ISSN 1518-3548

BANCO CENTRAL DO BRASIL

Creditor's Protection and Bank Loans: market power and bankruptcy reform's effects

Supplementary Material

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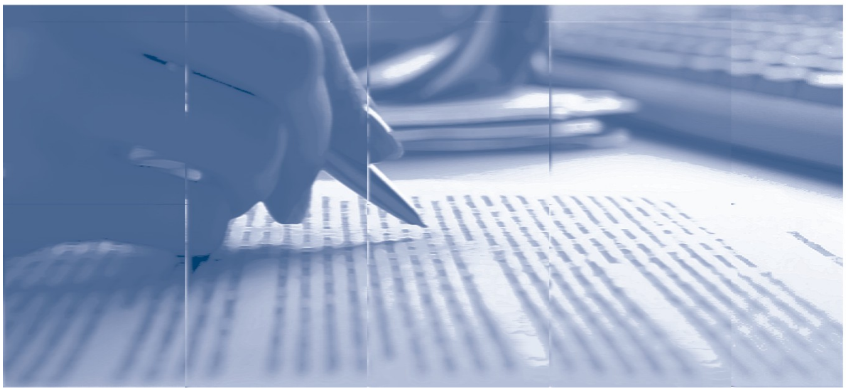
April 2020

Working Papers



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The Degree of Competition in Bank Loans and Bankruptcy Reforms: a two-stage strategy

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Abstract

This is the supplementary material for "Creditor's Protection and Bank Loans: Market Power and Bankruptcy Reform's Effects." It contains additional tables and figures that are necessary to fully document the research contained in the paper and to facilitate the readers' ability to understand the work.

Keywords: Bank Competition, Creditor's Protection Reforms, Interest Rate of Loans.
JEL Classification: G21, G33, L11.

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“The Degree of Competition in Bank Loans and Bankruptcy Reforms: A Two-Stage Strategy”

S1 Introduction

This supplementary material presents the estimation of the effect of market power level in Brazilian bank credit market on hampering the reducing effects of the new Brazilian bankruptcy legal statement. Instead of industry concentration indexes, we use a modification of the H-Statistics proposed by Panzar and Rosse (1987). We build a two stage econometric strategy to accomplish with the estimation of H-Statistic and the difference-in-difference method, which we use to identify the limiting effect of the market power on the reducing effects of the Brazilian Bankruptcy Reform on the interest rate of corporate loans. Our H-Statistic has a credit type specific component, which enables the identification of the law effect over credit types with different market power.

We face important challenges when using Panzar and Rosse in our differences-in-differences econometric model. First, we need to estimate H-Statistics for the different credit markets, since the same credit institution operates with a variety of credit types, previously classified in ten credit type categories. Second, we need to replace our measure of bank concentration by the Panzar and Rosse H-Statistic in our differences-in-differences econometric model. In this supplementary material we describe a two-stage estimation procedure that we developed to use Panzar and Rosse in our differences-in-differences econometric model. That procedure will require the use of a bootstrapped correction procedure.

An estimation of H-Statistic for each credit type is a challenge task, since the Panzar and Rosse's methodology was not originally developed to estimate the H-Statistic of each product of a multi-product firm. To overcome this problem, we modify the estimation strategy proposed by Barbosa et al. (2015), who proposed a the modified H-Statistic as MultiProduct-H. Intuitively, we introduce new dummy variables into Barbosa et al. (2015)'s empirical strategy to estimate H-Statistic of each credit type. Those dummy variables capture specific credit type variations and allow us to identify the H-Statistic by each credit type based on a singular equation of input prices.

S2 A Two-Stage Empirical Strategy

Our proposed two-stage strategy aims to estimate the limiting effect of market power on the BBR effects on the interest rate of corporate loans. It consists of estimating the Multi-Product-H Statistics using an estimation procedure similar to Barbosa et al. (2015) in our first stage. We use an accounting information dataset provide by the Brazilian Central Bank, which consists of the monthly balance sheets of credit institutions. This new dataset observes accounting information and has no operation granularity. We observe revenues and expenses at the bank level.

