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Bank loan forbearance: evidence from a million restructured loans

Abstract

Forbearance is a concession granted by a lending bank to a borrower for reasons of financial difficulty. This paper examines why and when delinquent bank loans are forborne, using a novel dataset with over 13 million delinquent loans to non-financial firms in Brazil, from which 1.1 million are forborne. Our evidence shows that larger loans are more likely to be forborne, and that the greater the difficulty to seize collateral, the larger the probability of forbearance. Previous forbearances to a borrower are also positively associated to the probability of forbearance, which may be an indicative of loan evergreening. We also show that more than 80% of forbearance events occur in less than four months after a loan becomes more than 60 days past due (after which the bank may no longer accrue interest). Finally, we find that a regulatory rule that forces banks to increase provisions of non-delinquent loans when the same borrower also has a delinquent loan creates incentives for banks to forbear delinquent loans. Because loan evergreening may pose macroeconomic resource allocation problems and forbearance may be used to conceal loan losses, decrease provisions and manage earnings and capital, our findings have implications for the design of regulation and supervisory processes.

Keywords: *loan restructuring, debt renegotiation, evergreening, collateral*

JEL Codes: G21, G23, G28, K12, E44

1 Introduction

Given the incompleteness of financial contracts (Hart & Moore, 1988), the possibility of renegotiation is almost intrinsic to loan contracts. Despite the importance of the topic, little is known about what drives the renegotiation of privately placed debt, and particularly of bank loans.

Debt renegotiation may occur under many different circumstances. For example, it can be initiated by the borrower in response to a change in its relative bargaining power, or by the lender due to a payment violation. Roberts and Sufi (2009) use a sample of private credit agreements between lenders and publicly traded firms in the US, and show that the main triggers for renegotiations are related to the improvement in the credit quality of the borrower, such as a decrease in leverage or a reduction in the cost of competing sources of funds. These increase the bargaining power of the borrower relative to the lender, which allows the first to negotiate a lower interest rate or additional credit. Roberts (2015) shows that most renegotiations of bank loans in the US are started by the borrowers in response to changing conditions, and that less than a third of renegotiations occur due to default or a covenant violation.

Although the study of the renegotiation of non-distressed loans is important to the comprehension and design of financing contracts, renegotiations triggered by a credit deterioration (such as the observation of a default or its imminence) have more importance for financial stability. For example, the study by Gilson *et al.* (1990) shows that financially distressed US public firms that rely more on bank loans than on other sources of debt are more likely to restructure their debt out of court. Demiroglu and James (2015) find that loans made by a single bank lender are relatively easier to restructure compared to loans from institutional lenders. Yet, they show that only 37.8% of debt restructuring events occur after the borrower actually misses a payment.

When a borrower violates loan payments, the lending bank may foreclose the troubled loan and seize the collateral, or give the borrower concessions, restructuring loan terms. These concessions are also known as "forbearance"[1].

We use a novel and detailed dataset of forborne loans in Brazil. We focus on loans that are more than sixty days past due, which we hereafter call "non-accrual loans" because local regulation prevents the banks from accruing any additional interest for such loans. Our sample has almost 13 million non-accrual loans – from which more than 1 million are forborne - granted by over 1,000 financial institutions to more than 2 million firms. To the best of our knowledge, this is the largest and most comprehensive dataset on restructured loans ever used in the literature. Our data enables us to describe the features of forborne loans, and investigate the main drivers of loan forbearance, including economic and regulatory incentives.

Our main findings are fourfold. First, on average 8.8% of non-accrual loans are forborne. Loans with greater value are more likely to be restructured, and more than 80% of forbearance events occur in less than four months after the loan becomes non-accrual. Second, the probability of forbearance is 3.6 percentage points larger for loans not collateralized by fiduciary lien (for which the seizing and selling of collateral occurs out-of-court). This suggests that the greater the difficulty to seize the collateral, the larger is the probability of forbearance, presumably because banks want to avoid a costly in-court process of seizing and selling collateral.

Third, previous forbearances at the bank-firm level increase the probability of another forbearance. The probability of forbearance of a non-accrual loan increases by 0.84 percentage points for each previous month with an observation

[1] We use the term "forbearance" to adhere to the Basel Committee on Banking Supervision (2017) guideline, published with the purpose of promoting harmonization in the measurement and application of two measures of asset quality: non-performing exposures and forbearance. In this publication, the concept of forbearance is given by: "Forbearance is a concession granted to a counterparty for reasons of financial difficulty that would not be otherwise considered by the lender. Forbearance recognition is not limited to measures that give raise to an economic loss for the lender."

of a forborne loan (considering the same bank-firm relationship). One important implication of this result is that the widespread behavior of successively forbearing loans (loan evergreening) may be in the roots of a macroeconomic problem of misallocation of credit (Peek & Rosengren, 2005).

Finally, we find that banks are more likely to forbear a non-accrual loan made to a firm with which it also has a non-delinquent loan outstanding. This behavior may be the result of a bad incentive created by regulation. A regulatory rule states that: i) banks must constitute provisions to all the loans of a given borrower considering the borrower's loan with the worst credit rating; ii) the rating of any given loan is upper bounded by its number of days past due (meaning that its provision is lower bounded by the number of days past due). This rule creates a bad incentive, since banks may use forbearance as a tool to avoid provisions, and consequently window-dress their results, even if the borrower does not have the ability to fulfill the new obligations.

In sum, besides describing in detail the time when forbearance occurs and how loan characteristics (more specifically loan value and type of guarantee) affect the probability of forbearance, this study sheds light on possible macroeconomic issues that forbearance may cause, and the role of bad policy incentives that stimulate forbearance.

This works adds to the literature of renegotiation of financial contracts (Gilson, John and Lang (1990); Roberts and Sufi (2009); Demiroglu and James (2015); Roberts (2015); Campello, Ladika and Matta (Forthcoming)) for a number of reasons. First, because it uses a broader and larger sample of forborne loans. Second, it explores other loan characteristics not previously used in the literature, and third, it looks at the incentives to forbear created by regulation.

This paper is also related with a large body of literature that draws relationships between law features, the quality of institutions and financial decisions. The seminal paper by La Porta *et al.* (1997) shows that countries with poorer investor protection have smaller and narrower capital markets. In turn, La Porta *et al.*

(1998) study the relation between investor protection and ownership concentration. Taken together, these studies describe a link from the legal system to economic development. Other studies (Levine (1999); Djankov, La Porta, Lopez-de-Silanes and Shleifer (2003); Safavian and Sharma (2007); among others) investigate the role of legal rules and the quality of enforcement aiming on cross-country differences. The focus on a single country allows us to abstract from between-country variation that could possibly confound the analysis.

