Effects of sharing public positive credit information on personal loans

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Abstract

We use a change in regulation that improved financial institutions' information about borrowers with good credit repayment history as a natural experiment for investigating the causal effect of reducing informational asymmetries on credit outcomes. Brazilian SCR contains data for all loans with amounts above a certain threshold. The SCR information contains individual information derived from financial institutions' loans and is shared with all lending institutions. We exploit a reduction in the SCR individual debt threshold that made information about a group of borrowers suddenly available to all lending institutions. We investigate whether this improved positive information benefited households with loan amounts between the new and the previous thresholds. According to our estimation, after the threshold change, the cost of credit for those borrowers decreased by 33.5 p.p., the size of new loans increased while the average maturity was not changed. We also document that the results were driven by smaller banks. Our results indicate that information asymmetry is an important determinant of lending rates. Thus, measures to improve positive information access should increase the efficiency of credit markets, benefiting on-time borrowers.

Keywords: Information asymmetry; credit; interest rate

JEL Classification: G21; G51

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1. Introduction

Loans interest rate spread[1] are relatively high across emerging markets (eg. 32.2% in Brazil, 12.3% in Argentina, 7.4% in Colombia[2]) and access to credit limited (Reed et al. (2015)). These affect the ability of households to smooth consumption overtime[3] (Antunes et al. (2013)), to invest in physical (e.g. capital to start a small business), and human capital (e.g. training) with implications for welfare and economic growth (De Gregorio (1996)). These facts could be explained by the lack of information sharing about a potential borrower's capability to repay its debt (Pagano and Jappelli (1993)). In this context, information sharing of credit records by credit registries appear as a potential remedy for information asymmetry (Demirguc-Kunt and Klapper (2012)). Yet, credit registries have a broad heterogeneity in borrower's information across countries and there is still a limited understanding of its effects on the credit market.

Credit registries store both positive (ie. outstanding loan amounts and a pattern of on-time repayments) and negative (ie. late-payments and the amount of defaults) borrowers' information. Despite empirical evidence indicating that sharing positive information improves the ability of banks to predict the probability of clients repaying their loans (Powell et al. (2004); Turner (2010)), 40% of countries' credit registries do not distribute positive credit information[4,5].

In this paper, we study the effect of sharing positive credit information on households' cost of credit, loan size, maturity, and risk assessment by banks. In July 2016, the Central Bank of Brazil (BCB) started collecting credit information on loans of borrowers that had maximum total liabilities per financial institution between R$ 200 and R$ 1,000, encompassing information from 41 million new users[6]. Until then, only loans from clients that had total liability per financial institution above R$ 1,000 were reported. With detailed information from the Brazilian public credit registry (SCR) and using this change in regulation as a source of exogenous variation, we can evaluate the causal effect of sharing positive credit information on credit variables, once negative information was already shared by private bureaus. Additionally, we explore the different effects that information can have for small and mid-sized banks, and large banks.

[1] Lending rate minus deposit rate

[2] Source: World Development Indicators (World Bank). Data from 2018.

[3] In 2018, American households spent 8% of their income in interest rates and amortization (Source: Bank for International Settlements), while Brazilian families spent 17% (Source: Central Bank of Brazil).

[4] Source: 2018 Doing Business (World Bank)

[5] 88% are developing countries and sharing positive credit information is part of the World Bank's directives in Doing Business.

[6] Source: 2016 Annual Report - Central Bank of Brazil

Regardless of the information type, theory predicts that exchanging credit information eases adverse selection and helps financial institutions better screen good borrowers. Consequently, those institutions can offer larger loans with lower interest rates for on time payers (Pagano and Jappelli (1993)). However, regardless of theoretical prognosis, the few empirical papers that analyze reduction of information asymmetry on the credit market use limited databases or study aggregate effects, not finding significant consequences of sharing positive credit information on interest rates (eg. Foley et al. (2019); Behr and Sonnekalb (2012)). Thus, the implications of improving access to positive credit information of households on their loans outcomes needs to be better understood.

We use a difference-in-differences (DiD) framework to estimate the effects of sharing positive credit information. We define the treated group as individuals that had maximum total liabilities in any financial institution between R$ 500 and R$ 1,000, as of June 2016, and whose information was not disclosed in SCR previously the threshold change. We use as control the group of borrowers that had maximum total liabilities per bank between R$ 1,000 and R$ 1,500[7] and, consequently, had information mandatorily reported to the SCR before June 2016. The identifying assumption is that absent the threshold change, the outcomes in treated and non-treated individuals would have followed parallel trajectories.