In the second stage, we replace the HHI used in the paper as the proxy for the bank market power by the estimated statistics. The second stage is a differences-in-differences estimation model and we use a data set different from the dataset used to estimate the 1st Stage. This dataset is the same that we used in the paper. This second dataset is shown as bank b, credit type l, risk class r and collateralized operations c.

As we use a regressor estimated in our first stage, we use a bootstrap method to correct limited sample bias and confidence interval. The bootstrap simulations use an algorithm we created. We report the algorithm in subsection S2.3.

S2.1 The First Stage

The first stage in our econometric strategy is the estimation of the H-Statistic per credit type using the balance sheet information of credit institutions. We access the contribution of each credit type to the H-Statistic by Barbosa et al. (2015), which proposed a methodology to estimate the Multi-Product-H. This method applied to our data allows our model to obtain cross-section variation of the H-Statistic to the ten categorized credit types (Table 3 in the paper). In this supplementary material, we define each market as each credit type. To estimate Multi-Product-H by each credit type, we estimate the following equation:

$$\ln(TRCred_{bt}) = \alpha + \ln(w_{bt})'\Theta + \ln(w_{bt}) \times dmMultProd'_{bt}\theta + Z'_{b,t}\pi + \eta_b + \varepsilon_{bt}, \qquad \text{(S1)}$$

where b is the bank identification and t is the monthly period of observation.

The dependent variable, $TRCred_{bt}$, is the natural logarithm of the Total Credit Revenue observed by banks (credit institutions) for each month, t. We use an intercept term α. The input prices consist of the vector w_{bt}, which we detail below. We use a Fixed Effect Panel estimator and η_b is the notation of the banks' unobserved fixed effects.

The vector $dmMultProd_b$ is a vector of 10 dummy variables defined as:

$$dmMultProd_b(dm_mkt_{1bt}, dm_mkt_{2bt}, dm_mkt_{3bt}, ..., dm_mkt_{10bt}),$$

where dm_mkt_{ibt} is a dummy variable which is equal to 1 if a bank b loan contract belongs to a credit type l, described in Table 3. The dummies assume the value of 1 if the credit institution b reports at least one operation in the specific credit type in month t.

We included all ten dummies in our first stage. These is not a source of collinearity because the dependent variable is Total Credit Revenue, which includes revenues from other credit types beyond the 10 credit types described Table 3. We should remember that to use the differences-in-differences estimation method, we must choose a control group and a treatment group of credit operations. We classify this operation in the 10 credit types in Table 3. A bank operates other credit types, like real estate financing, subsidized agricultural types or payroll attached credit types. As we use the Total Credit Revenue from the balance sheet, the dependent variable in our first stage includes an "eleventh" credit type aggregated with all other credit types that we do not consider as a treatment or control group in our second stage.

In the vector of input prices, we used similar concepts to those used in Barbosa et al. (2015) to estimate the H-Statistic; however, we do not work with the same database. Our work uses accounting information from credit institutions, whereas the referenced work uses the consolidated accounting of financial conglomerates. Our focus is on the credit market, and if we use an aggregate data set, we may have a worse contamination issue. Income and expenses from other businesses in a credit institution might be a non-identified source of variation and we must previously estimate the revenues from credit and financing operations. As we use non-consolidated balance sheets, we directly observe the revenues from credit and financing operations; however, we do not observe the specific revenue of each credit type. We do not control for the economies of scope as posited by the second estimated model in Barbosa et al. (2015).

Our model considers the credit operation's total revenues and not the credit institution total revenues. By using credit revenue instead of total revenue we better estimate when credit institutions operate in more inelastic sectors of the credit market.