Another branch of the literature focuses on within-country microdata to study each channel separately. Some authors have focused on the quality of enforcement and court efficiency (Ponticelli and Alencar (2016); Schiantarelli, Stacchini, and Strahan (2016)), while others have focused on the channel of legal rules (Araujo, Ferreira and Funchal (2012); Vig (2013); Campello and Larrain (2016)), measuring the effects of legislation reforms on markets. The results we find are in line with this last stream of literature, as fiduciary lien loans have specific legal rules that increase creditor rights, and lenders are less prone to forbear loans with this type of collateral. The contribution in this field of study is to show that the increase in creditors rights may not only expand loan origination, but also affect the forbearance of loans.

This work also speaks to the financial stability literature. Evidence reported by recent studies shows that banks have the ability to hide loan losses (e.g., Rojas-Suarez and Weisbrod (1996) from Latin America; OECD (2001) from the Russian Federation; Kanaya and Woo (2000), Hoshi and Kashyap (2004), Peek and Rosengren (2005) from Japan; Gunther and Moore (2003) from the US). Successive loan forbearance is a means of concealing loan losses, especially by rolling over bad loans with the accrual of interest. Niinimaki (2007) develops a model of financial intermediation similar to Holmstrom and Tirole (1997), but considering that banks may hide loan losses. He shows that even when loan risks are quite diversified, moral hazard may arise if the bank can hide its loan losses by rolling over the defaulted loans. As such, loans seem to be performing but the bank is actual insolvent. Our results bring additional empirical evidence that loan forbearance may be used to conceal loan losses. Besides reporting the occurrence of successive forbearances, the results also show that the probability of forbearance is increasing on the number of occurrences of previous forbearances.

The present work is also related with the literature of earnings and capital management. Although the literature refers to "discretionary provisions" as a means of managing earnings and capital, they do not discuss the possible mechanisms to change non-discretionary provisions. This study offers a new view of possibly managing non-discretionary provisions through the use of loan forbearance.

The use of loan loss provisions by banks to manage earnings is almost a consensus over researchers. In a study of banks across 48 countries, Shen and Chih (2005) conclude that most banks manage their earnings. Recent papers on this literature usually try to identify how the practice of earnings management is affected by factors such as auditor reputation (Kanagaretnam, Lim, and Lobo (2010); Magnis and Iatridis (2017)), and by institutional factors as investor protection, bank regulation and supervision (Shen and Chih (2005); Fonseca and González (2008)).

The same consensus does not exist about the use of loan loss provisions for capital management. Some studies (Beatty, Chamberlain, and Magliolo (1995); Ahmed, Takeda, and Thomas (1999)) support that loan loss provisions are used as techniques for capital management, whereas other (Collins, Shackelford, and Wahlen (1995); Kim and Kross (1998); Lobo, and Yang (2001)), in contrast, conclude that loan loss provisions are not used for managing capital. The recent literature presents results that are more refined. Shrieves and Dahl (2003) conclude that banks with less than required capital increase their regulatory capital by decreasing loan loss provisions, entailing a greater capital adequacy ratio for the core capital through higher earnings. Magnis and Iatridis (2017) conclude that there is a greater manipulation in earnings and capital adequacy ratios through loan loss provisions, whereas Pérez et al. (2008) reject the hypothesis of capital management in Spanish banks.

Our findings have important implications for policy design and bank supervision, as they suggest that regulation may be one of the drivers of loan forbearance, possibly leading to sub-optimal allocation of credit. They also suggest that bank supervisors should devote special attention to the provisioning process of forborne loans, since forbearances can be used to circumvent regulation on provisions and artificially improve earnings and capital.

The remainder of the study proceeds as follows. Section 2 describes the data, its sources, and shows the univariate analysis. Section 3 presents the empirical methods. Section 4 shows the regression results and robustness tests. Section 5 concludes.

2 Data

2.1 Sources of Data

The initial dataset comprises virtually all loans granted to non-financial firms in the Brazilian financial system, by different types of financial institutions: commercial banks, savings banks, exchange banks, investment banks, development banks, universal banks, credit unions, and non-banking credit companies. We use data at the financial conglomerate level, consistent with most of the previous literature for US banks (Kashyap *et al.* (2002); Gatev and Strahan (2006)) and Brazilian banks (Oliveira *et al.* (2014); Oliveira *et al.* (2015); Schiozer and Oliveira (2016)). For the sake of simplicity, we call all these types of financial institutions or financial conglomerates "banks".

Loan-level data come from the Credit Information System (SCR, for its acronym in Portuguese) of the Central Bank of Brazil. It is a confidential credit registry database protected by the Brazilian Law of banking privacy. The SCR contains monthly loan-level information from all credit relationships of individuals and firms that have a total exposure with a financial institution above 1,000 BRL (approximately 250 USD)[2]. The dataset does not include loans made by branches and subsidiaries of Brazilian banks abroad[3]. Although there are some specific loans made to borrowers located outside Brazil, these comprise a very small part of the credit supplied by banks in Brazil and are not considered in this study.

The SCR provides, for each loan, information on the characteristics of the borrower and the loan itself. Information about the borrower used in this work includes the initial date of relationship with the bank, the location (municipality) of the borrower, its CNAE industry code (the Brazilian classification equivalent to SIC code in the US), and its type of controllership (private or governmental). Information on banks includes the segment and the type of controllership (governmental, foreign or domestic private). Loan information includes the type of loan, the initial and due dates, the loan currency, end-of month information about the value of the installments due in the next periods, the credit risk classification (rating), and the type and value of collateral, if there is any. In the case of loans in arrears, the system also informs the number of days past due and the values not paid in previous periods[4].

The second dataset used in this study, also provided by the Central Bank of Brazil, contains information on forborne loans. This dataset is built by an algorithm developed by the Central Bank of Brazil that identifies non-performing loans converted back to the status of performing loans without the amount past due debt being fully repaid (Central Bank of Brazil, 2016), indicating that the

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[2] This threshold is gradually decreasing over time, and decreased to 200 BRL (approximately 50 USD) from May 2016 onwards. For consistency, the sample considers the threshold of 1,000 BRL (approximately 250 USD) for the whole period, i.e., all loans from any firm-bank relation with less than 1,000 BRL of total credit exposure on any month are dropped.

[3] More details about the loan information reported by financial institutions used in this work can be found at the website http://www.bcb.gov.br/?doc3040 (only in Portuguese).