Our set of empirical results focus on the effect of the threshold change on financial variables. After the change, we find a decrease in spreads of approximately 33.5 p.p. (of a sample average of 304%) and no significant change in new credit origination size, maturity or in the risk rating given to the new borrower by the bank. We also investigate if sharing positive information can have heterogeneous effects depending on the size of the bank. Results indicate that the impact of the change in the information environment matters mostly for smaller banks. With the new regulation, the loan spread rate decreased 42 p.p., and the contract size increased 24%. Lastly, we show that our results are robust to different specifications.

Our paper is connected to several strands of the academic literature. First, our work relates to the theoretical literature that assesses the effects of credit information sharing. Theory predicts that sharing information (not only positive) can decrease the cost of loans and increase credit access through different channels: i) by mitigating adverse selection it increases lender's ability to screen good payers and, consequently, leads to better pricing (Pagano and Jappelli (1993))[8]; ii) by reducing moral hazard it increases the default costs of higher-risk borrowers (Padilla and Pagano (2000))[9]; iii) breaking the banks' information

[7]The equivalent in US dollars of 2016 is 143-287 USD and 287-430 USD, respectively.

[8]de Janvry et al. (2010) note that interest rates can remain fixed over the short run.

[9]Yet, sharing positive information may not produce a disciplinary effect, since a high-quality borrower is less concerned about the consequences of default as long as they can remain a high-quality borrower (Hahm and Lee (2011)

monopoly, which can limit banks from charging higher interest rates, decreasing the possibility of extracting rents from high-quality borrowers (Pagano and Jappelli (1993)). Our paper contributes to this literature by providing evidence consistent with those arguments, highlighting a potentially positive effect of the type of information shared on credit market.

Second, our work relates to the empirical literature that investigate the relation between information asymmetry and credit market outcomes. The empirical evidence on the effects of information sharing on the credit market is based on both macroeconomic and microeconomic data. Only a few papers use micro data to assess the impact on interest rates. Behr and Sonnekalb (2012) uses loan-level data from only one bank in Albania to analyze the effect of adopting a public credit registry (with both positive and negative information). Their results suggest that information sharing does not affect credit access or cost but improves loan performance. Foley et al. (2019) identify the causal effect of information sharing on ex-post competition and conclude that public credit information increases competition in credit markets for good borrowers but can hinder financial inclusion for clients with low creditworthiness. With a different and limited database (Chile has interest caps), they also conclude the main margin of adjustment is credit limits rather than interest rates, as they don't find any difference in the rate at the time of origination. Our work distinguishes itself from the empirical work done so far by focusing on borrowers with positive information and using a comprehensive database that comprises consumer credit loans of all banks in Brazil.

Third, our work relates to the literature that explores the distinct effects of positive or negative information sharing. Powell et al. (2004) tested the predictive power of debt default and showed that the added value of having positive and negative information about borrowers is significantly higher. In the same way, Turner (2010) finds that systems that cover positive credit information are more accurate than systems with only negative information, and this helps to identify borrowers with low and high credit risk, generating positive net effects such as broader access to credit.

We proceed as follows section 2 describes the institutional background. Section 3 describes the data, its characteristics and also discusses our empirical framework. Section 4 presents the empirical results. Section 5 concludes.

2. Institutional Background

The Credit Information System (SCR) is managed by the Central Bank of Brazil. Credit suppliers (banks, credit unions, and non-banks) mandatorily report monthly detailed information on credit relationships with their clients[10], including overall debt exposure, term structure of scheduled repayments and past-due amounts. Also, banks can only have access to aggregate information of a client on a credit type basis and comprising only the past 12 months[11]. Thus, lenders don't have information about who lent to each client.

At the beginning of SCR, in 1997, financial institutions were required to submit individualized loan information of each borrower with total liability equal to or greater than R$ 5,000. This amount was later reduced to R$ 1,000 in 2012 and, as of June 2016, this limit was further reduced to R$ 200[12], which increased the number of individuals at SCR from 64 million to 105 million, encompassing 99% of all credit transactions in the financial system. This characteristic makes the SCR the most comprehensive credit registry operating in Brazil regarding financial institutions' credit transactions.

