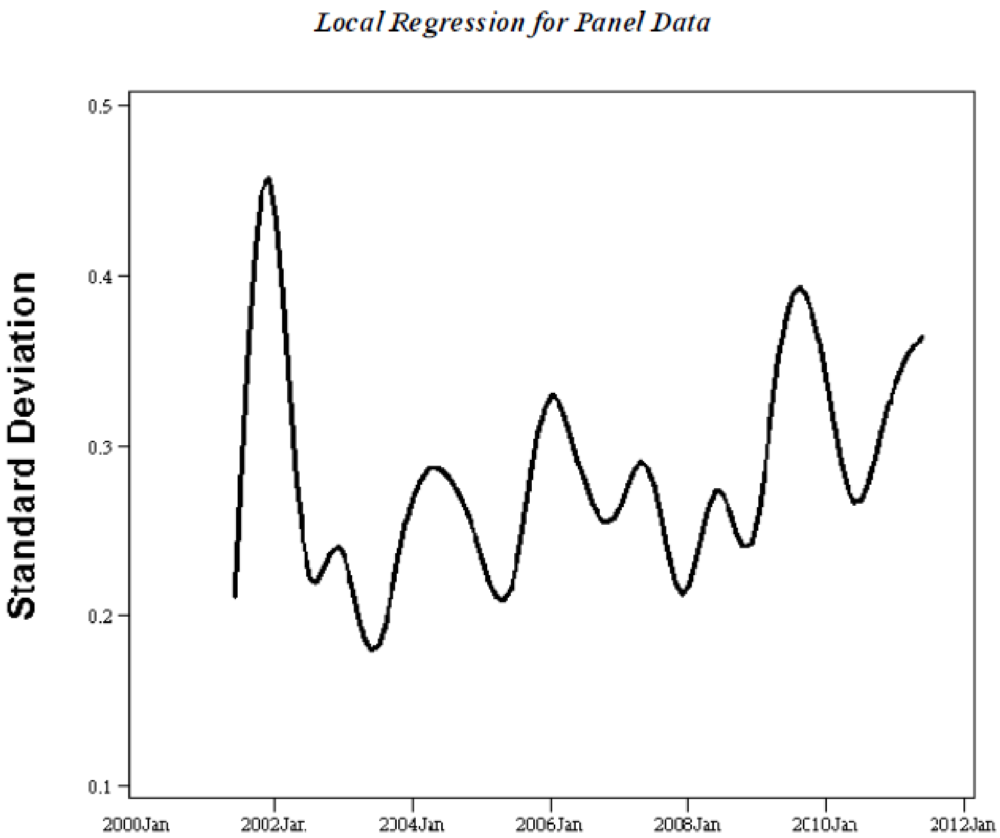
The figure reports the average H-statistic kurtosis in time. We obtain this average H-statistic computing the mean of the banks' H-statistic for period.

Figure 5: Average H-statistic skewness in time



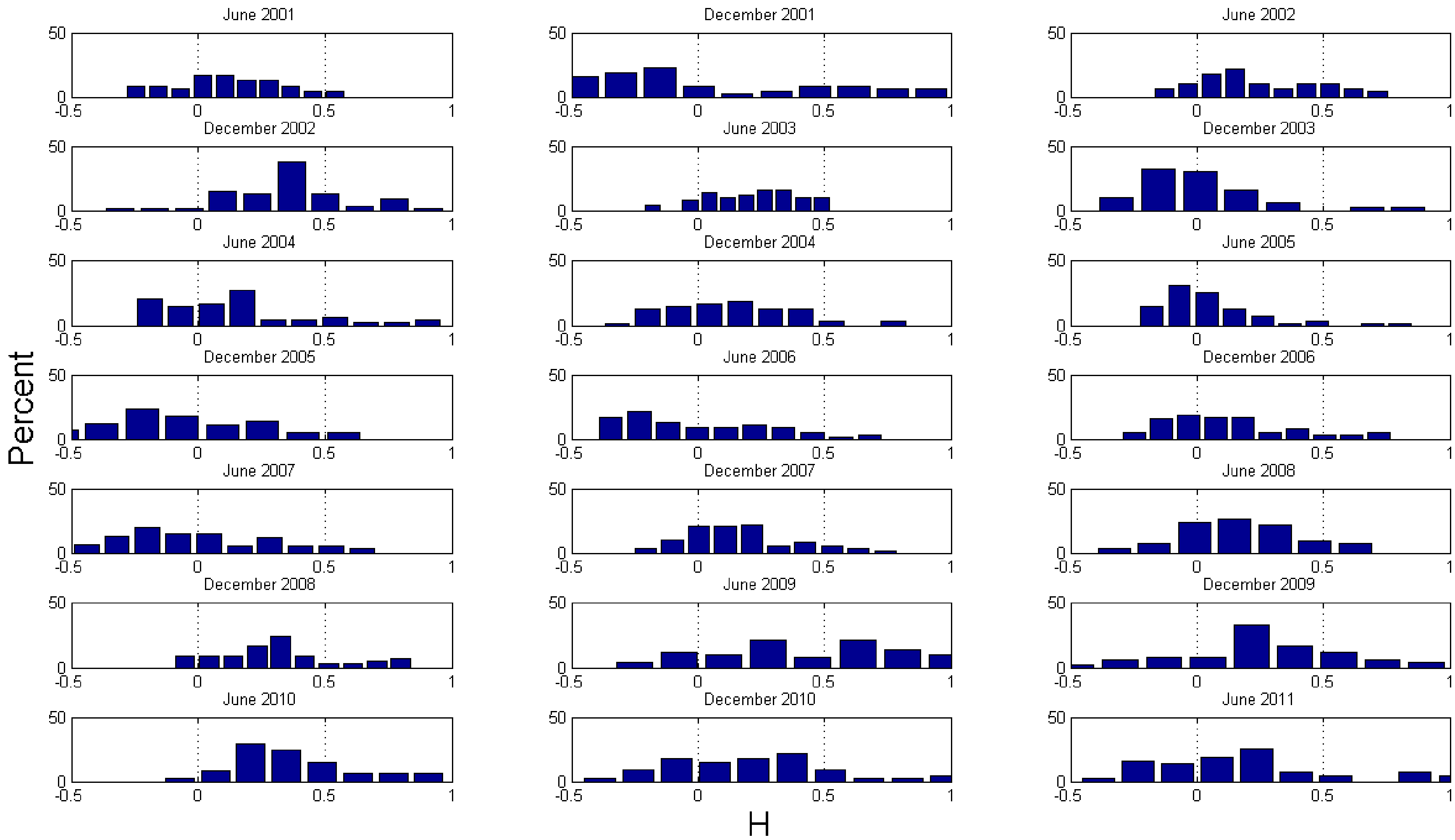
The figure reports the average H-statistic skewness in time. We obtain this average H-statistic computing the mean of the banks' H-statistic for period.

Figure 6: Average H-statistic standard deviation in time



The figure reports the average H-statistic standard deviation in time. We obtain this average H-statistic computing the mean of the banks' H-statistic for period.

Figure 7: Histograms of average H-statistic for period



The histograms present the distribution of the H-statistic at bank level obtained from the estimation of Panzar and Rosse model with local regression, where *Percent* is the percentage of banks and H is the H-statistics of banks.

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