The input prices vector used to estimate the statistics is $w_{bt} = (w_{1bt}, w_{2bt}, w_{3bt})$, and we use similar concepts of Barbosa et al. (2015) to define the vector of input prices:

- Cost of Funding w_{1bt}: the ratio of Funding Expenses and Bank Funding Intermediation Expenses over Shareholder Net Capital;

- Cost of Fixed Capital w_{2bt}: the ratio of Total Fixed Capital less leased asset to credit institutions clients over Shareholder Net Capital;

- Cost of Wages w_{3bt}: The ratio of Total Payroll over Shareholder Net Capital, and we included wages, social benefits expenses and sharing profit expenses.

The set of control variables Z_{bt} includes four covariates:

- Provision Rate: balance sheet registered provision over shareholder equity;
- Profitability: measure as net profit to shareholder equity;
- Market Share TA: the market share calculated with respect to total assets (TA);
- HHI TA: Herfindhal-Hirschman Index calculated as the square sum of the Market Share TA.

We additionally include control variables to Credit Portfolio concentration:

- Market Share - Credit Portfolio: the market share calculated using the total value of credit assets from the bank's balance sheet;
- HHI - Credit Portfolio: Herfindhal-Hirschman Index calculated as the square sum of Market Share - Credit Portfolio.

The Standard-H is calculated as the sum of the estimated coefficients Θ, which consist on the estimated elasticity of the Total Credit Revenue with respect to the input prices.

$$Standard - H = \sum_{p=1}^{P} \widehat{\Theta}_p, \tag{S2}$$

where $\widehat{\Theta}_p$ is the estimated coefficient of the natural logarithm of the input price p.

To obtain the H for each credit type, we compute the Multi-Product-H as:

$$Multiproduct - H_l = \sum_{p=1}^{P} \widehat{\Theta}_p + \sum_{p=1}^{P} \widehat{\theta}_{pl}, \tag{S3}$$

where p indicates the input price, and l refers to each credit type. The coefficient $\widehat{\theta}_{pl}$ is the estimated coefficient of the interaction variable of the input price w_p with the dummy variable $dm_{mkt_{lbt}}.MultiProduct - H_l$ is the estimated H-Statistic of Panzar and Rosse for credit type l.

The identification purpose of the coefficient β_6 in the term $\beta_6 \Lambda_{lrct} T_{blrct} dmLaw_t$ of equation (6) in the paper requires cross-section and time variation of our estimated measure. In the paper, we replaced the market power concept Λ_{lrct} by the observed variable HHI calculated with respect to credit type l, risk class r and collateralized operations c, which allows the required cross-sectional variation. Time variation of HHI is easily calculated because we have monthly information of Market Share. This supplementary material uses H-Statistics for each credit type as a proxy for market power.

To obtain time variation, we should estimate the H-Statistics by period. Since we use a Panel Data Fixed Effect estimator to address unobserved fixed effects, we should estimate the H-Statistic using cross sections of a defined number of months. We accomplish these two requirements by using a moving window of Panel Data.

We use a quarterly moving window to obtain time variation for H-Statistics. For each three-month period, we estimate the H-Statistics to a period. For instance, to estimate the H-Statistics to July/2004, we use a FE Panel Data estimator with accounting information from May/2004 to July/2004. The accounting information dataset used to calculate H is available from January 2004; thus, we have no loss of degrees of freedom. We estimate the first statistic for July 2004, our first period to observe the contracted interest rate on our credit operations dataset using the accounting information panel from May to July 2004; the second period, August 2004, we move the quarterly window from June 2004 to August 2004, and so on.[S1]

S2.2 The Second Stage

In the second stage, we follow the same empirical strategy of the differences-in-differences estimation method reported in the paper. We maintain the same set of regressors, replacing the Herfindahl-Hirschman Index for the H, estimated in the first stage, as a proxy to the market power, Λ_{lt}. In the economic model presented in Section 3 in the paper, we used the market power concept, λ, to derive our testable hypothesis. We established the hypotheses that the cross effects of market power with respect to two elements of the bank lending costs are both positive. These are the cross effects of market power with respect to the recovery rate δ, and the cross effect of market power with respect to the probability of firms succeeding p. To test the hypotheses, we use the HHI as proxy for market power λ, in our economic model or Λ in our econometric model.