In Brazil, there are also private credit bureaus. Despite covering almost the same proportion of the adult population in Brazil as public credit registries[13], credit bureaus provided until very recently mainly socio-economic characteristics and negative information of borrowers, due to the lack of a conducive legal framework [14]. Thus, the most important difference between SCR and private bureaus in Brazil before 2019 was that the former added positive information (e.g. the total consumer's exposure with financial institutions and its characteristics).

3. Empirical Strategy and Data

3.1. Empirical Strategy

We want to identify the average effect that the decrease in information asymmetry of households with good payment history has on consumer credit cost, loan size, and credit maturity (i.e., the average impact of treatment on the treated group). In an ideal experimental setting, we would have randomly selected households to have their information revealed and would compare credit outcomes with clients that didn't have their information disclosed. Unfortunately, the credit information disclosure process is typically not random.

[10] All financial institutions must send the detailed information about their active loans to the BCB up to the 9th business day of each month. Usually, BCB process the information and makes it available to be consulted by banks within a week.

[11] After May 2018, banks can access the information history of borrowers from the past 24 months.

[12] This change, despite being public, wasn't campaigned by the media and banks to consumers.

[13] Data from 2018 Doing Business shows that private credit bureaus covered 79% of adult population, while credit registry 76%.

[14] As of October 2019, credit bureaus can share positive information of borrowers without explicitly requiring borrowers' consent. Until then, only 5% of borrowers had positive credit information shared by private credit bureaus (Information based on a Administrative Council for Economic Defense vote).

Nevertheless, we treat the information threshold change of the credit registry by the BCB in July 2016 as a quasi-natural experiment and apply a difference-in-differences methodology to analyze the improvement in information sharing on credit market variables.

We investigate borrowers with maximum total liability per bank ranging between R$ 500 and R$ 2,000 in June 2016 (month of the threshold change). In this set, only 0.3% of originations were earmarked. Of the non-earmarked, the main credit line is overdrafts (33%). The second most important credit line is (non payroll-deducted) personal loans, accounting for 20% of originations in this set. We focus on the latter in this study. Besides being widespread among credit consumer loan types, they generally do not embed collateral, so that the assessment of borrower credit risk is of primary importance for banks' supply decsions. All loans originations are reported in Table 1.

We divide all observations of individuals with personal credit into two groups i) treatment: individuals that had total liabilities between R$ 500 and R$ 1,000 in any financial institution as of June 2016 and had no information disclosure in SCR since January 2015.[15]; ii) control: individuals that had total liabilities between R$ 1,000 and R$ 1,500 per financial institution and, consequently, had information mandatorily shared through SCR before June 2016. We also restrict to individuals that didn't have new information disclosed with the threshold change [16]. The individuals from the first group are the households for which we expect a reduction in information asymmetry after the threshold change and, consequently, have the cost of credit relatively lowered and supply of credit relatively increased.

Also, we segregate the database into two periods: originations made between January 2016 and June 2016 (pre-change) and between August 2016 and January 2017 (post-change). We exclude July 2016, the transition month.

As described in the previous section, prior to the change, banks could only know if an individual from the treatment group had a bad payment history[17]. Thus, the threshold change would only affect clients that were on-time with their loans. This setting in Brazil is ideal for assessing how positive information (good payment history) impacts credit market.

The impact of the shift in the threshold might affect differently banks' perception of the creditworthiness of the client if she is a current client or a prospective clients. A strand of literature supports that because of the opaqueness of small borrowers, lenders value the

[15]The use of the threshold cut-off is not enough to define the treatment group as one individual could have had in the past a loan above R$ 1,000 and had information available for other banks through SCR.

[16]There is a group of borrowers who have more than one banking relationship and who, despite being in the SCR for having loans with a specific bank above R$ 1,000, may have exposure with another bank below the threshold.

[17]In some States (eg. Law 15.659/2015 of São Paulo State), banks can send information of non-performing clients to credit bureaus after 15 days of payment delay and it is unexpensive (the cost is less than 1% of the minimum loan amount considered).

preexisting client relationship to reduce information asymmetries (eg. Boot (2000)). Consequently, for current clients, the analyzed event would not change the hard information that the bank had. For potential clients, however, the change alleviates the lack of information. Thus, another important consideration for our analysis is that we restrict our sample to first-time borrower with a financial institution, as the information revealed with the threshold change might not be important for old clients, as the bank could already assess the client's capability of paying.

