Private Credit Bureaus and Positive Information Sharing

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Abstract

This study exploits a legal change in Brazil to identify the extent to which new information generated by credit bureaus translates into different loan interest rates. The legal change enabled the private credit bureaus (PCBs) to build new credit scores based on a broader scope of positive information, such as patterns of loan flows and repayments. We find an average reduction of 3.7% in the interest rates of personal loans to borrowers whose new scores were available for sale by the PCBs, compared to borrowers who only had old credit scores available. The effects are stronger in the cases where the new score is much higher than the old score, reaching an average reduction of 8.7%. We also find stronger results for new clients and for private banks. We also provide empirical evidence that information sharing can lower the ability of lenders to informationally capture their clients and extract rents.

Key Words: Credit Bureau; Information sharing; Banking; Relationship Lending.

1. Introduction

Information sharing of credit records by public credit registries and private credit bureaus (PCBs) appear as a potential remedy for information asymmetries between borrowers and lenders (Miller, 2003; Kallberg and Udell, 2003; Powell et al., 2004). Theory suggests that exchanging credit information can decrease the cost of loans and increase credit access by easing adverse selection and helping financial institutions better screen borrowers (e.g., Pagano and Jappelli, 1993). Information sharing also limits banks' informational monopoly, restricting their ability to extract rents from good borrowers and ultimately fostering bank competition (Padilla and Pagano, 1997; Hauswald and Marquez, 2003; Dell'Ariccia and Marquez, 2004).

The scope of information collected and shared by credit bureaus or registries is usually categorized into two groups: the somewhat more commonly shared negative information (*e.g.* missed payments, defaults, and amounts past due) and the so-called positive information (*e.g.* patterns of loan flows and repayments).[1] Although it is generally very costly to add positive information on top of negative information in any credit data repository, there is evidence that this leads to lower credit cost and greater loan access to good borrowers. However, this evidence is mostly driven by comparative cross-country studies (Jappelli and Pagano, 2002; Djankov et al., 2007; Brown et al. 2009) or simulation exercises (Miller, 2003; Powell et al., 2004). Very few studies exploit cleaner identification strategies based on quasi-natural experiments, such as Liberti et al. (2021), Bonomo et al. (2021) and Beck et al. (2023), which examine the loosening in the borrower eligibility threshold for positive information sharing in public credit registries on loan spreads and amounts[2]. Foley et al (2019) is another example and investigate the consequences of a private market transaction that changes the positive information-sharing environment of a credit card portfolio.[3]

There is also some evidence that credit bureau reforms ease access to finance more strongly than credit registry reforms (e.g. Martinez Peria and Singh, 2014). However,

[1] Legal restrictions, privacy concerns or interests in the preservation of informational rents are possible reasons behind jurisdictional frameworks based solely on *negative* informational sharing.

[2] In particular, Bonomo et al. (2021) and Beck et al. (2023) examine those eligibility changes in the Brazilian registry itself, in 2016 and 2012, and find positive causal effects of information sharing in access to finance for individuals and very small firms, respectively. Other effects associated to public credit registry expansions are also studied in the literature, such as incentives for coordination between banks (Hertzberg et al. 2011), rating manipulation (Giannetti et al. 2017) and changes in banking organizational structure (Liberti et al. 2021).

[3] They find statistically significant effects on credit card limits but on not interest rates.

most of the literature is silent about the interplay of coexisting credit registries, private credit bureaus, negative and positive information. The goal of this paper is to examine if new positive information collected and disseminated by private credit bureaus translates into lower loan interest rates by also making use of a quasi-natural experiment but in a context where some positive information was already included in the public credit registry.

Our identification strategy explores a legal change in Brazil in 2019 that authorized private credit bureaus to sell credit risk scores of individuals based on a wider range of data, basically new positive information, turned available to the PCBs in an opt-out regime.[4] The setting is particularly interesting because, throughout our sample period, the only sources of positive information gathered by the private credit bureaus to build the new credit scores were banks, which means that the information was basically of the same type that had been feeding the credit registry administered by the country's central bank[5], which could suggest a priori a low or insignificant effect of the new scores available. On the other hand, given that PCBs receive more disaggregated and timelier positive data about a borrower than what banks can access through the credit registry, and further apply credit modeling to distill it into new credit scores, it is also possible to expect a high or significant effect from them. Additionally, while banks can access borrower's information in the credit registry only upon explicit borrower consent (akin to an opt-in feature), the new scores from the PCBs are readily available for sale to all banks (unless the borrower opts out), which likely strengthens the degree of information sharing effectively conducted, possibly resulting in additional significant effects.

Our empirical analysis focuses on unsecured personal loans for two main reasons. First, personal loans are widespread among individuals[6]. Second, because they generally do not embed collateral, the assessment of borrower credit risk should be of primary importance for setting the interest rates. Our analyses are based on confidential data from the central bank's credit registry and data on the scores computed by the private credit bureaus. The richness of our data includes borrower and loan characteristics and both the scores that include positive information (hereafter new scores), and those based on negative information (hereafter old scores), for each individual.

[4] This regime implies that individuals need to explicitly opt out of the information sharing setup if they do not wish to have their new scores, based on positive information, available for sale.

[5] Other sources of credit information, such as utilities, are likely to be incorporated in the near future into the new scores.

[6] During the sample period, PCBs had not yet fully developed new credit scores for firms.

For causality, we exploit the fact that not all borrowers had their new scores available for sale simultaneously. The bureaus serially registered individuals and proceeded to compute their new scores. This resulted in lenders being able to buy new scores for some individuals and old scores for others. Additionally, the bureaus reported that this sequential process led to the availability of new scores for certain individuals ahead of others in a seemingly random manner. Consequently, the staggered availability of new credit scores operates as a quasi-natural experiment, introducing exogenous variation in the informational landscape accessible to banks. This distinctive feature enhances our ability to analyze the causal impact of updated credit scores on lenders' decision-making processes.

Our baseline specification uses the log of loan interest rate as dependent variable and the new score availability as main independent variable. The results show an average reduction of 3.7% in the interest rates of unsecured personal loans to borrowers that had new scores available for sale, compared to borrowers who only had old credit scores. This drop is equivalent to 6.7 p.p. when considering the average loan interest rate observed in our sample of 182 p.p. per year. Furthermore, the effects are greater in the cases where the new scores are much higher than the old scores[9] (fourth quartile of the new score minus old score distribution), reaching an average reduction of 8.7%. The not-so-high economic significance of our results is consistent with a not yet fully incorporated use of the new scores by lenders during the sample period, besides the *ex-ante* presence of some positive information sharing already conducted by the registry. On the other hand, we find a statistically significant increase of 1.4% in loan interest rates for borrowers whose new score is generally lower than the old score (first quartile of the new score minus old score distribution).