[4] Part of the information contained in the SCR comes from the Receita Federal do Brasil (Brazilian equivalent to the Internal Revenue Services in the US) records, such as the location of the borrower and its industry code. Financial institutions feed monthly information about loans.

loan has been forborne. The available data starts in April 2012. We claim that this dataset has several advantages over the ones previously used in the literature. First, it covers virtually all loans granted in the Brazilian financial system, being thus probably the most representative sample of forbearance available in any given country. Second, the forbearance measure does not rely on subjective judgments, as in other studies. As a comparison, the study by Arrowsmith *et al.* (2013) uses survey data for UK banks, so it is prone to present differences between each bank's interpretation of forbearance. The research by Homar *et al.* (2015) uses data gathered on an Asset Quality Review from the European Central Bank at the bank level (whereas we use granular data at the loan level). Moreover, the data comprise information from various countries, and the definition of forbearance may be affected by differences on the interpretation about forbearance from each supervisory team. Although the main concept of forbearance is reasonably equally accepted between practitioners, the identification of forbearances - specifically in terms of what to consider as a concession or financial difficulty - in general, depends on the person analyzing the loan, and the measure used in this work does not have this potential problem. To the best of our knowledge, this is the first study to use the information on this dataset.

2.2 Sample

Our main sample comprises the period from April 2012 to October 2018. The period is restricted by the initial availability of loan forbearances data and the last month available at the time of writing. Regulation imposes that after sixty days past due no interest accruals can be made to the loans, and therefore banks may not recognize any revenues from it. Besides, at this stage of the loan, most collection actions have already been taken[5]. For these two reasons our main

[5] Collection actions vary across bank and type of loan, but typically involve phone calls by the account manager, electronic messages and letters to inform that the loan is past due.

sample contains only loans that are more than sixty days past due (hereafter *non-accrual loans*).

To avoid selection problems, we exclude from the sample all loans from any firm-bank relation with less than 1,000 BRL of total credit exposure on any month. Even with this threshold, data on identified loans represent more than 99.9% of all the bank credit supplied to non-financial firms in Brazil.

We also exclude written-off loans. According to Brazilian regulation, a loan must be informed to SCR for at least five years after it has been written off. Therefore, this exclusion is justified, given that these loans are rarely forborne and their number of observations is large (because it is mostly comprised of repeated information over sixty months after a loan has been written off).

We end up with more than 100 million observations (loan-month) of non-accrual loans. For any of these loans, the first month in the sample represents the first time it became non-accrual (i.e. more than sixty days past due). The last month of the loan in the dataset represents the time it is forborne, paid or written-off. In some cases (e.g., loans forborne more than once) the same loan enters the sample, leaves the sample, and then re-enters the sample. In these situations, every time a loan leaves and re-enters the sample, it is considered as a distinct loan. To avoid selection problems, left censored loans (with more than ninety-one days past due in the first month of the sample) and right censored loans (last month exactly in October 2018) are excluded.

In the sample used in our main regressions, we use the information at the loan level (i.e., each non-accrual loan corresponds to one observation, regardless of how many months it appears in the sample). The final dataset used in the regression analysis has almost 13 million observations, more than 2 million firms and more than 1,000 banks. From this total, there are more than 1.1 million forborne loans. In other words, conditional on being non-accrual, approximately 8.8% of the loans are forborne.

2.3 Variable Definitions and Univariate Analysis

In this topic, we describe and make a preliminary analysis of the main variables in the sample. We also describe each one of the control variables, focusing on their definition and data manipulation details when necessary.

2.3.1 Number of Periods

The number of periods for each loan is the time lapse in months between the time the loan becomes non-accrual and the month when the loan was forborne, paid or written-off, that is, one month after the last time it appears in the database.

We define "time to forbear" as the number of periods given that a loan is forborne. In other words, "time to forbear" is the number of months a loan takes to be forborne since it became non-accrual. Among all forborne loans, approximately 82% were restructured in four months or less (after the loan becomes non-accrual), 92% in six months or less, and more than 99% in ten months or less, as shown in Figure 1.

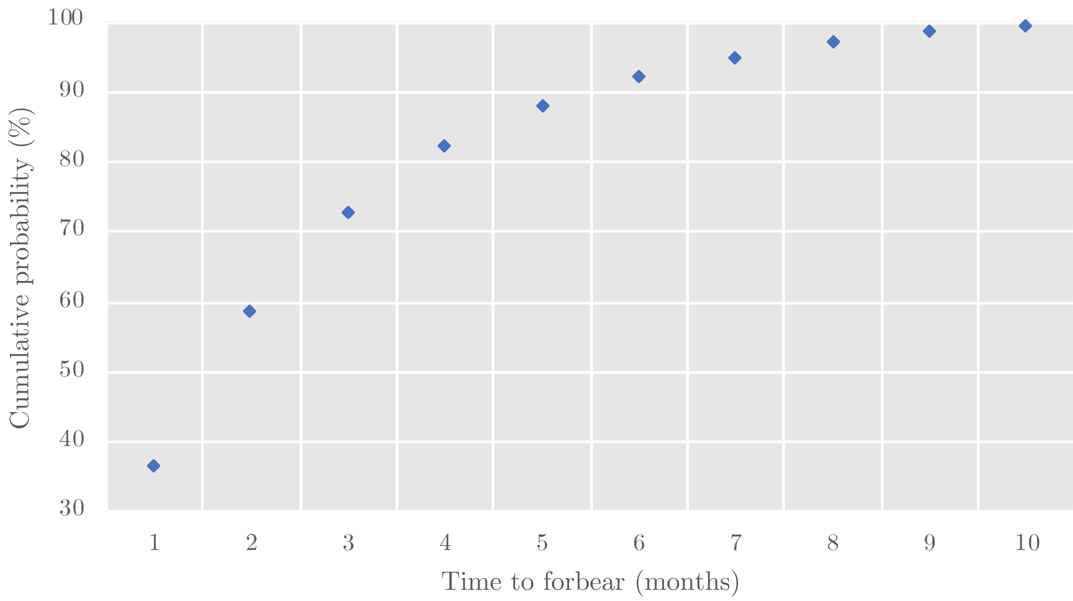
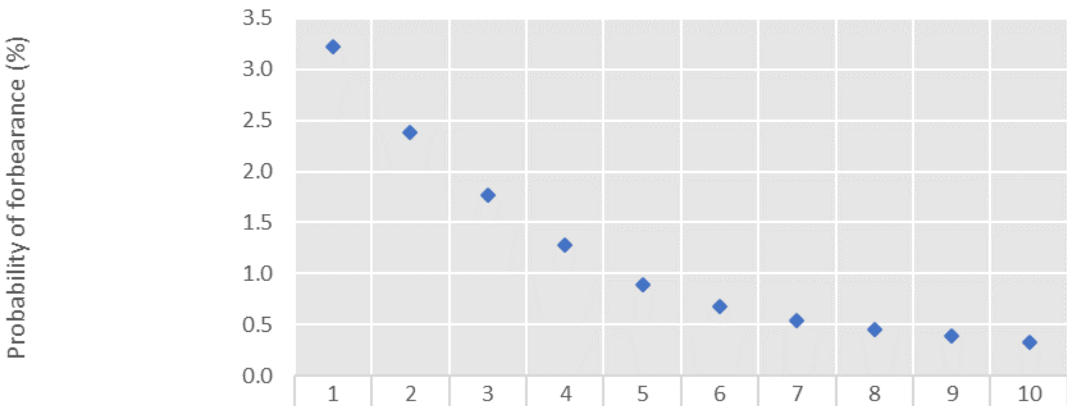