The first identifying assumption in our approach is that the particular outcome variable develops in a parallel way for the two groups if information sharing is unchanged. We assume that while there may be a difference in the outcome between groups, this difference is time-constant and would have prevailed had the improvement in information sharing not occurred. Although we cannot observe what would have happened in the absence of the credit registry reporting change, observing a parallel trend before would make us confident about this assumption. A graphical analysis to support this conjecture is provided below. If this assumption holds, we can attribute any divergence of this parallel trend after the change to the effect of improving information sharing between lenders. Figure 1 shows that this assumption seems justified.

Another concern is that financial institutions could be supplying credit just below R$ 1,000 before June 2016 not to have their creditworthiness customers exposed to other banks. In Figure 2, we present the frequency of loans' size as a piece of evidence that banks were not manipulating the size of contracts.

3.2. Data and Descriptive Statistics

The change in the threshold required that financial institutions in July 2016 transmitted to BCB all active credit relationships of their clients that had total exposure to the bank above R$ 200 in June 2016. Before July 2016, this threshold was R$1,000. Thus, for our treatment group - new borrowers with loans between R$500 and R$1,000 that were not in the SCR after January 2015[18] - we only observe a one month picture of their loans before the threshold change. However, with the information of the date of origination, we can generate our monthly database of new originations since January 2016.

We need to point that our database has a bias for longer term credit for our treatment group, as we only observe active loans, not having information of those that expired before June 2016. To deal with this, we use the same selection (active loans in June 2016) for the control group and show in robustness tests that our result still holds considering different

[18] We use the 12-month search window imposed by the BCB to delimit our treatment

maturities.

Our sample ranges from January 2016 until January 2017[19]. We winsorize the financial variables at the 2/98% level. Table 2 has the descriptive statistics for treatment and control groups, divided into pre and post threshold change. The final dataset has 1,475 observations. When we restrict our analysis to borrowers with only first time loan with a bank, we loose a considerable amount of observations, as borrowers tend to stay in the same bank.

The average spread (lending rate minus national level deposit rate) is around 326% across groups. As initially highlighted, Brazil has one of the highest credit spreads in the world, especially for lower income clients that are considered as more risky. Also, from the simple descriptive statistics, it is not straightforward that borrowers who were not in the SCR before the regulation had higher interest rates compared to those who already had information being shared. However, this fact could be due to the composition of the banks' profile (shareholding control and size) in which they borrowed in comparison to the control group: higher percentage in state-owned and larger banks. The average size of the contract and total financial debt have a considerable difference after the change, but this is because more financial institutions had to report about the same individual after the threshold change.

In terms of demographics (Panel B), the heterogeneity across group is not prominent. 64% of the originations were to female borrowers. The average age of the borrowers was 45 years old. The average monthly income was R$ 1,241, equivalent to 1.2 times the minimum wage of 2016. The usual income of Brazilian borrowers is above 5 minimum wages, indicating that the threshold change impacted mostly small borrowers.

Regards the financial characteristics (Panel C), around 90% of the originations came from private banks. The total indebtedness of individuals was, on average, 18% of their annual income. However, the monthly commitment of the monthly income paying credit amortization and interest rates were close to 47%. An important characteristic of our sample is that the majority of the borrowers in the control group got credit with small and mid-sized banks (SMB) and the share for our treatment group increased after the change in the SCR, indicating a market segmentation.

4. Empirical Framework and Results

This section presents evidence on the effects of improving credit information using data described in the previous section.

[19]Before arriving at the final data sample, we apply several data filters, excluding i) clients that are not Brazilian; ii) loans with variable interest rate rates; iii) clients' with age below 18 or above 65; iv) clients with contract risk above D rate (renegotiation).

4.1. Empirical Framework

In our baseline estimation, we investigate the effect of reducing information asymmetry for good borrowers on credit market outcomes using an exogenous change in regulation employing a DiD research design. We compare credit contract outcomes of treated individuals (exposed to SCR with the regulation change) with those in the control group (already exposed at the time of the registry expansion), before and after the threshold variation.