One threat to this identification strategy is that the new scores could still correlate to other characteristics not captured by the regression control variables. To tackle this issue, the credit bureaus calculated[10] the new score retroactively for August 2019. For this placebo period, again not all individuals could have the new score retroactively calculated. These new scores served as a counterfactual to be used in a placebo test, since at that time

[9] Higher scores mean lower credit risk. Both the old and the new scores vary on a scale from 0 to 1,000.

[10] This retroactive calculation of scores were computationally demanding, and we would like to thank private credit bureaus that kindly performed this calculation. It is worth noting that this backwards calculation was only possible because positive information is normally received for the last 13 months, and this encompassed August 2019.

these new scores were not being commercialized and had not even been calculated. Using this counterfactual new score, we run placebo tests using loans granted in August 2019 (before any new score was available) finding no statistically significant effect of the new scores pseudo-availability on the interest rates.

Our results are consistent with a better assessment of borrower credit risk by banks, prompted by the use of new scores in their credit analyses. They are also consistent with increased bank competition for good borrowers, fostered by the availability of the new scores to every potential lender, regardless of reassessment of risk by incumbent lenders. It is challenging to disentangle these two channels, but we try to assess their relative strengths in our setting, by comparing the effects for new and old borrowers. The new information coming from the new score is probably important for the risk assessment of new borrowers. However, for old borrowers, about which banks have already acquired proprietary knowledge through their relationships, the additional information brought by the new score is likely to be smaller. Therefore, for the latter, effects on interest rates would mostly come from increased bank competition with outside lenders.

Our empirical analysis shows that the interest reduction for new clients is around 5.8 %, whereas for old clients the reduction is around 2.5 %. If we assume that the effects on old clients are mainly due to the competition channel, the relative strength of this channel in the overall effect is likely to be quite relevant. We also find that private banks are the most affected by the PCB's positive information sharing and seem to be driving our baseline results.

Finally, we shed light on the interaction of information sharing and relationship banking. The borrower-lender relationship duration may proxy for the amount of private information the lender has on the borrower. In the cases of high switching costs or lack of an effective information sharing mechanism, incumbent lenders may lock-in their long time borrowers and increase interest rates as the relationship evolves (see Degryse et. al., 2009, for a review). There is evidence that Brazilian private banks lock-in their clients in the corporate loan market (Ornelas et. al., 2022). Alternatively, longer relationship durations lead to lower information asymmetries and, possibly, lower loan interest rates. Our empirical setting is ideal to check what happens with the lock-in behavior when information sharing suddenly increases. In our sample, for individuals not affected by the positive information - for whom the new score was unavailable - there was no pass-through of lower information asymmetry into lower interest rates by private institutions, i.e., the coefficient of loan interest rates and relationship duration is statistically not significant. However, this coefficient decreased significantly after the legal change for those who the new score was available (i.e., affected by the new positive information), becoming negative and statistically significant for private institutions. This result is consistent with the prevalence of the competition channel, since incumbent banks cannot exert market power anymore due the fading of their information monopoly.

Our findings are important because we assess the implications of a regulatory change that affected approximately 100 million adults[12] in Brazil, in sharp contrast to similar but much narrower shocks previously studied. We contribute to the literature that makes use of quasi-natural experiments to test and measure the value of positive information sharing. In particular, we are able to show the incremental value of private credit bureaus in a context where some positive information sharing was already conducted *ex-ante* by the country's public credit registry. The effects of positive information sharing by the PCBs in Brazil may become larger in the future when lenders fully incorporate their use into their credit analyses and positive data from other sources become available to PCBs.

We also contribute by using a novel identification strategy based on counterfactual credit scores: a counterfactual new score before the law and a counterfactual old score after the law. Having a counterfactual for the same individual in the same point in time is a great advantage for identification purposes. This is an improvement when comparing to studies that relies on the simple implementation or reform of information sharing mechanisms (for instance, Brown et al. 2009). The novel methodology also corroborates/complement studies that exploit identification strategies based on changes of the eligibility threshold over time, such as Liberti et al. (2021), Bonomo et al. (2021) and Beck et al. (2023).

Finally, we contribute by providing empirical evidence that information sharing can lower the ability of lenders to informationally capture their clients and extract rents, so that the competition triggered by information sharing lowers interest rates. In this way, we provide empirical support for theoretical predictions of Padilla and Pagano (1997) and Hauswald and Marquez (2003).

[12] This figure corresponds to approximately 66% of the adult population, according to estimates from the Brazilian bureau of statistics, IBGE.

2. Institutional Background

Credit information sharing available for financial institutions in Brazil relies on the public credit registry (SCR, as for the acronym in Portuguese), owned and managed by Banco Central do Brasil (BCB), and a few private credit bureaus, PCBs.

The SCR does not produce or divulge any credit score. Beck et al. (2023) describe the information available from SCR to financial institutions: the date that the borrower opened its first credit account in the financial system, the number of outstanding loans, the number of lenders, the number of loans with disagreements or under justice, coobligations, and the amounts due, in arrears and in losses by time buckets, loan types and currency denominations. Banks can access that information upon explicit borrower consent, generally obtained after some borrower-bank interaction at the start of a potential credit relationship. Although the need for borrower consent possibly restrains the information sharing effectively conducted by the SCR and the information therein that is made available to banks is somewhat aggregated, the benefits of (positive) information sharing through the SCR is still found to be material according to Bonomo et al. (2021) and Beck et al. (2023). Indeed, those studies find positive causal effects of positive information sharing in access to finance for individuals and very small firms, respectively.

The private credit bureaus would sell (*old*) credit scores based essentially on negative information, such as missed payments, defaults, and amounts past due, until the first quarter of 2020. In fact, until mid-2011, the legal framework did not allow the collection and sale of information regarding the (positive) performance of individuals and firms to build a credit history record. The Law 12,414 of June 9, 2011 started changing this scenario but determined that firms and individuals had to contact each bureau and agree to have their performance and other types of credit information available to each one of them. A very limited number of individuals[13] opted in to allow their information to be shared with the bureaus. The lack of a critical data mass on borrowers across different risk profiles hindered the development and sale of scores based on positive information.