Figure 1 - Time to forbear - Each point corresponds to the percentage of all forborne loans that were restructured within the number of periods on the horizontal axis. For example, the third point shows that roughly 73% of forborne loans were restructured within three months or less after being sixty days past due.

We also compute the probability of forbearance of a non-accrual loan, for each number of periods. This probability is computed as the number of loans that are forborne with exactly the number of periods divided by the number of non-accrual loans that last for the same number of periods or more. Figure 2 shows that the probability of forbearance decreases as the number of periods increases. For example, the probability that a non-accrual loan is forborne in the first month is approximately 3.2%, whereas the probability of a loan being forborne in the second month after it becomes non-accrual (given that it was not forborne, paid or written-off in the first month) is approximately 2.4%. The probability of forbearance of a non-accrual loan in the tenth month is smaller than 0.4%.



	1	2	3	4	5	6	7	8	9	10
Probability of forbearance	3.2	2.4	1.8	1.3	0.9	0.7	0.5	0.5	0.4	0.3
Number at Risk (thousands)	12,938	10,456	9,215	8,353	7,253	6,621	5,942	5,286	4,456	2,965

Number of Periods

Figure 2 - Probability of forbearance (%) by number of periods - Each point corresponds to the probability of a loan that lasts at least the number of periods to be forborne. For example, the third point shows that 1.8% of the loans that appear in the dataset for three months or more after being sixty days past due are forborne.

This finding is consistent with the idea that, after the bank has taken regular collection actions to a delinquent loan without success, the decision to forbear or not a loan is usually made within the first few months.

2.3.2 Loan Value

As mentioned earlier Brazilian regulation does not allow a bank to accrue interest on a loan after it becomes sixty days past due. Therefore, the value of the loans that enter our sample do not increase over time. On the other hand, the loan value may decrease if the borrower makes a payment. If the payment covers all the debt past due (or at least the debt more than sixty days past due), the loan leaves the sample. Therefore, unless there is a partial payment, the loan value does not change between the first and last month it appears on the dataset.

When building the final sample (one observation per loan), we compute the loan value as the average loan value between the first and last month in which the loan appears in the sample.

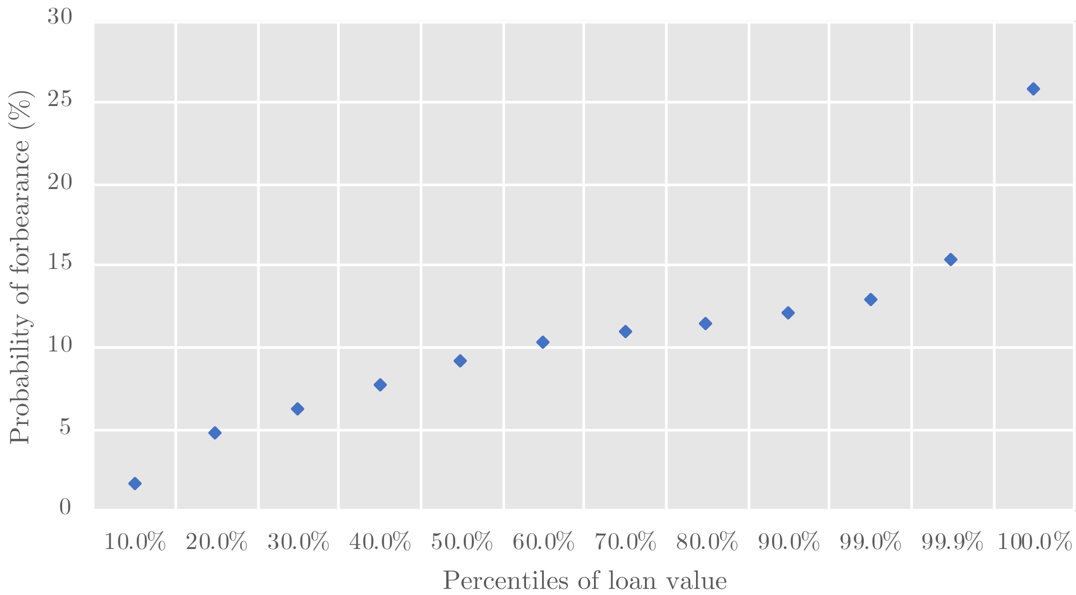


Figure 3 - Probability of forbearance by loan value percentiles - Loans are grouped into percentiles of loan value, and for each percentile the probability of forbearance corresponds to the proportion of forborne loans over non-accrual loans in that decile. For example, the last point shows that approximately 26% of the loans in the top 0.1 percentile loans of the sample (largest loans) are forborne. On the other hand, less than 2% of the bottom decile loans are forborne.

To understand how the loan value affects the probability of forbearance, we split the sample into deciles of the loan value, and compute the proportion of forborne loans for each decile. We also compute the probability of forbearance for the loans that are larger than the 99$^{\text{th}}$ and the 99.9 percentiles. Figure 3 shows that the larger the loan value, the greater the probability of forbearance. For example, the probability of forbearance of a non-accrual loan in the first decile (i.e., the smallest loans), the probability of forbearance is approximately 1.7%, whereas the probability of forbearance in the top 0.1 percentile (largest loans) is approximately 25.8%. This may indicate that the benefits of forbearance are positively correlated with the loan value, and the cost (effort) is almost independent of it.

2.3.3 Previous Forbearances

For each loan in the sample, we count the number of months in which other loans granted by the same bank to the same firm are forborne previously to the first month that the loan appeared in the sample. It is defined as the number of months in which forbearances on loans of the same firm-bank pair occur previous to the month in which the variable is evaluated, that is, the number of months with forbearance loans of the same firm-bank relationship that occur before the loan becomes non-accrual.