We estimate the following regression using OLS:

$$y_{ijt} = \alpha + \beta_1 Treatment_i Post + \theta_i + \theta_{jt} + X_{it} + u_{ijt} \tag{1}$$

Where y is our variable of interest - cost of credit (spread), log of the size of contract, and maturity -, for client i in bank j at time t. $Treatment_i$ is a binary variable equal to one for the individuals that had information revealed by the change in the threshold of SCR (change in the cut-off from R$ 1,000 to R$ 200) and zero for individuals that already had the information in the SCR before June 2016 and no new data were disclosed[20]. $Post$ is a binary variable equal to one for observations after the change of the credit registry in June 2016 and zero otherwise. The coefficient of interest is β_1, from the interaction of $Treatment_i$ and $Post$, that measures the average treatment effect of the improvement in information about the borrower through the credit registry. Additionally, we control for the general time-varying individual characteristics (X_{it}): income, total indebtedness in the financial system[21], debt-to-service ratio[22], number of bank relationships, number of banks in the municipality of the borrower. Also, we include month-bank fixed effects (θ_{jt}), which account for bank policy unobservables. Finally, we control for individual fixed effects (θ_i), which captures time-invariant unobserved heterogeneity across borrowers. As we control for the described fixed effects, the single variables $Treatment_i$ and $Post$ are not estimated. The standard errors are clustered at the bank level to account for a possible dependence of setting contract levels[23]

We note that controlling for contract characteristics after the registry expansion in eq. 1 would bias the coefficients. Thus, our empirical setting is the reduced form effect of reduction in the information asymmetry.

[20] A small group of borrowers who already had information in SCR but had loan with a different bank below R$1,000 was affected by the new regulation. In our baseline estimation, we exclude this group, but use for robustness check in the next section.

[21] Total debt in the financial system divided by the annual income.

[22] Ratio of debt service payments (principal + interest) to monthly income.

[23] Our results are still robust if estimated without this clustering option.

4.2. Baseline Results

Table 3 presents the results estimates of equation 1 on borrower-bank level data using different dependent variables: loan's spread, natural log of contract size, and maturity. In all estimations, we control for client and bank-month fixed effects, and some client's time-varying characteristics. In Column (1), our outcome variable is the lending spread and we observe that spread has decreased by 33.5 p.p. (of a sample average of 304%) and is statistically significant at 5% after the positive information of a borrower is made available.

Column (2) shows the result for the size of the contract as dependent variable. Despite being positive, the coefficient is not statistically significant. We don't exclude the possibility that positive information decreases credit restriction, since we are analyzing only one credit line (personal loan) and the increase may occur in other lines of credit[24].

In Column (3) of Table 3, we evaluate change in the regulation on loan maturity. The effect is unexpected negative, but not statistically significant.

Lastly, we ran Equation 1 but with data on client level:

$$y_{it} = \alpha + \beta_1 Treatment_i Post + \theta_i + \theta_t + X_{it} + u_{it} \tag{2}$$

The outcome variable is number of different banks that the borrower has a loan. Despite not finding any result about the size of loan (intensive margin), it might be that the effect was on the number of loans with different banks (extensive margin). The result of the coefficient of interest is shown in column (4) of Table 3. No significant effect is found (economically and statically).

In sum, sharing positive information of borrowers has meaningful changes in the cost of credit for borrowers, but not in other loan characteristics. We recognize the limitations of our database in capturing the whole effect. However, the initial results suggest the importance of information sharing in the well functioning of the credit market.

4.3. Heterogeneity

Different characteristics of management practices of financial institutions could drive heterogeneous outcomes even in the absence of differences in their credit information disclosure requirements. Although these differences can be understood as being at least partly endogenous to the credit information setting, in our analysis, any change in the lending outcomes can be causally assigned to the change in the informational environment.

The size of the bank can affect differently credit outcomes. Small and middle sized banks

[24]Data from other credit lines are not available for our analysis.

can have an advantage as they could develop better ways to screen specific types of borrowers (Nakamura (1991)). At the same time, getting information about borrowers could be more costly as they are smaller and not part of bank conglomerates. In the first case, the change of the information set would not largely affect their lending practice. In the last case, this could give them a greater advantage in better screening good borrowers. To test the heterogeneous response of different size of financial institutions, we split our sample into two based on the size of bank: i) small and middle size (the majority of our sample), and ii) large banks[25]. The results of Eq. 1 with the subsamples are in Table 4. Columns (1) and (2) in Panel A show that the impact of the change in the information environment matters just for smaller banks. With the new regulation, the loan spread rate decreased 42 p.p., and the contract size increased 24%. The sample size of our regressions for big banks is very small, so we interpret it with a pinch of salt. These findings indicate that the average result found in the previous section were driven by smaller banks that could have problems better screening borrowers.