We assume that the relations of HHI with the unobserved market power are positive because the higher the concentration index, the higher the market power of firms in the market. The H-

[S1]The Brazilian Central Bank regulates the Brazilian accounting standards for financial institutions. The accounting information provided by a credit institution follow a biannual appropriation standard with respect to revenues and expenses. Financial institutions accumulate monthly revenues and expenses and biannually incorporate profit to capital and/or pay shareholder dividends. To address our monthly information, we roughly adjusted the accounting results from biannual to monthly standards. We add to the credit institution's book capital the monthly difference of revenues less expenses. To calculate shareholder's capital, we mimic a monthly incorporation of profits instead of incorporating the accounting profit biannually.

Statistic definition implies a homogeneous decreasing function. As posited by Panzar and Rosse, if markets operate in a perfectly competitive environment, the expected value to the H-Statistics is 1. When the market operates in monopoly or in a collusive market, H-Statistics assume the value in the interval $(0, -1)$. Shaffer (1983) demonstrated the relation between H-Statistic of Panzar and Rosse and Bresnahan's index of market power, also represented by the symbol λ:

$$\lambda = \frac{E}{H-1}, \tag{S4}$$

where E is the elasticity of total market output, Q, with respect to price, $E = \frac{p}{Q}\frac{dQ}{dp}$. From this relation, we assume that the increase of market power implies a decrease of the estimated H-Statistics.

Once the H-Statistics consist of a decreasing function of λ, under the linearity assumption we expect the cross partial derivatives to became negative. Looking our term $\beta_6 \Lambda_{lt} T_{blrct} dmLaw_t$, directly replacing Λ_{lt} by the H-Statistic we expect the coefficient $\beta_6 < 0$.

The econometric model in the 2nd Stage is similar to equation (6) that we estimated in Section 6. The next equation represents the empirical equation we estimated in the 2nd Stage:

$$\begin{aligned} Y_{blrct} \quad = \quad & \beta_0 + \beta_1 \Lambda_{lt} + \beta_2 dmLaw_t + \beta_3 T_{blrct} dmLaw_t + \beta_4 \Lambda_{lt} T_{blrct} + \beta_5 \Lambda_{lt} dmLaw_t + \\ & + \beta_6 \Lambda_{lt} T_{blrct} dmLaw_t + \sum_{c=1}^{C} \varphi_c BankControls_{bt} + \sum_{m=1}^{M} \mu_m MacroControls_t + \\ & + \sum_{f=1}^{F} \phi_f dmYear_t + \sum_{h=1}^{H} \phi_h dmMonth_t + \eta_{b,l,r,c} + \varepsilon_{b,l,r,c,t}. \end{aligned} \tag{S5}$$

We describe the notation in Section 4 in the paper. We use Multi-Product-H per credit type for market power Λ_{lt}. In the paper, we measure the market power considering credit risk level r and collateral level c, in addition to credit type l. The market power was a finer measure Λ_{lrct}. Using *Multi-Product-H*, we can measure market power only in credit type l; however, we have an economically more precise measure.

S2.3 Bootstraping procedures

The concentration indexes come directly from observed variables. We built the HHI, C4 and market share using the observed accounting value of each credit operation. Our new measure of competitions level (H-Statistics) is the sum of a set of estimated coefficients instead of this simple calculation. The second stage uses the H-Statistics as a generated regressor. Under the exogeneity assumptions of the Fixed Effect Panel Model for consistency, replacing the H-Statistic with the estimated $H - \widehat{Statistics}$ causes no problem, Wooldridge (2002). Unfortunately, the t-Statistics and F-Statistics will not be asymptotically valid to test the statistical significance of the estimated coefficients of the 2nd stage. We should correct the confidence of the estimated coefficients of the 2nd stage to obtain a valid test of significance.