In April 2019 Complementary Law 166 changed Law 12,414 and introduced an opt-out approach. A new regulatory framework followed suit, with executive acts and regulations issued by the Central Bank. The opt-out regime implies that all individuals are

[13] Most of the ones that did, were in fact only answering an invitation by a bureau, that occurred when they approached the bureau to clear their names after a debt had been settled.

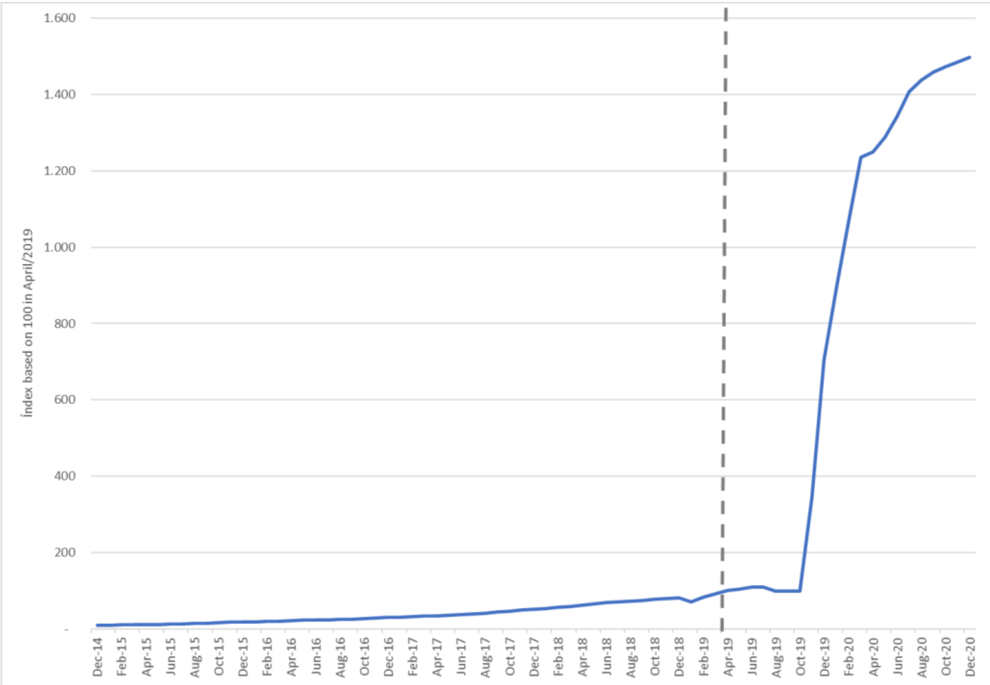
eligible to have their (positive) performance available to all credit bureaus. The actual use of the credit information can only happen 60 days after at least one bureau sends a message to the person informing her registration and the possible channels she can use to opt-out and cancel the registration.

Figure 1 shows the evolution of the number of registered individuals in the credit bureaus. There is a spike after the shift from a regime in which individuals had to opt in, to the new regime in which they could opt-out if they chose not to be registered. By the end of 2020, just under 330 thousand individuals had opted out. In contrast, at least 100 million individuals had an active record, which represents approximately 66% of the population aged over 19 years[14]. Both the small number of registered individuals during the opt-in regime and the large number after the regulatory change can be explained by human inertia. Inertia is called *status quo* bias by the behavior economics literature and can explain why it is hard for someone to get around doing something different, even if they would like to (Oliver, 2019).

Despite the sharp increase in the number of registered individuals in November 2019, the process is continuous. In other words, the bureaus process and register individuals daily. This feature is key to our empirical strategy detailed in Section 3.

[14] According to the projections of the Brazilian Institute of Geography and Statistics (IBGE) for the period 2010-2060

Figure 1. Evolution of the number of registered individuals

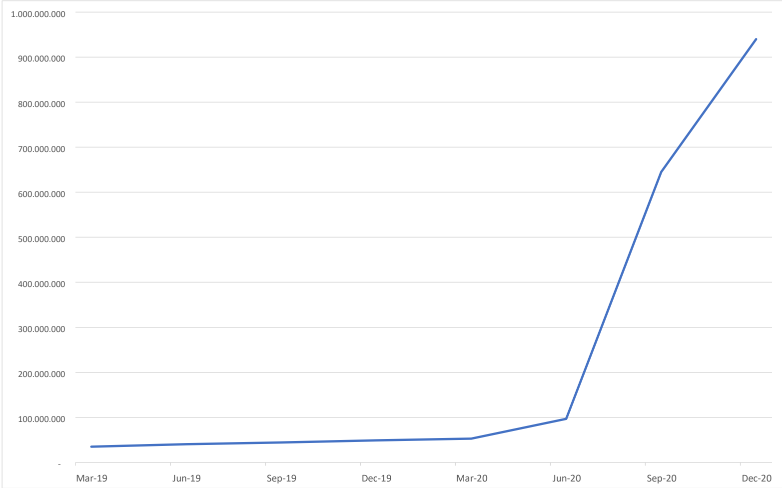


The law determines which types of entities are required to send credit data to the bureaus. The coordination between the sources of data (financial institutions, utilities, mobile service providers and others) and the bureaus is a major challenge because sending information is costly to these entities and the law does not define punishment for those that do not comply. Until mid-2021, the bureaus relied on data sent by financial institutions, essentially of the same type that is sent to the SCR, to estimate the new scores[15].

The bureaus started selling the new scores of individuals in the first quarter of 2020. Figure 2 shows a takeoff in the number of new scores queries in the third quarter.

[15] There is room for further improving in the scores through the inclusion of information from telecommunication services in 2021, and other service providers (not yet scheduled), such as electricity, gas, water and sewage.

Figure 2. Quarterly number of new scores queries to registered individuals



According to a survey conducted by the BCB, the largest lenders started incorporating the new scores in their credit assessment procedures for consumer loans in the third quarter of 2020 (BCB, 2021?) [16]. The ones that did generally reported an increase in the discriminatory power of their internal credit risk models and in the approval rates of new borrowers. The BCB also surveyed all the bureaus and heard that most individuals migrated to other ranges of credit risk when the bureaus included positive information to estimate new scores[17].