Figure 4 presents the probability of forbearance by each number of months with previous forbearances for the full sample (blue dots). As the measure of previous forbearances may be underestimated in the first months of the sample (as it does not consider forbearances occurred before the beginning of the sample period), we also compute the probability of forbearance for a subsample of loans that become non-accrual from 2014 onwards (orange dots). For both series, there is a positive correlation between previous forbearances and the probability of forbearance. This means that, on average, the more loan forbearance events in the past, the greater is the probability that a loan forbearance occurs again. For example, the probability of forbearance for a bank-firm pair with zero previous forbearances is approximately 8.5% for the full sample, whereas this probability is 18.6% for the bank-firm pairs that have five or more months with previous forbearances. This result may suggest the occurrence of what some authors (e.g., Caballero *et al.*

(2008); Watanabe (2010); Bruche and Llobet (2014)) call "zombie lending" or "evergreening", that is, the practice of successive "bad" forbearances, particularly by extending more credit to impaired borrowers, with the purpose of window-dressing non-performing loan indicators and avoid increasing loan loss provisions.

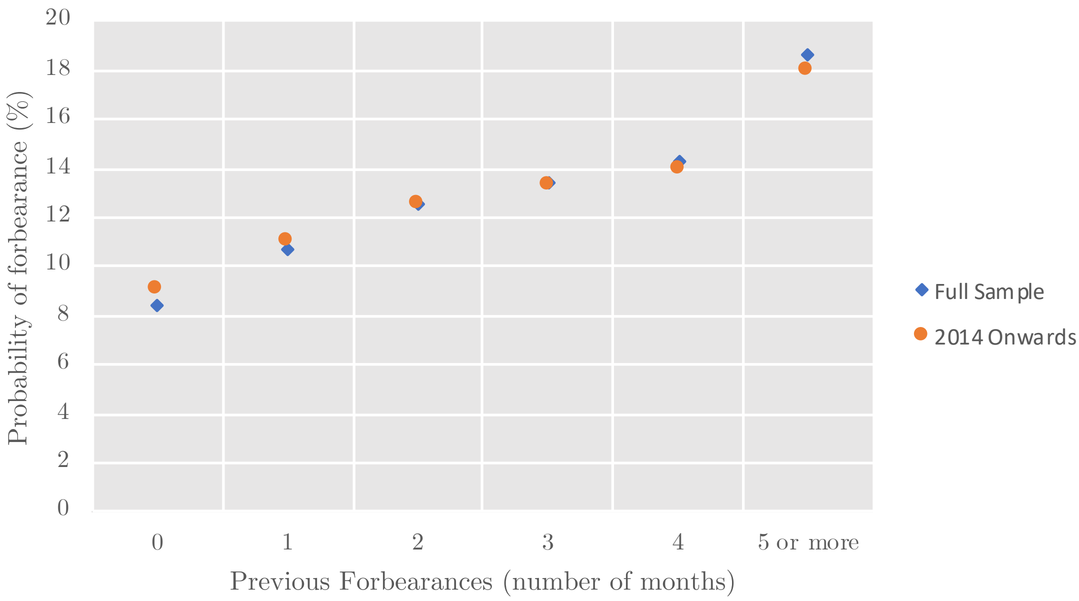


Figure 4 - Probability of forbearance by previous forbearances - Each point correspond to the percentage of loans that were forborne among all loans of firm-bank relationships with the same number of months with previous forbearances. As previous forbearances is underestimated in the first months of the sample, two series are presented. Blue points consider the full sample and orange points exclude loans with first month before the year of 2014.

2.3.4 Guarantee Type

Each loan may have more than one guarantee and banks have to inform the value and type for each one of them. We classify guarantees into three different categories: fiduciary lien, mortgage, and other. We choose to consider these categories because in case of bankruptcy these guarantee types present different levels of protection to creditors.

Under fiduciary lien, the creditor has the property of the collateral, which is therefore not shared among other creditors in case of bankruptcy. On a mortgage, the creditor has preference over the value of the collateral. Finally, for any other type of collateral, its value is divided among all creditors in case of default.

We assign each loan to only one guarantee type in the following way. First, each guarantee is classified into one of the categories above. Then we compute the sum of the value of the collaterals by category for each loan. Finally, the loan is assigned to the category with greater collateral value. Loans without any type of guarantees are assigned to the "other" category.

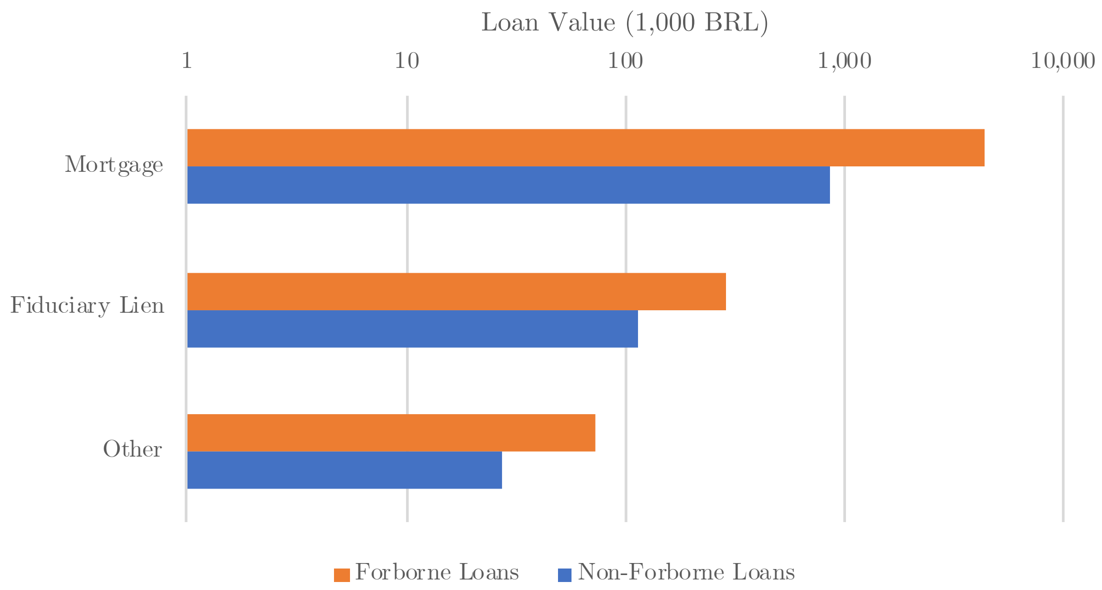


Figure 5 – Average loan value by guarantee type - The graph shows the average loan value by guarantee type and forborne status. Orange bars correspond to the mean value of forborne loans and blue bars to the mean value of non-forborne loans.