Wooldridge (2002) suggests adjusting the original variance matrix for a generated regressor. However, we do not have a simple 1st stage. Our 1st stage is a moving window of quarterly panel data. From July/2004 to December/2007, we have 48 generated regressors and 48 different covariance matrixes, as a result. We also use these 48 generated regressors interacted with the dummy for the treatment group of observations and with the dummy for the month of the Brazilian reform. We choose to use a bootstrapping technique to obtain an adequate confidence interval (Efron, 1979) instead of analytically correcting the covariance matrix because of the number of generated regressors. We do not have the same number of observations in our panel data, and the estimations use different sample sizes to obtain the H-Statistics for each month.

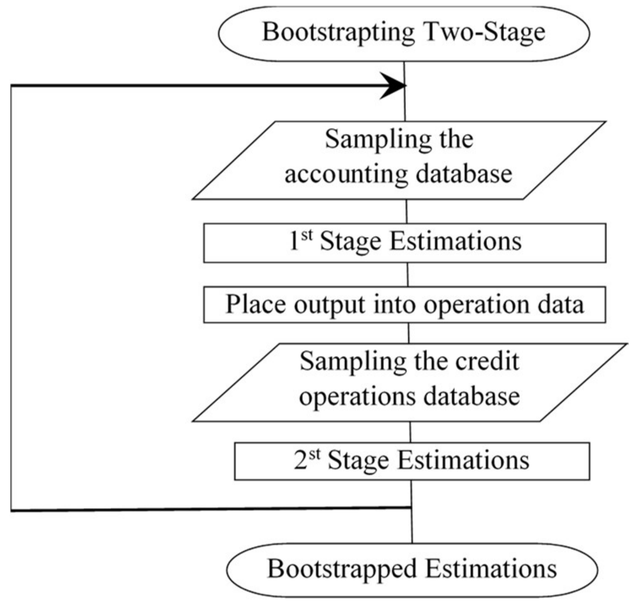
Therefore, we must adjust the covariance matrix estimated by the second stage to reduce the possible sample bias. We implement a bootstrap algorithm that addresses these two issues. We describe this algorithm in the following paragraphs.

To address the considerable complexity of the correction covariance matrix, we choose to use the Monte Carlo sampling method proposed by Efron (1979). The bootstrap theory, as developed by Bickel and Friedman (1981) and Singh (1981), is a workhorse of empirical research.

Bootstrapping the two-stage model must be undertaken with caution because we are working with two databases. The accounting database we use to estimate the H-Statistics and the credit operation database we use to estimate the differences-in-differences model. Thus, we process two samples in our bootstrapping algorithm. First, we sample the accounting database using our estimations of H-Statistics in the 1st stage. We aim to reduce the sample size bias by sampling the 1st stage. Second, we use the H-Statistics estimation into our credit operation database as a proxy for competition, then we process the sampling of the credit operation with the generated regressor. This second sampling procedure aims to obtain the confidence interval for the estimated coefficients in the 2nd stage.

First, we sample the accounting information dataset we use to estimate H, then we use this sample to estimate the H-Statistics for each credit type by month. We use a moving window method with a 3-month Panel Data that estimates H month by month. Once we obtain the estimations of H by credit type and by month, we add these estimations to our second set of data. To process the estimations from the 2nd stage, we also sample the second dataset before we estimate the differences-in-differences equation from the 2nd stage. The first sample corrects

Figure S1: Bootstrapping Flowchart



Notes: The number of samples on a bootstrapping procedure is fundamental to achieving the required variation of the bootstrapped estimated coefficient (Chernick, 2007). When the STATA program calculates the confidence interval, it will take less variability and considers a short confidence interval. In this way, we use 700 repetitions with re-positions. This is not a large number of repetitions, when we consider bootstrapping. Nonetheless, we also estimate the models with 100 and 200 repetitions and we observe a reduction in the confidence interval. Since we have considerable limitations with respect to computational resources, we choose to report the results with 700 repetitions.

the possible bias of the H-Statistics because we use only a 3-month FE Panel Data to estimate the H-Statistics by each period. In the second sample, we aim to correct the confidence interval of the estimated coefficients from the 2nd Stage.