3. Data and Empirical Strategy

3.1. Data

Two main sources of data are used: loan-level information from the SCR credit registry, managed by the BCB, and credit scores calculated by the private credit bureaus. Our dataset was built by first randomly[18] sampling 100 thousand individuals who got nonpayroll personal credit in the months of August to December 2020 – our main analysis period – and other same number of individuals who got that type of credit in August 2019

[16] In February 2021, BCB surveyed banks, credit unions and fintechs regarding the purchase, use and their first impressions of the new scores in their credit analyses (BCB, 2021).
[17] On average, approximately 41% of individuals migrated to lower risk ranges, 33% remained in the same range and 26% migrated to higher risk ranges.
[18] We performed a geographic stratified sampling to assure a minimum number of observations in each Brazilian region.

– our placebo period. After that, we extracted from the credit registry all nonpayroll personal loans at origination from the sampled individuals. Very few individuals have more than one personal loan in the period. The final sample is further restricted to individuals above 18 years-old.

The credit bureaus provided two types of scores for the sampled individuals for each month. As mentioned previously, the old score is mainly based on negative information, whereas the new score also includes positive information. The old score is available for all individuals. For the placebo month of August 2019, the credit bureaus computed retroactively the new score. This was possible because credit bureaus receive positive information for the last 12 months, so that they were able to calculate the new score for August 2019, although these scores were not being commercialized at that time.

The new score is in general higher than the old score, meaning that the new information benefits the clients on average. When we group borrowers into quartiles based on the (new score – old score) difference, it is worth noting that clients on the first quartile have the new score lower than the old score, but in all other quartiles the new score is higher than the old one[19]. Therefore, the default risk estimated by the scores increased with the new information on the first quartile, but decreased on the 2nd, 3rd and 4th quartiles.

From the credit registry we obtain information about the loan characteristics (interest rate, maturity, amount, regulatory rating[20]), borrower's information (gender, age, geographic location, occupation, and income) and the lender's identification. We exclude from our analysis collateralized loans. We winsorize interest rates and other continuous control variables at the 1st and 99th percentiles. We also have information about the credit relationship duration of the borrower with the financial institution, and, in some exercises, we focus on those individuals who get their first loan from that financial institution (i.e., new borrowers) whereas in other exercises the focus is on old borrower-bank pairs.

[19] PCBs have suggested there is comparability between the scales of the new and old scores, so that subtracting them is a meaningful operation.

[20] Attributed by the financial intuition to the loan according to the scale of the BCB Resolution 2682, from December 22, 1999.

Table 1 – Summary Statistics

Panel A – All Clients – Before and After the New Law

	Aug-Dec 2020			**Aug-2019 (Placebo)**		
	Mean	**Median**	**Standard Deviation**	**Mean**	**Median**	**Standard Deviation**
Int. Rate (% p.y.)	180	138	181	194	149	202
Loan Amount (R$)	3,388	1,190	7,227	2,834	1,016	5,736
Loan Maturity (days)	463	267	554	385	185	470
New Score Available (0/1)	0.91	1	0.28	0.90	1	0.30
Old Score	581	575	111	572	567	115
New Score	644	645	128	647	647	140
Monthly Income (R$)	6,069	3,552	8,035	5,201	3,326	6,144
Female (0/1)	0.499	0	0.500	0.518	1	0.500
Age	47.27	45.68	15.54	45.43	43.59	15.22
# Observations	73,097			26,864		

Panel B – Old and New Clients – After the New Law

	New Clients			**Old Clients**		
	Mean	**Median**	**Standard Deviation**	**Mean**	**Median**	**Standard Deviation**
Int. Rate (% p.y.)	283.8	173.6	313.4	169.9	134	159.4
Loan Amount (R$)	2,581	1,501	3,555	3,465	1,137	7,480
Loan Maturity (days)	495.3	381	396.4	460.1	239	566.7
New Score Available (0/1)	0.6731	1	0.4691	0.9362	1	0.2443
Old Score	538.1	534	111.8	585.1	578.7	110
New Score	599.5	604.7	129	647.7	648.7	126.6
Monthly Income (R$)	4,344	2,300	10,971	6,234	3,782	7,675
Female (0/1)	0.4785	0	0.4996	0.5004	1	0.5
Age	43.86	40.9	15.84	47.59	46.15	15.47
# Observations	6,387			66,710		

3.2. Empirical Strategy

We compare the loan interest rates of borrowers with similar characteristics, including similar old scores, though only some have new scores available. The rationale is that borrowers with similar old scores and other characteristics would be *ex-ante* informationally homogenous to financial institutions This strategy allows us to conceive a counterfactual on how interest rates would have behaved if the change to the opt-out regime had not occurred, and no positive information were added to the estimation of the scores. The difference in rates between similar borrowers with and without new scores available is then attributed to the inclusion of positive information in the new score.[21]

Our most saturated specification incorporates the elements highlighted above, and is represented by the following loan-level equation:

$$\ln(r_{libt}) = \alpha + \beta\ \mathbf{1}[NSA_i] + \gamma\ old\_score_{it} + \theta_{bt} + \pi_{mt} + \mathbf{X_{it}}\boldsymbol{\lambda} + \boldsymbol{L}_{\mathbf{l}}\mathbf{r} + \varepsilon_{libt} \qquad (1)$$

where l denotes the loan, i is the individual borrower, b the creditor financial institution and t the period (month) when the loan was granted. The variable $\ln(r_{libt})$ represents the logarithm of the nominal interest rate. The function $\mathbf{1}[NSA_i]$ assumes the value 1 if there is a new score available by all credit bureaus for individual i in the sample period and 0 otherwise[22]. The variable old_score_{it} represents the average of the old scores calculated by credit bureaus for individual i in period t.

The set of borrower controls $\mathbf{X_{it}}$ includes gender (assuming the value 1 for female and 0 otherwise), age in years, municipality, level of personal income (dummies for ten buckets) and fixed effects for the borrower's professional occupation. Loan controls ($\mathbf{L_l}$) include maturity (in days) and the amount granted (in logarithm of Brazilian Reais) as of its origination.

[21] For example, we compare the loan interest rates of two borrowers that have old scores of 650 points, but one of them has a new score of 700 points, whereas the other one does not yet have a new score available for sale.

[22] Purposefully, this dummy does not have a subscript t, as no borrower in the sample had his new scores made available during our short sample period. Therefore, admittedly our specification is not a difference in difference model. Nevertheless, PCBs reported to us that the selection of which borrowers would acquire new scores was quite random and any left systematic difference between the borrowers is likely to be controlled to a great extent by the old score variable and other controls.