Only 6% of the non-accrual loans are collateralized by fiduciary lien, less than 1% has a mortgage as a collateral and 93% of loans have other type of guarantees.

Although one could expect the probability of forbearance to be decreasing with the level of protection of the collateral, the unconditional means do not show that. Mortgage backed loans are the ones that present the greatest percentage of forborne loans (13.0%), followed by loans with other guarantees (8.8%) and loans guaranteed by fiduciary lien (8.3%). This may be explained by the fact that mortgage backed loans are the ones with greatest average value as shown in Figure 5, whereas loans categorized under "other" types of collateral are the smallest on average.

In line with the idea that loans with greater values are more prone to be forborne, Figure 5 also shows that the loan value of forborne loans are greater than the loan value of non-forborne loans across all three types of guarantees. The effect of guarantee type on the probability of forbearance is better explored in a regression framework presented in the next section.

2.3.5 Existence of a Performing Loan

Banks inform to the SCR the credit rating for each loan on a monthly basis. Credit ratings are standardized into nine different categories, according to Resolution 2,682 of the National Monetary Council (CMN, 1999). This Resolution sets minimum boundaries, including the number of days past due, for a loan to be classified in each of the possible ratings as shown in Table 1. It also sets minimum provision percentages for each rating. For example, a loan that is between 61 and 90 days past due must be rated "D" or worse, and therefore the bank has to provision at least 10% of the value of the loan amount outstanding.

Table 1 - Maximum days past due and minimum provisions for each loan rating

Rating	Days Past Due	Minimum Provision
AA	- - -	- - -
A	- - -	0.5%
B	15 to 30	1%
C	31 to 60	3%
D	61 to 90	10%
E	91 to 120	30%
F	121 to 150	50%
G	151 to 180	70%
H	more than 180	100%

Resolution 2,682 also determines that any loan granted to a firm must be rated according to the riskiest loan of that firm with the bank, with a few exceptions. Therefore, if a firm has a non-delinquent loan and a loan that is 70 days past due with the same bank, then the non-delinquent loan cannot be rated better than D.

This rule has a direct impact on provisioning, since the bank must make provisions (as a percentage of loan value), for all loans to a given firm, according to the riskiest loan to that firm. This regulatory feature creates an incentive for a bank to forbear a non-performing loan if the borrower has other performing loans, otherwise the bank is forced to increase the amount provisioned for the performing loans that the same firm may have with the bank.

To test the hypothesis that the probability of forbearance is also influenced by this regulatory rule, we create a dummy variable "has performing" for each non-accrual loan. It is set to one if the firm has at least one other loan that is performing during the first six months that the referring loan appears in the dataset or zero otherwise. We choose the six months period because, as discussed earlier, more than 90% of forbearances happen within this number of periods after the loan becomes non-accrual.

Approximately 55% of non-accrual loans have this variable set to one (meaning that more than half of the loans that become non-accrual are to firms that also have a performing loan with the same bank). Among the loans to firms that have other performing loans, 8.2% are forborne, while 9.5% of loans to firms that do not have other performing loans are forborne.

This result is apparently inconsistent with the hypothesis that banks forbear loans to avoid increasing loan loss provisions. Once again, this result may be driven by the fact that the loan value is larger for the group of loans without other performing loans (average of 51 thousand BRL) than for the other group (average of 32 thousand BRL). We further explore this hypothesis in our regression analysis.

The remainder of the variables described in this section are used as control variables in our regressions.

2.3.6 Loan Modality

We use the term "loan modality" to describe the type of operation being financed with the loan. Financial institutions have to inform a modality (chosen from a comprehensive list of available options provided by the Central Bank of Brazil) for each loan. This study groups the loan modalities into the following categories: working capital, loans on receivables, investment, foreign trade financing, real estate, infrastructure/project finance, rural and agroindustrial, and others.

Almost 90% of non-accrual loans are classified into three modalities: working capital, other, and loans on receivables, with respectively 36%, 33%, and 19% of the loans. Unsurprisingly, loans in these three modalities have smaller average values, as shown in Figure 6.

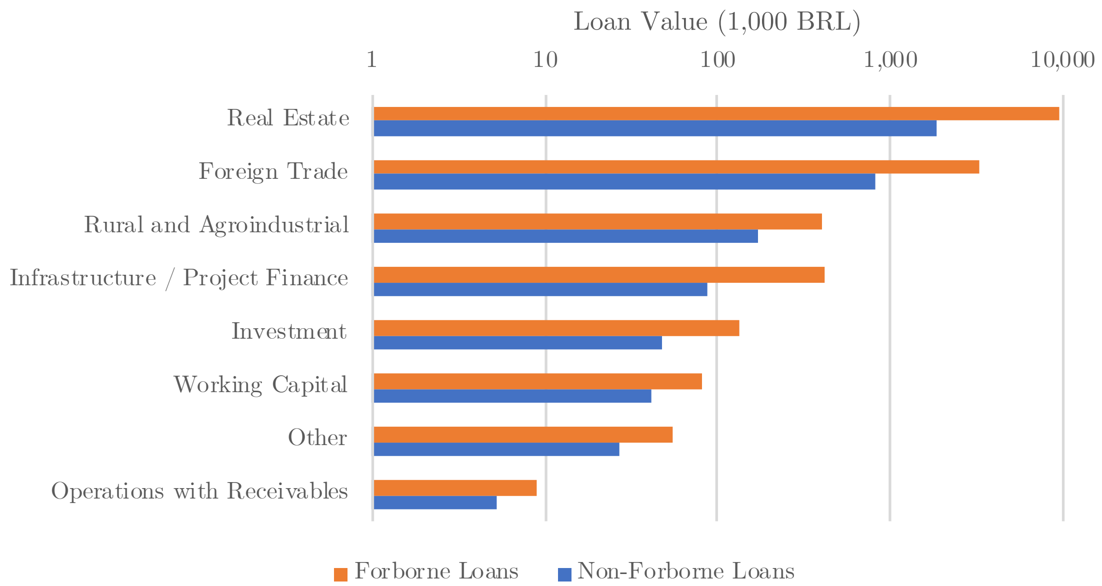


Figure 6 – Average loan value by modality - The graph shows the mean loan value by modality and forborne status. The orange bars correspond to the mean value of forborne loans and the blue bars to the mean value of non-forborne loans.