4.4. Robustness Tests

In this section, we present a series of robustness tests and extension exercises reported in Table 5 for loan spreads. First, to stress our point that it is the change in the informational environment that affected banks' evaluation of borrowers' creditworthiness, we drop the sample restriction for first-time borrowers in a bank and run Eq. 1 with borrowers that got loans in financial institutions that he already had a previous loan - for both treatment and control group. The result is shown in Column (1) which we see no decrease in spread, indicating that information setting didn't change for relationship bank, underscoring our result. We highlight that this finding doesn't exclude the competitive response of banks to a contestable market as in Foley et al. (2019). Our analysis ends six months after the change in the regulation and the response can take more time.

Another concern is that not only the positive information disclosed by SCR is the driver of the decrease in spreads. If the threshold change was to improve other type of information, we would expect an impact for clients with any delay history. As pointed, financial institutions could cheaply have this information from private bureaus. Column (2) presents the results of Eq. 1 with the sample of clients with delay history. We find no statistical and economic impact on the spread. Additionally, we test if the result would change with different levels of default. With our data, we only know if a client is in default within a range of days. We test the change in the information setting for interest rate spread including clients that

[25]Classification based on the number of clients. The first group are those with less than 4 million clients and the second, above this number.

delayed repaying their debts between 0 and 15 days. Column (3) report the result. Our sample almost doubles, but the previous result vanishes. By law, institutions can send the information to private credit bureaus just after a few days.

Further, to rule out that our result came from other financial information other than the positive, we run again Eq. 1 but with the treatment being borrowers that already had info in SCR at the time of regulation but new information was made available with the change in the threshold (ie. had loans below R$1,000 with another bank). Banks could already infer the creditworthiness of these clients with the information that were already visible at the SCR. So, we would expect no effect with the threshold change. Indeed, Table 6 shows the results for this new estimation and no variable significantly changed with more information of those borrowers.

In sum, we find evidences that the decrease in the credit cost for clients is due to the change in informational environment about good borrowers' creditworthiness.

5. Conclusion

This paper presents evidence on the causal effect of reducing informational asymmetries on credit outcomes using a comprehensive dataset of Brazilian loans to households. We use a change in regulation, in June 2016, that enhanced the information set of financial institutions about borrowers with good credit repayment history to identify impacts on the cost of getting credit, loan size, and maturity. We employ a difference-in-differences approach to compare households whose financial institutions could already access positive information about them, with households whose banks could not have any positive information before the change in regulation.

Our main result shows a moderate decrease in the credit cost for borrowers. We estimate a reduction of 33.5 p.p. in the loan spreads. Also, we show evidence that our result is driven by smaller banks that could better and cheaply screen good borrowers.

Our result may have potential effects on the real economy. On the one hand, it can reduce financial inclusion for bad payers (Foley et al. (2019)). On the other, it can alleviate credit restrictions for good payers. All, information asymmetry is an important determinant of lending rates. Thus, measures to improve positive information access should increase the efficiency of credit markets, benefiting on-time borrowers.

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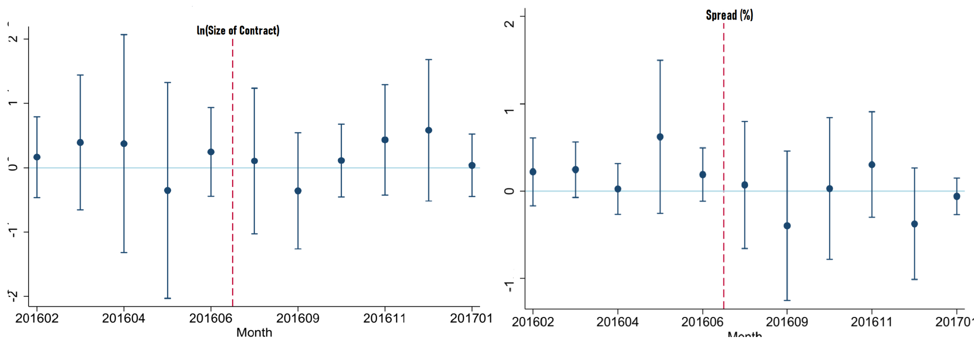
Figure 1. Development of log of the size of credit and interest rate spread for first-time borrowers with no delays in loan repayment



Note: Coefficients β_1 from Eq. 1 for each month before June 2016. Bars show 99% confidence intervals. We normalize Jan/06 $=$ 0.