The term θ_{bt} represents the fixed effect of financial institution b in period t, which captures unobservable effects related to the credit supply, including funding costs. Similarly, π_{mt} represents the fixed effect of municipality m in period t and controls for local demand conditions, including greater or lesser need for credit due to restrictions on mobility and economic activity during the pandemic.[23] In equation (1), the coefficient of interest is β, which captures the average effect of access to new positive scores on loan spreads. More specifically, it should be interpreted as the average percentual difference on the loan interest rate between similar borrowers with and without new scores.

What is the expected signal of β? Since new scores encompass more information about the (positive) behavior of borrowers, they likely reduce information asymmetry to banks because they are more accurate than the old scores[24], and this would then lead to a negative coefficient β. Furthermore, notice that Table 1 shows that the inclusion of positive information leads to new scores that are generally higher than the old ones. This could indicate that the new information added to the old score generally increases the predicted creditworthiness of the borrower[25], prompting again a negative expected β.

Another mechanism that influences β is related to the increased competition environment that the enhanced information sharing fosters, as all banks gain equal access to the new scores. Because of the fear of losing their current borrowers or targeted new ones to outside potential lenders that are now knowledgeable of the borrowers' new scores, banks would also likely decrease loan rates, regardless of any updated assessment of the borrowers' creditworthiness. That leads similarly to a negative expectation for β.

A way to gauge the relative strength of the competition channel is to examine the change in loan rates for *existing* borrower-bank pairs with and without new scores available. For those borrowers, the informational gain to banks from the new scores is likely less material, because banks have already gained knowledge about them from their relationships (and even more so the longer the relationship). Therefore, observable

[23] Fixed effects related to the regulatory rating attributed to the loan at origination by the financial institution were also employed in many cases.

[24] Recall the bias-variance trade-off in statistics, where more complex models with more explanatory variables (e.g., new scores) usually display lower bias (higher accuracy). The premium charged for the bias would then be lower under the new scores.

[25] That is, the bias of the old score in predicting creditworthiness was probably negative. Notice too that PCBs have suggested there is comparability between the scales of the new and old scores, which implies subtracting them is a meaningful operation.

reactions from incumbent banks to the new scores are more likely derived from the fear of losing their borrowers to competitors than from a reassessment of risk.

We also investigate whether the effects on interest rates depend on the relative magnitudes of the new scores. If there is a large (small) difference between the new and the old score, we could expect a large (small) difference in the interest rates. We calculate the average difference between the new score and the old score for each client across credit bureaus.

We group borrowers into quartiles based on this (new score – old score) difference. For each quartile d of the difference in scores, we create a dummy variable d_{qi} and estimate a coefficient β_q, analogous to β in equation (1), allowing the assessment of heterogeneous effects across those groups, measured against the reference group of borrowers with no new scores available. The specification is the following:

$$\ln(r_{libt}) = \alpha + \sum_{q=1}^{4} \beta_q d_{qi} + \gamma * old\_score_{it} + \theta_{bt} + \pi_{mt} + \mathbf{X_{ibt}}\boldsymbol{\lambda} + \boldsymbol{L_l}\mathbf{r} + \varepsilon_{libt} \quad (2)$$

where d_{qi} assumes the value of 1 when individual i belongs to quartile q of the distribution of the score difference, and zero otherwise.

Our coefficients of interest in equation (2) are the β_q's, and they should be interpreted as the average percentual difference of loan rates between borrowers with, not only new scores available, but also located in the quartile q of the score difference, and similar borrowers lacking the new scores. In this way, if the relative magnitudes of the new scores are effective in predicting creditworthiness, reducing asymmetries and potentially fostering competition, these coefficients should be decreasing on q – besides being negative, as in (1), for the most part.[26]. Finally, we also apply specification (2) on existing borrower-bank pairs to investigate the strength of the competition channel.

4. Empirical Analyses

4.1. Baseline results

Our first baseline results unveil the average effect of borrowers having new scores based also on positive information. They are based on specification (1). Columns 1 and 2

[26] On the other hand, clients in the first quartile of the score differences, which generally experience a decrease in scores, may suffer an increase in interest rates (i.e., β_1 positive).

of Table 2 show the effect of the availability of new scores on interest rates paid by borrowers in non-payroll personal loans.

As described in the previous section, the specification of column (1) has the logarithm of the loan interest rate as the dependent variable and a dummy for the availability of new scores as the main independent variable. The specification has several control variables, including the old score (statistically negative, as expected) as well as the fixed effects of the municipality, financial institution, and time. The coefficient on the existence of the new score indicates an interest rate 3.5% lower for those clients and statistically significant at 1%.

Column (2) presents a more saturated specification by allowing the loan maturity coefficient and fixed effects of the financial institution and municipality to vary over time. The coefficient for availability of new score indicates an average interest rate reduction of 3.7%, statistically significant at 1%. The decrease is equivalent to rates approximately 6.7 p.p. smaller when considering the average interest rate of 182% per year observed in our sample.

One concern with the specifications employed is that it is not possible to completely rule out the existence of confounding characteristics not captured by the control variables that correlate with the availability of new scores. To tackle this issue, we ran a placebo test using loans from August 2019, when the new scores had not yet been marketed. As mentioned previously, these counterfactual scores for 2019 were computed retroactively by PCBs to support our analysis.

Column (3) of Table 2 shows the results of the placebo exercise. The coefficient for the fake availability of new scores is not statistically significant. This provides further confidence that the drop in interest rates observed for borrowers with new scores available stems from the sharing of new positive information contained therein and not from variables omitted from the specification.

Table 2 – New Score Availability and Interest Rates – All Clients

	(1) **Aug-Dec 2020** **Ln(Int. Rate)**	(2) **Aug-Dec 2020** **Ln(Int. Rate)**	(3) **Aug 2019** **Ln(Int. Rate)**
New Score Availability (0/1)	-0.0352***	-0.0369***	0.0040
	(0.007)	(0.007)	(0.011)
Old Score	-0.0005***	-0.0005***	-0.0002***
	(0.000)	(0.000)	(0.000)
# Observations	72,166	66,018	25,505
R^2	0.76	0.77	0.74
Controls	y	y	y
Municipality FE	y	n/a	y
Month FE	y	n/a	y
Financial Institution FE	y	n/a	y
Month x Municipality FE	n	y	n/a
Month x Fin. Inst. FE	n	y	n/a
# Financial Institutions	346	254	177
# Municipalities	3564	2550	2120
# months	5	5	1
% treated	0.91	0.92	0.90
Average Int. Rate (% p.y.)	180	182	197

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The second set of baseline results examines the effect of the magnitudes of the new scores, which go beyond the average availability effect just investigated. Borrowers are grouped into quartiles, according to the difference between their new and old scores. This difference is calculated only for the borrowers that have new scores available for sale. The borrowers for whom the new score increased signaled higher credit risk (new score lower than old lower score) are generally found to be located in the first quartile of the score differences. The estimation of (2) is shown in Table 3. The coefficient of a quartile of the score difference should be interpreted as the percentual interest rate difference of loans in that quartile and the control group of loans to borrowers with no new scores available.