Figure 6 depicts the mean loan value of forborne loans (orange bars) and non-forborne loans (blue bars) by loan modality. The mean value of forborne loans is greater than the mean value of non-forborne loans for every modality. This reinforces the importance of loan value to the probability of forbearance discussed above.

2.3.7 Risk Category

Risk categories represent the credit risk ratings given by banks to each loan as described in Table 1.

To consider the risk category on the evaluation of the probability of forbearance, we use the loan rating at the first month in which the loan became non-accrual. As we explain above, non-accrual loans (past due over 60 days) must be rated "D" or worse, except for a few cases. That is why there are less than 1.5% of loans classified between AA and C. The other loans are distributed between risks D and H with approximately 43.2% (rating equal to D), 20.4% (E), 9.4% (F), 7.1% (G), and 18.4% (H) respectively.

2.3.8 Loan Currency

Loan currency is a dummy indicating if the loan is denominated in a foreign currency. There are only 15.3 thousand non-accrual loans in foreign currency in the sample (slightly over 1 % of the observations), of which 1.1 thousand (or 7.2% of them) are forborne at some point in time.

2.3.9 Loan maturity

Loan maturity is computed as the natural logarithm of the difference in days between the contract date and the loan due date.

2.3.10 Value Past Due

We compute this variable as the value past due divided by the value of the loan in the first month it becomes non-accrual.

2.3.11 Firm Size

Firm size is defined based on its number of employees, following the recommendation of the Commission of the European Community (2003). According to the recommendation, small firms have fewer than 50 employees, medium-sized firms have between 50 and 249 employees, and large firms have 250 or more employees.

The number of employees comes from a database called RAIS (the Portuguese acronym to Annual Report of Social Information maintained by the Ministry of Labor). As the RAIS has annual frequency and the SCR has monthly data, the number of employees is considered to be static over each year and equal to the reported value at the end of the previous year.

Firm size is then determined for each year considering the most recent information available for that year. Firms that do not have any information on RAIS are classified as small firms. Finally, when building the final sample (one observation per loan), we consider the firm size as the size in the first month that the loan appeared in the dataset. Almost 98% of loans of the sample are made to small firms, 1.4% to medium firms and less than 1% to large firms.

2.3.12 Firm type of control

Banks also report the firm's type of control to SCR. The sample includes both private and government controlled firms. In addition, the government controlled firms are distinguished between federal, state and local government. Almost all loans (more than 99.9% of loans) in the sample are granted to private firms.

2.3.13 Industry Sector

The industry classification code in the SCR dataset is used to classify the borrowers into groups of economic activity. The two-digit CNAE codes are aggregated resulting in 21 categories (letters A to U), following the classification of the Brazilian Institute for Geography and Statistics (IBGE). The full list of the categories and corresponding two-digit CNAE codes are presented in Appendix A. Categories related to financial services, public administration, and international organizations (K, O and U respectively) are excluded from the sample, following Schiozer and Oliveira (2016).

The sample has loans to all industry sectors, being the retail category (G) the most representative with approximately 50% of all the loans, followed by the processing industry (C) with 15% of the loans.

2.3.14 Firm-bank Relationship

Banks inform SCR the date of their first relation with each firm. With this date, we compute the length of relationship (in days) of the first month each loan appears in the dataset. The contract date and the days past due variables are also informed by banks for every loan and are used to exclude inconsistencies of dates among data. The natural logarithm of the number of days of relationship is used as a control variable.

2.3.15 Bank Controllership

Bank controllership is divided into domestic private, foreign private and governmental.

2.3.16 Bank Segment

Financial institutions are categorized into four segments, according to the classification of the Central Bank of Brazil: banks (groups all types of banks, except for development banks), development banks, credit unions, and non-banking credit institutions. Almost 95% of loans in the sample are granted by banks (136 institutions among bank and development banks).

3 Empirical Methods

Our preliminary univariate analysis of the main variables suggests that given a loan past due over sixty days its probability of forbearance is positively correlated with the value of the loan and negatively correlated with the number of periods.

In this section, we present a regression framework to confirm the univariate results and to test our three main claims, that the probability of forbearance is also affected by: i) the type of guarantee that secures the loan; ii) the occurrence of previous forbearances at the bank-firm pair and; iii) the existence of performing loans of the firm with the bank.

Equation 1 presents the basic form of the model to be estimated:

$$\begin{aligned} Forborne_{i,j,k} &= \alpha + \beta_1 Has\ Performing_{i,j,k} + \Lambda'\ Guarantee\ Type_{i,j,k} \\ &+ \beta_3 Previous\ Forbearances_{j,k} + \beta_4 \log\left(Number\ of\ Periods_{i,j,k}\right) \\ &+ \beta_5 \log\left(Loan\ Value_{i,j,k} + 1\right) + \Gamma' X_{i,j,k} + \varepsilon_{i,j,k} \qquad (1) \end{aligned}$$

where the subscripts i, j and k refer to loan i granted to firm j by bank k. The dependent variable, *Forborne*, is a dummy variable indicating whether the non-accrual loan has been forborne (at any point in time). The covariates are defined in detail in the previous section. *Has Performing* indicates the existence of a performing loan in the bank-firm pair, *Guarantee type* is a series of dummies for the three guarantee types (lien, mortgage and other), *Previous Forbearances* is the number of months in which bank k has forborne a loan of firm j, *Number of Periods* is the number of months between the loan became non-accrual and that the loan leaves the dataset, and *Loan Value* is the loan amount outstanding. To deal with the right-tail asymmetry of *Loan Value* and *Number of Periods*, we use their natural logarithms. We also add 1 BRL to *Loan Value* before applying the natural logarithm to avoid values between zero and one (BRL cents). X is a set of control variables (as described in the previous section) and ε is the error term.

We run five different specifications of the main model. The basic one with the full set of controls, and four others with incremental fixed effects. Month fixed effects capture any unobserved heterogeneity that affects equally the group of loans that become non-accrual for the first time during the same month. These include any source of macroeconomic or regulatory variation that impacts the probability of forbearance homogeneously across loans.

Municipality fixed effect is added to account for differences on the probability of forbearance between distinct municipalities. One can think, for example, that firms and banks in municipalities with poor economic conditions may behave differently (in respect to negotiation on forbearance terms) that firms and bank in more developed cities.

Bank fixed effects account for differences on the probability of forbearance across distinct banks. These can be thought of differences in forbearance policies among banks. In the model with bank fixed effects, bank characteristics are dropped from the list of covariates to avoid multicollinearity issues.

Finally, we use fixed effects for, municipality-month, industry-month, and bank-month interactions. These fixed effects capture the impact of any economic condition on a specific municipality or industry for each month, and any bank specific behavior for each month.