S3 Descriptive Statistics

In this supplementary material, we use some variables that we previously described from Table 7 to Table 11 in the paper. We do not replicate this information. Table S1 describes only the new variables we use to estimate the 1st Stage.

[Table S1 Here]

The 2nd Stage of our estimation model uses the H-Statistics generated from the 1st stage. We also construct the interaction variables using these statics and the dummy of the treatment and the dummy for the BBR variables. The other regressor in the 2nd stage is the same set of variable we use to estimate our main results discussed in the paper. Table S2 shows the descriptive statistics of the variables estimated in the 1st Stage: the H-Statistics per credit type and its interactions in our differences-in-differences empirical strategy.

[Table S2 Here]

We also report the descriptive statistics by control group of observation and by treatment group of observations.

[Table S3 Here]

Both tables consider the estimated value of Multi-Product-H. The mean and standard are calculated direct from the estimated values of the 1st Stage.

[Table S4 Here]

Using the differences-in-differences empirical strategy, we should observe the statistical mean of the dependent and interaction independent variables to calculate the effect in the treated group of observations with respect to the control group of observations. Tables 28 and 29 in the paper show the descriptive statistics by each group.

S4 Results

In this section we report the estimated results. We first present the Multi-Product-H to each one of the ten credit markets (Figure S5). Tables 24 and 25 show the estimated results without bootstrap correction. Following Woodridge (2002), the results are consistent, but the confidence interval is not correct as a consequence of our generated regressor. Tables 34 and 35 show our results, when we estimated the same models using our bootstrap algorithm. We note that for some credit types, the statistics reach some limits of the interval. We expected these results because we do not restrict the estimated coefficients; because we use linear models, the estimation methods do not guarantee any limits to the coefficients.

The graphics (Figure S5) also show some spikes for some of the credit types in February/2005, Credit Type 2 - Leasing and Goods Financing - Consumers and Credit Type 3 - Vehicle Financing - Consumers. It is not within the scope of this work to investigate these variations, but we take note that in February/2005 the leasing market related to vehicles decreased 45,7% in comparison with February/2004; moreover, the credit to consumers decreased 21,6% and the total sales of vehicle decrease 29,9% in the same period.[S2] These unusual movements in the leasing and vehicle markets may possibly explain why we capture those spikes in our estimations of the H-Statistics.

The Multi-Product-H estimated in the final months of the second half of 2005, October and November, also has more variation than other periods. This period coincides with the new regulation of the payroll credit market. The National Institute of Social Security limited the amount of credit attached to social security benefits to 30% of the net benefits and established minimum formal statements to allow credit installments to be charged on social benefits. We exclude payroll credit types from our sample of credit operations, but the Multi-Product-H are possibly showing some point adjustments in the credit institutions' cost structure to the new regulation. As we are not able to identify the source of these variations, we include the estimated statistics in our second stage without any specific statistical treatment. We expect that these are not systematic effects and that the inclusion of monthly dummies variables adequately captures these point-in-time variations.

S5 Conclusions

In this supplementary material we build a two stage econometric strategy to accomplish with estimation of H-Statistic and the difference-in-difference method, which we use to identify the limiting effect of the market power on the reducing effects of the Brazilian Bankruptcy Reform on the interest rate of corporate loans.