Column (1) shows a statistically significant reduction in interest rates, of 8.5%, for borrowers in the fourth quartile. We also find statistically significant, but lower interest rate reductions, for borrowers in the second and third quartiles - when compared to the control group. In the first quartile, where the new scores are lower than the old score, coefficients are positive.

Indeed, the point estimates of the quartile coefficients monotonically decrease the higher the quartile, as expected. Those estimates suggest that the higher the relative improvement in creditworthiness coming from the new score, the lower the interest rate.

The more saturated specification in column (2) has similar results, both in terms of statistical significance and magnitudes. Thus, the fourth quartile, with the highest score differences, reaches an average interest rate reduction of 8.9% (or approximately 16,2 p.p. when considering the average rate of 182% for the underlying sample).

The last lines of Table 3 show equality tests between the coefficient among quartiles, thus making formal statistical tests. The tests corroborate monotonically decrease of the coefficients as the quartile increases. Those results confirm that the relative magnitudes of the score differences improve the identification of borrowers' risk profiles, reducing informational asymmetries and potentially increasing competition relatively more for reassessed lower-risk borrowers. It is important to emphasize that the updated scores play an important role in bolstering market discipline and fostering differentiation among borrowers, and consequently, bringing a fairer determination of interest rates.

Column (3) of Table 3 shows the results of a placebo test using data from August 2019, before the implementation of the positive information sharing. Similar to results of Table 2, we do not find statistically significant effects in the placebo period, reducing the concern of omitted variables in our models.

Table 3 – Score Difference Quartiles and Interest Rates – All Clients

	(1)	(2)	(3)
	Aug-Dec 2020	**Aug-Dec 2020**	**Aug 2019**
	Ln(Int. Rate)	**Ln(Int. Rate)**	**Ln(Int. Rate)**
Quartile 1	0.0148**	0.0141*	0.0067
	(0.007)	(0.008)	(0.012)
Quartile 2	-0.0199***	-0.0217***	-0.0022
	(0.007)	(0.008)	(0.012)
Quartile 3	-0.0458***	-0.0492***	0.0092
	(0.007)	(0.008)	(0.012)
Quartile 4	-0.0836***	-0.0872***	0.0025
	(0.007)	(0.008)	(0.012)
Old Score	-0.0005***	-0.0005***	-0.0002***
	(0.000)	(0.000)	(0.000)
# Observations	72,166	66,018	25,505
R^2	0.76	0.77	0.74
Control	y	y	y
Municipality FE	y	n/a	y
Month FE	y	n/a	y
Financial Institution FE	y	n/a	y
Month x Fin. Inst. FE	n	y	n/a
Month x Municipality FE	n	y	n/a
# Financial Institutions	346	254	177
# Municipalities	3,564	2,550	2,120
# months	5	5	1
% treated	0.91	0.92	0.90
Average Int. Rate (% p.y.)	180	182	197
p-value Q2=Q1	0.0000	0.0000	0.3316
p-value Q3=Q1	0.0000	0.0000	0.7887
p-value Q4=Q1	0.0000	0.0000	0.6419
p-value Q4=Q3	0.0000	0.0000	0.4378
p-value Q3=Q2	0.0000	0.0000	0.2028
p-value Q4=Q2	0.0000	0.0000	0.5997

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2. Results for Old and New Clients

Next, we investigate what happens to our results when we split our sample into new borrower-bank pairs and existing old ones. The former includes borrowers most likely to be affected by an updated assessment of their creditworthiness revealed by the new scores to their new lenders that do not know them so well. The latter includes borrowers affected mainly by the fear from their incumbent lenders of increasing competition from potential outside lenders that are now knowledgeable of their new scores. For the sample of old borrower-bank pairs, we only include borrowers that have multiple bank credit relationships, in order to make this sample more comparable to the sample of new borrower-bank pairs, where almost all borrowers have existing relationships with other banks.[27]

As new and old clients are significantly different in terms of profile and interest rate distribution, we fit the control variables and fixed separately. Therefore, we use specification (1) with all controls and fixed effects interacted with a dummy equal to one if the client is new. Therefore, this is a more saturated specification than those of Table 2. Column (1) of Table 4 shows results for this specification for all clients. Column (2) shows results for new clients, and column (3) for old clients.

The new score availability coefficient of Table 4, column (1) indicates an overall drop of 2.7% on interest rates, which is less intense of the 3.5% to 3.7% drop on columns (1) and (2) of Table 2. We then differentiate by new (column 2) and old (column 3) borrower-bank pairs. The new score availability coefficient for new borrower-bank pairs indicates a drop above 5% in the interest rates charged to individuals with new scores available and a drop around 2.2% for old borrower-bank pairs. Therefore, the rate drop for old borrower bank pairs is around 43% of the variation realized for new ones. If the whole rate reduction of the former were due to the competition channel, this might suggest that at most the same 43% fraction of the observed decrease in rates for new borrower-bank pairs would also be driven by underlying competition (between the new lender and others)[28]. In that case, more than half of that variation would then be attributed to the mechanism of risk reassessment.

Table 5 shows that the reductions in loan rates increase with the quartile quartiles of the score differences[29] for both new and old borrower-bank pairs. However, although this pattern is very clear for old clients, for new clients the pattern is cloudy. For instance, quartiles 2 and 3 for new clients have very similar coefficients, which are statistically indistinguishable. It is interesting to see also that the first quartile of new clients has a negative (but not statistically significant) coefficient, so that even if those clients have a

[27] See, for example, Degryse et al (2016) for the impact of outside loans.
[28] The others include incumbent lenders of that borrower as well as potential new lenders too.
[29] We build a distinct quartile score difference distribution for new and old client samples.

reduction in the score, they had no statistically significant reduction on interest rates. Furthermore, the reductions seem to be larger in all quartiles for new borrower-bank pairs, consistent with Table 4 and with the view that the risk reassessment has stronger effects than competition channel.