Figure 2. Frequency of loan contracts size before and after June 2016 (histogram)

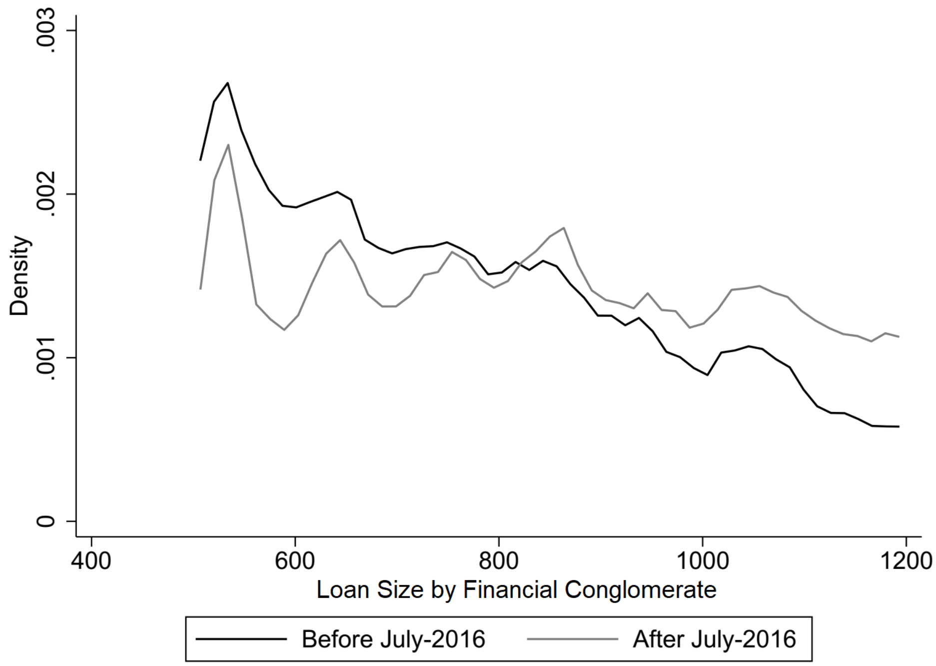


Table 1: Share of oiginations for clients with maximum total liability per bank ranging between R$500 and R$2,000 in June 2016

Credit Line	**Share**
Overdraft	33%
Personal Loans	20%
Revolving credit card	19%
Payroll-deducted loans	9%
Other	19%

Table 2: Descriptive Statistics

	(1)	(2)	(3)	(4)
	Control		***Treatment***	
	Before	**After**	**Before**	**After**
Panel A: Loan Outcomes				
Origination per Bank (R$)	951	1,540	668	1,370
Spread	280%	350%	271%	402%
Maturity (Months)	10	14	9	13
Risk (AA = 1 to D = 5)	2.3	2.2	2.4	2.2
Panel B: Borrower Characteristics				
Monthly Income (R$)	1,327	1,342	1,076	1,219
Age (Years)	45	47	44	45
Gender (Female)	65%	63%	66%	65%
Panel C: Financial Characteristics				
Private Banks	90%	92%	84%	94%
Loans with Small & Medium Size Banks	69%	71%	57%	68%
Indebtedness (Total Credit/Annual Income)	14%	27%	11%	22%
Debt Service Ratio (Principal + Interest)	37%	68%	30%	54%
Personal Credit/Total Debt	74%	99%	81%	85%
# of banks in the Municipality	13	13	12	14
# of observations	108	311	441	615

Table 3: Baseline results for difference-in-differences estimation on the cost of credit, loan size, loan maturity, and number of banks that a borrow has a loan

	(1)	(2)	(3)	(4)
	Lending Spread	**ln(Loan Size)**	**Maturity**	**# of Bank Relationship**
Post * Info Disclosured	-0.335**	0.077	-3.127	-0.152
	(0.159)	(0.129)	(1.866)	(0.212)
Controls	Y	Y	Y	Y
Time-Bank FE	Y	Y	Y	N
Borrower FE	Y	Y	Y	Y
Time FE	N	N	N	Y
Avg Dep. Variable	304%	R$ 911	10.6 months	2.2
Obs		1,475		258
R-squared	0.954	0.851	0.842	0.893
# Banks		37		-