[S2] Information from CETIP, a Brazilian publicly held company that offers services related to registration, central securities depository (CSD), trading and settlement of assets and securities and ANFAVEA - the Brazilian National Association of Vehicles Manufacturers.

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Table S1: Descriptive Statistics - H-Statistic Estimation (1st Stage Variables)

	Before BBR			After BBR		
Dependent Variable	**Obs.††**	**Mean**	**Sd. Dv.**	**Obs.**	**Mean**	**Sd. Dv.**
Total Revenue of Credit Operation	3288	0.093	0.1672	8855	0.095	0.2077
Input Prices						
Cost of Funding	3317	0.5533	2.1254	8979	0.8541	3.212
Cost of Wages	3288	0.0039	0.0211	8855	0.0046	0.0108
Cost of Fixed Capital	3288	0.2745	0.6309	8855	0.2668	0.4247
Control Variables						
Provision Rate†	3288	-0.1011	0.8488	8855	-0.14	0.3938
Profitability	3288	0.009	0.1394	8855	0.0108	0.152
Market Share TA	3172	0.0035	0.0144	8536	0.0036	0.0141
HHI TA	3317	0.0634	0.0011	8979	0.0584	0.0011
Market Share - Credit Portfolio	3317	0.0010	0.0000	8979	0.001	0.0000
HHI - Credit Portfolio	3317	0.0003	0.0000	8979	0.0003	0.0000
Dummies† † †						
Dummy of Bank operations in Credit Type 1	3317	0.8043	0.3968	8979	0.7632	0.4251
Dummy of Bank operations in Credit Type 2	3317	0.795	0.4038	8979	0.7705	0.4206
Dummy of Bank operations in Credit Type 3	3317	0.8279	0.3776	8979	0.7935	0.4048
Dummy of Bank operations in Credit Type 4	3317	0.8933	0.3088	8979	0.8742	0.3317
Dummy of Bank operations in Credit Type 5	3317	0.943	0.2318	8979	0.9122	0.283
Dummy of Bank operations in Credit Type 6	3317	0.8592	0.3479	8979	0.8259	0.3792
Dummy of Bank operations in Credit Type 7	3317	0.8221	0.3825	8979	0.7898	0.4074
Dummy of Bank operations in Credit Type 8	3317	0.8206	0.3837	8979	0.7838	0.4117
Dummy of Bank operations in Credit Type 9	3317	0.8291	0.3765	8979	0.7993	0.4005
Dummy of Bank operations in Credit Type 10	3317	0.7826	0.4125	8979	0.7423	0.4374

This table presents the number of observations (Obs.), mean and standard deviation of the variables used to estimate the MultProduct-H statistics.
† The Provision Rate is less than zero because we followed the accounting standard to the Brazilian Financial Institutions with respect to provision, which is a negative register.
†† Observation is treated as missing if the financial institutions do not inform shareholders equity or total assets. If the financial institution do not inform provision or leased assets, we consider zero to both accounting registers.
† † † The Dummy of Bank operations assume the value of 1 if the credit institution operates the respective credit type. A bank can operate in more than one credit type. For instance, the mean of this dummy with respect to credit type 1 means that in the period before the BBR, the monthly mean of the percentage of credit institutions that operates credit type 1 is 80.4%.

Table S2: Descriptive Statistics - Estimated MultProduct-H Statistic and Interaction Variables

	Before BBR			After BBR		
Dependent Variable	**Obs.††**	**Mean**	**Sd. Dv.**	**Obs.**	**Mean**	**Sd. Dv.**
$Y^{\dagger}_{b,l,r,c,t}$	6655	0.3614	0.2602	22590	0.3633	0.2837
$S^{\dagger}_{b,l,r,c,t}$	6620	0.1529	0.2174	22402	0.1933	0.2433
Interactions						
MultProduct - $H_{b,l,t}$	6655	0.4565	0.3337	22590	0.4131	0.3233
Dummy of BBR	6655	0	0	22590	1	0
*Dummy of BBR * Dummy of treated group*	6655	0	0	22590	0.6820	0.4657
*MultProduct - $H_{b,l,t}$ * Dummy of treated group*	6655	0.3326	0.2953	22590	0.2836	0.3300
*MultProduct - $H_{b,l,t}$ * Dummy of BBR*	6655	0	0	22590	0.4131	0.3233
*MultProduct - $H_{b,l,t}$ * Dummy of treated group * Dummy of BBR*	6655	0	0	22590	0.2836	0.3300