Table 4 – New Score Availability and Interest Rates – New and Old Clients

	(1)	(2)	(3)
Dependent Variable: Ln(Int. Rate)	**All Clients**	**New Clients**	**Old Clients**
New Score Available (0/1)	-0.0272***	-0.0585***	-0.0223***
	(0.008)	(0.021)	(0.009)
# Observations	63,647	3,926	59,721
R^2	0.78	0.85	0.77
Controls	n/a	y	y
Month x Municipality FE	n/a	y	y
Month x Fin. Inst. FE	n/a	y	y
Controls x New Client	y	n/a	n/a
Month x Muni x New Client FE	y	n/a	n/a
Month x Fin. Inst. x New Client FE	y	n/a	n/a
# Financial Institutions	230	54	224
# Municipalities	2,406	457	2,386
# months	5	5	5
% treated	0.82	0.71	0.94
Average Int. Rate (% p.y.)	180	300	172

Table 5 – Score Difference Quartiles and Interest Rates – New and Old Clients

	(1)	(2)	(3)
Dependent Variable: Ln(Int. Rate)	**All Clients**	**New Clients**	**Old Clients**
Quartile 1	0.0238***	-0.0142	0.0293***
	(0.009)	(0.027)	(0.009)
Quartile 2	-0.0136	-0.0518*	-0.0081
	(0.009)	(0.028)	(0.009)
Quartile 3	-0.0383***	-0.0583**	-0.0336***
	(0.009)	(0.027)	(0.009)
Quartile 4	-0.0785***	-0.1200***	-0.0730***
	(0.009)	(0.029)	(0.009)
# Observations	5,294	3,904	65,784
R^2	0.83	0.85	0.75
Controls	n/a	y	y
Month x Municipality FE	n/a	y	y
Month x Fin. Inst. FE	n/a	y	y
Controls x New Client	y	n/a	n/a
Month x Muni x New Client FE	y	n/a	n/a
Month x Fin. Inst. x New Client FE	y	n/a	n/a
# Financial Institutions	230	54	224
# Municipalities	2406	457	2386
# months	5	5	5
% treated	0.92	0.71	0.94
Average Int. Rate (% p.y.)	180	300	172
p-value Q2=Q1	0.0000	0.1824	0.0000
p-value Q3=Q1	0.0000	0.1137	0.0000
p-value Q4=Q1	0.0000	0.0005	0.0000
p-value Q4=Q3	0.0000	0.0361	0.0000
p-value Q3=Q2	0.0000	0.8183	0.0000
p-value Q4=Q2	0.0000	0.0206	0.0000

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3. Results for Private and Public Institutions

An important feature of the Brazilian financial system is the presence of both private and public banks. Next, we investigate the heterogeneity of our results, analyzing the effects on the subsamples of private and public financial institutions. Table 6 shows that the availability of new scores significantly lowers the interest rate of loans granted by private institutions, not by public ones. Table 7 shows that public banks lower the interest rate of loans to individuals located in the 4th quartile of the score difference, whereas private banks behave similarly for individuals across quartiles 2nd, 3rd and 4th, and increase the interest rate for individuals in the 1st quartile. Those results indicate that most of the action is driven by the behavior of private banks. Since the availability of new scores was a quite recent phenomenon during our sample period, the results of Tables 6 and 7 are consistent with private banks being quicker towards incorporating the new scores into their risk assessment models and pricing strategies. On the other hand, the new scores seem to have mattered so far for public banks only when they were much larger than the old ones.

When the subsamples are further split into new and old borrower bank pairs, the fourth quartile for public banks loses significancy only for new borrowers, where the risk reassessment should be the main channel. That is, public and private banks differ more in that channel, consistent with the explanation provided.

Table 6 – New Score Availability and Interest Rates – Public and Private Institutions

	(1)	(2)	(3)	(4)	(5)	(6)
	Private Institutions			**Public Institutions**		
Dependent Variable: Ln(Int. Rate)	**All Clients**	**New Clients**	**Old Clients**	**All Clients**	**New Clients**	**Old Clients**
New Score Available (0/1)	-0.0327***	-0.0617**	-0.0265**	-0.011	-0.0333	-0.0099
	(0.010)	(0.027)	(0.011)	(0.014)	(0.037)	(0.014)
# Observations	42,486	3,057	39,429	17,338	436	16,902
R^2	0.75	0.84	0.74	0.47	0.62	0.46
Controls	n/a	y	y	n/a	y	y
Month x Municipality FE	n/a	y	y	n/a	y	y
Month x Fin. Inst. FE	n/a	y	y	n/a	y	y
Controls x New Client	y	n/a	n/a	y	n/a	n/a
Month x Mun. x New Client FE	y	n/a	n/a	y	n/a	n/a
Month x FI x New Client FE	y	n/a	n/a	y	n/a	n/a
# Financial Institutions	211	47	206	9	4	9
# Municipalities	1,830	370	1,809	1,017	69	1,010
# months	5	5	5	5	5	5
% treated	0.93	0.74	0.95	0.9	0.62	0.91
Average Int. Rate (% p.y.)	230	347	221	70	83	69

Table 7 – Score Difference Quartiles and Interest Rates – Public and Private Institutions