Note: OLS estimation of Eq.1 results for loans originations from January 2016 up to January 2017 for new clients in the conglomerate with no default history. Post is a binary variable equal to one for loan originations after June 2016, the date of the credit registry reduced the threshold. Treatment is a binary variable equal to one for clients with no history in the credit registry (SCR). Controls: income, total indebtedness in the financial system, debt-to-service ratio, number of bank relationships (except for column (4)), and number of banks in the municipality of the borrower. Standard errors are clustered at the conglomerate level and reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Results for difference-in-differences analyzes on with different banks classified by size

	(1) Lending Spread	(2) ln(Loan Size)	(3) Maturity
Panel A: Small & Middle Sized Banks			
Post * Info Disclosed	-0.424***	0.240***	0.157
	(0.107)	(0.082)	(1.499)
Obs		595	
R-squared	0.961	0.900	0.908
# Banks		30	
Panel B: Large Banks			
Post * Info Disclosed	-0.037	-0.473	-0.112
	(0.087)	(0.523)	(1.145)
Obs		142	
R-squared	0.957	0.934	0.913
# Banks		13	
Controls	Y	Y	Y
Time-Bank FE	Y	Y	Y
Household FE	Y	Y	Y
Time FE	N	N	N

Note: OLS estimation of Eq.1 results for loans originations from January 2016 up to January 2017 for new clients in the conglomerate with no default history. Post is a binary variable equal to one for loan originations after June 2016, the date of the credit registry reduced the threshold. Treatment is a binary variable equal to one for clients with no history in the credit registry (SCR). Controls: income, total indebtedness in the financial system, debt-to-service ratio, number of bank relationships, and number of banks in the municipality of the borrower. Small-Mid sized banks are those with less than 4 million clients and large banks above this number. Standard errors are clustered at the conglomerate level and reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Results for difference-in-differences analyzes - Robustness

	(1)	(2)	(3)
Dependent Variable Spread	**Clients with any default**	**Clients w/ default below 15 days**	**Old Clients**
Post * Info Disclosed	0.125	-0.264	-0.011
	(0.108)	(0.167)	(0.014)
Controls	Y	Y	Y
Time-Bank FE	Y	Y	Y
Household FE	Y	Y	Y
Obs	4,107	2,192	293,543
R-squared	0.953	0.936	0.959

Note: OLS estimation of Eq.1 results for loans spread originations from January 2016 up to January 2017. Post is a binary variable equal to one for loan originations after June 2016, the date of the credit registry reduced the threshold. Treatment is a binary variable equal to one for clients with no history in the credit registry (SCR). Controls: income, total indebtedness in the financial system, debt-to-service ratio, number of bank relationships, and number of banks in the municipality of the borrower. Column (1) uses a sample of borrowers that were on default. Column (2) uses a sample of borrowers that had arrears between 1 and 15 days. Last column uses a sample of borrowers that took a loan with a bank that she already had a credit relationship. Standard errors are clustered at the conglomerate level and reported in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Results for difference-in-differences analyzes for borrowers that already had info in SCR at the time of regulation but new information was made available with the change in the threshold

	(1)	(2)	(3)
	Lending Spread	**ln(Loan Size)**	**Maturity**
Post * Info Disclosured	-5.121	0.082	0.271
	(16.216)	(0.100)	(1.364)
Controls	Y	Y	Y
Time-Bank FE	Y	Y	Y
Household FE	Y	Y	Y
Time FE	N	N	N
Avg Dep. Variable	183%	R$ 879	8.3 months
Obs		1,261	
R-squared	0.941	0.847	0.853
# Banks		34	

Note: OLS estimation of Eq.1 results for loans originations from January 2016 up to January 2017 for new clients in the conglomerate with no default history. Post is a binary variable equal to one for loan originations after June 2016, the date of the credit registry reduced the threshold. Treatment is a borrowers that already had info in SCR at the time of regulation but new information was made available with the change in the threshold. Controls: income, total indebtedness in the financial system, debt-to-service ratio, number of bank relationships (except for column (4)), and number of banks in the municipality of the borrower. Standard errors are clustered at the conglomerate level and reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1