This table presents the number of observations (Obs.), mean and standard deviation the estimated MultProduct-H statistics to the 2nd Stage of our Econometric Strategy.
† We also reported this statistics in Table 1: Descriptive Statistics - Dependent Variables.

Table S3: Descriptive Statistics - Control Group of Observations - Complete Sample

	Before BBR			After BBR		
Dependent Variable	**Obs.††**	**Mean**	**Sd. Dv.**	**Obs.**	**Mean**	**Sd. Dv.**
$Y^{\dagger}_{b,l,r,c,t}$	1946	0.4424	0.3100	7184	0.4711	0.3583
$S^{\dagger}_{b,l,r,c,t}$	1944	0.2220	0.2619	7142	0.2920	0.3101
Interactions						
MultProduct - $H_{b,l,t}$	1946	0.4230	0.4882	7184	0.4072	0.3226
*Dummy of BBR * Dummy of Treated Group*	1946	0	0	7184	0	0
*MultProduct - $H_{b,l,t}$ * Dummy of Treated group*	1946	0	0	7184	0	0
*MultProduct - $H_{b,l,t}$ * Dummy of BBR*	1946	-0.0008	0.0150	7184	0.4072	0.3226
*MultProduct - $H_{b,l,t}$ * Dummy of Treated group * Dummy of BBR*	1946	0	0	7184	0	0

This table shows the number of observations (Obs.), mean and standard deviation the estimated MultProduct-H statistics to the 2nd Stage of our Econometric Strategy. The statistics considers the complete dataset.
† We also reported this statistics in Table 1: Descriptive Statistics - Dependent Variables.

Table S4: Descriptive Statistics - Treatment Group of Observations - Complete Sample

	Before BBR			After BBR		
Dependent Variable	**Obs.††**	**Mean**	**Sd. Dv.**	**Obs.**	**Mean**	**Sd. Dv.**
$Y^{\dagger}_{b,l,r,c,t}$	5342	0.3345	0.2321	15406	0.3131	0.2241
$S^{\dagger}_{b,l,r,c,t}$	5305	0.1282	0.1909	15260	0.1470	0.1875
Interactions						
MultProduct - $H_{b,l,t}$	5342	0.4144	0.2777	15406	0.4159	0.3236
*Dummy of BBR * Dummy of Treated Group*	5342	0.0878	0.2830	15406	1	0
*MultProduct - $H_{b,l,t}$ * Dummy of Treated group*	5342	0.4144	0.2777	15406	0.4159	0.3236
*MultProduct - $H_{b,l,t}$ * Dummy of BBR*	5342	0.0000	0.0486	15406	0.4159	0.3236
*MultProduct - $H_{b,l,t}$ * Dummy of Treated group * Dummy of BBR*	5342	0.0000	0.0486	15406	0.4159	0.3236

This table shows the number of observations (Obs.), mean and standard deviation the estimated MultProduct-H statistics to the 2nd Stage of our Econometric Strategy. The statistics considers the complete dataset.
† We also reported this statistics in Table 1: Descriptive Statistics - Dependent Variables.

Table S5: Multi-Product-H Estimated by Credit Type

This table shows Multi-Product-H statistics we estimate in the 1st Stage of our two-stage econometric strategy. We use these results as proxy for the market power in our 2nd State. The graphics are organized from Credit Type 1 to 10 according to the credit type definitions.