	(1)	(2)	(3)	(4)	(5)	(6)
	Private Institutions			Public Institutions		
Dependent Variable: Ln(Int. Rate)	**All Clients**	**New Clients**	**Old Clients**	**All Clients**	**New Clients**	**Old Clients**
Quartile 1	0.0205*	-0.0007	0.0267**	0.0209	-0.0086	0.0221
	(0.011)	(0.033)	(0.012)	(0.015)	(0.045)	(0.015)
Quartile 2	-0.0206*	-0.0530	-0.0138	-0.0007	0.0310	-0.0002
	(0.011)	(0.034)	(0.012)	(0.015)	(0.046)	(0.015)
Quartile 3	-0.0474***	-0.0799**	-0.0407***	-0.0117	-0.0930	-0.0100
	(0.011)	(0.033)	(0.012)	(0.015)	(0.060)	(0.015)
Quartile 4	-0.0805***	-0.1225***	-0.0734***	-0.0508***	-0.0657	-0.0498***
	(0.011)	(0.036)	(0.012)	(0.015)	(0.055)	(0.015)
# Observations	42,486	3,057	39,429	17,338	436	16,902
R^2	0.75	0.84	0.74	0.47	0.62	0.46
Controls	n/a	y	y	n/a	y	y
Month x Municipality FE	n/a	y	y	n/a	y	y
Month x Fin. Inst. FE	n/a	y	y	n/a	y	y
Controls x New Client	y	n/a	n/a	y	n/a	n/a
Month x Mun. x New Client FE	y	n/a	n/a	y	n/a	n/a
Month x FI x New Client FE	y	n/a	n/a	y	n/a	n/a
# Financial Institutions	211	47	206	9	4	9
# Municipalities	1,830	370	1,809	1,017	69	1,010
# months	5	5	5	5	5	5
% treated	0.93	0.74	0.95	0.9	0.62	0.91
Average Int. Rate (% p.y.)	230	347	221	70	83	69
p-value Q2=Q1	0.0000	0.1139	0.0000	0.0213	0.4020	0.0179
p-value Q3=Q1	0.0000	0.0160	0.0000	0.0006	0.1952	0.0008
p-value Q4=Q1	0.0000	0.0007	0.0000	0.0000	0.2993	0.0000
p-value Q4=Q3	0.0000	0.2214	0.0000	0.0000	0.6939	0.0000
p-value Q3=Q2	0.0001	0.4195	0.0002	0.2333	0.0494	0.2965
p-value Q4=Q2	0.0000	0.0499	0.0000	0.0000	0.0756	0.0000

4.4. Relationship duration and information sharing

Our last set of empirical exercises evaluate if positive information sharing is affecting the competition among financial institutions for clients with existing relationships. Recall that, for clients with longer relationship, lenders can pass-through the benefits of a lower information asymmetry into lower interest rates to the borrower or they can lock-in the clients, since they have private information about of the client (Padilla and Pagano, 1997). We then evaluate if the information sharing brought by the new law prevents private institutions from lock-in their clients, creating a more competitive environment.

We focus on the sample of old clients from private institutions and interact, in specification (1), the dummy of new score availability with the borrower-bank relationship duration. Table 8 shows the results for three types of relationship duration measures: column (1) uses the logarithm of the bank-firm relationship duration; column (2) uses a dummy variable equal to one if the relationship duration is over 1 year; and column (3) uses a dummy variable equal to one if the relationship duration is over 2 years.

The *Relationship Length* coefficients have no statistical significance and are even positive on columns (1) and (2), suggesting that private lenders are locking-in[33] borrowers not affected by the information sharing, i.e., those who without the new score available. Old borrowers without new scores are therefore under limited competition forces, possibly due to an informational monopoly.

The *New Score Available* coefficients have no statistical significance in all columns, meaning that for old clients with short relationships, the availability of the new score is not making any relevant difference.

The negative *New Score Available* x *Relationship Length* coefficients suggests that the availability of the new score have beneficial effects in reducing interest rates as the relationship duration increases. For instance, this coefficient on column (2) suggests that, among borrowers with more than one year of relationship duration, those with the new score available have interest rates around 7% lower. The availability of the new score allows stronger competition forces among the lenders to take place, reducing the informational monopoly power of the incumbent banks. Thus, longer-term clients benefit relatively more (from lower rates) because they faced greater informational monopoly *ex-*

[33] These coefficients would be negative if lenders are passing through the benefits of lower information asymmetry into lower interest rates.

ante. The longer is the relationship, the higher was the informational switching costs for these borrowers before the new law.

At the end of Table 8, we show the sum of the *Relationship Length* coefficient with the *New Score Available* x *Relationship Length* coefficient. The value of this sum on column (1) would be the (full) elasticity of interest rates to relationship duration for borrowers with new scores, and it is significantly negative. Therefore, those borrowers experience interest rate reductions as relationship duration increases, since the information sharing through the new scores possibly removes the room for informational rent extraction from incumbent banks, the longer is the relationship.

Overall, the results of this section suggest that information sharing may be creating hurdles for lenders to lock-in their clients, because they no longer have the informational monopoly. While private lenders are able to lock-in clients not affected by the new law, they are passing through lower information asymmetry into lower rates for those with the new score available.

Our evidence is consistent with a reduction in relationship lending and is in line with Sutherland (2018), which find that following information sharing, lenders reduce contract maturities in new relationships, and are less willing to provide financing to their delinquent borrowers.

Table 8 – Relationship Duration, New Score Availability, and Interest Rates

	(1)	(2)	(3)
Dependent Variable: Ln(Int. Rate)	**Logarithm of relationship duration**	**Dummy for relationship over 1 year**	**Dummy for relationship over 2 years**
New Score Available (0/1)	-0.0119	0.0305	0.0048
	(0.0128)	(0.0245)	(0.0209)
Relationship Length	0.0042	0.0077	-0.0024
	(0.0054)	(0.0274)	(0.0243)
Relationship Length x New Score Available	-0.0121**	-0.0698**	-0.0416*
	(0.0050)	(0.0273)	(0.0245)
Relationship Length + Relationship Length x New Score Available	-0.0079***	-0.0621***	-0.0439***
	(0.0030)	(0.0143)	(0.0104)
# Observations	39,429	39,429	39,429
R^2	0.74	0.74	0.74
Controls	y	y	y
Month x Municipality FE	y	y	y
Month x Fin. Inst. FE	y	y	y
# Financial Institutions	206	206	206
# Municipalities	1,809	1,809	1,809
# months	5	5	5
Average Int. Rate (% p.y.)	221	39,429	221

5. Conclusion

In this paper, we evaluate if an increase in borrowers' positive information available to financial institutions through credit scores affects the loan interest rates charged to new and existing borrowers. We exploit the initial effects of a law in Brazil that allowed private credit bureaus to develop new scores of approximately 100 million individuals based also on positive information.

Overall, we find evidence of lower interest rates associated with the new positive information-sharing mechanism conducted by private credit bureaus. Our results show an average reduction of 3.7% in the interest rates of personal loans to borrowers that had new scores available for sale, compared to borrowers who remained only with old credit scores. The effects are stronger when the new scores are much higher than the old ones, reaching an average reduction of 8.7% in that case. Furthermore, the reductions in rates are higher for new borrower-bank pairs, where both a risk reassessment and a competition channel are possibly at play than for old ones, where possibly the competition channel is the main driver. Indeed, results modulated by the length of the borrower-bank relationship show evidence consistent with the existence of a competition channel for old borrower-bank pairs. Finally, the results are overall driven by the behavior of private banks.

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