All models are estimated using ordinary least squares (OLS) regression with robust standard errors clustered at the bank level. Clustering at the bank level is very conservative, as approximately 87% of loans from the sample are granted by only 5 of banks (although there are more than 1,000 banks in the sample).

We choose to estimate equation 1 using a linear probability model (instead of nonlinear models such as Logit or Probit) because, as noted by Angrist and Pischke (2009, p. 68), linear probability models require less identifying assumptions and are better suited to the inclusion of several levels of fixed effects.

4 Regression Results

4.1 Main Models

The results of the estimations of several variations of equation 1 are presented in Table 2. The estimates for the coefficient of *has performing* are practically the same across all models. They indicate that if the non-accrual loan is given to a firm that also has a performing loan with the same bank, its probability of forbearance increases by approximately 1.0 percentage point (compared to the case in which the firm does not have a performing loan with the bank), controlling for other features. These coefficients are significant at 5% or less, depending on the specification. We argue that this result may indicate that the regulatory rules on provisioning give an incentive for banks to forbear loans, even when firm does not have the capacity to honor the new terms of the restructured loan. As discussed earlier, this behavior may pose risks to financial stability (Basel Comimittee on Banking Supervision, 2017) if widespread in the banking system.

However, an alternative interpretation for the result cannot be ruled out. It is possible that the existence of another loan, not in arrears, to the same firm provides an indication that the firm has preserved at least some financial capacity to maintain one of the loans in good standing.

Coefficients for the guarantee type dummies show the impact in percentage points of having a *mortgage* as a collateral or having *other guarantees* compared with having a *fiduciary lien* (omitted dummy) as a collateral. In all the models, the point-estimates for the *mortgage* coefficient is positive and they do not vary much across specifications. However, only in models (4) and (5) they are statistically significant[6]. The coefficient in column 5 indicates that the probability of

[6] This is probably because, when treating all banks together, the mortgage collateral is not "important enough" to change the mean probability of forbearance, but when we look at banks that use mortgage more often, the difference in probability of forbearance is significantly different from loans with fiduciary lien. In fact, there are relatively few mortgage-backed loans on the dataset, but they are concentrated in a few banks. From all banks of the sample (1,064) more than 850 have less than 1% of loans with mortgage as a collateral.

forbearance is 3.6 percentage points larger for loans with mortgage type of collateral than for loans with fiduciary lien.

*Table 2 - OLS regression of the probability of forbearance. Column (1) is the basic model with all controls: loan controls (modality, risk category, currency, maturity, and value past due), firm controls (size, type of controllership, and industry sector), bank controls (type of controllership, and segment) and log of days of relationship. Columns (2) to (5) presents the same set of controls, and include fixed effects for month, month and municipality, month, municipality, and bank, and municipality-month, industry-month, and bank-month. Because of the bank and bank-month fixed effects, columns (4) and (5) does not include bank controls. All regressions are estimated with clustered errors at the bank level. Standard errors are shown in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.*

	Forborne Status				
	(1)	(2)	(3)	(4)	(5)
Has Performing Loan	0.0100 **	0.0111 ***	0.0113 ***	0.0104 **	0.0102 **
	(0.0040)	(0.0040)	(0.0038)	(0.0047)	(0.0044)
Guarantee Type					
Lien	-	-	-	-	-
	-	-	-	-	-
Mortgage	0.0292	0.0312	0.0301	0.0367 **	0.0362 **
	(0.0206)	(0.0206)	(0.0206)	(0.0147)	(0.0165)
Other	0.0483 ***	0.0497 ***	0.0491 ***	0.0385 ***	0.0360 ***
	(0.0131)	(0.0133)	(0.0129)	(0.0121)	(0.0114)
Prev. Forb. (# Months)	0.0150 ***	0.0130 **	0.0118 **	0.0083 *	0.0084 *
	(0.0050)	(0.0052)	(0.0051)	(0.0043)	(0.0044)
Ln(Number of Periods)	-0.0832 ***	-0.0849 ***	-0.0845 ***	-0.0839 ***	-0.0858 ***
	(0.0075)	(0.0080)	(0.0081)	(0.0082)	(0.0090)
Ln(Loan Value + 1)	0.0164 ***	0.0161 ***	0.0162 ***	0.0164 ***	0.0166 ***
	(0.0029)	(0.0030)	(0.0030)	(0.0035)	(0.0035)
Month FE	No	Yes	Yes	Yes	No
Municipality FE	No	No	Yes	Yes	No
Bank FE	No	No	No	Yes	No
Bank-Month FE	No	No	No	No	Yes
Industry-Month FE	No	No	No	No	Yes
Municipality-Month FE	No	No	No	No	Yes
Error Clustering	Bank	Bank	Bank	Bank	Bank
Observations	12,839,721	12,839,721	12,839,717	12,839,680	12,776,251
Adj. R-Sq	0.1005	0.1039	0.1072	0.1143	0.1538
Adj. Within R-Sq	0.1005	0.1001	0.0988	0.0851	0.0852

The estimates for *other* types of guarantees are also positive and statistically significant. Taking the estimates of our preferred specification (column 5), we infer that loans with other types of collateral (or no collateral) are also 3.6 percentage points more prone to be forborne than loans with fiduciary lien, controlling for other features. The point-estimates of the coefficient of *other guarantees* and of the coefficient of *mortgage* in columns (4) and (5) are not statistically different from each other at a 5% significance level. Therefore, the probabilities of forbearance of mortgage-backed loans and loans with other types of guarantees are not statistically different from each other.

We argue that loans under fiduciary lien have a smaller probability of forbearance because, as they allow the banks to seize collateral more easily, banks do not have to ease the loan conditions as much as loans with mortgage or other types of guarantees. This is consistent with the literature on the effects of collateral (Vig (2013); Assunção, Benmelech, and Silva (2014); Campello and Larrain (2016)) that shows that the ability to pledge and seize collateral increases creditors rights.

Our contribution in this is area is to show that the easiness in repossession, besides having effects on new contracts (expanding credit), also affects how much banks restructure existing contracts.

Estimates for the impact of *previous forbearance* is positive and relatively stable across all specifications (1) to (5). These estimates confirm the results shown in our univariate analysis. Considering the estimates of model (5), each previous occurrence of forbearance (each previous months with forborne loans) increases the probability of forbearance by 0.84 percentage points, controlling for other features. As discussed earlier, this behavior may suggest the practice of "zombie lending" or "evergreening", that is, the practice of successive "bad" forbearances, particularly by extending more credit to an impaired borrower.

The OLS results also confirm the univariate results about loan value and time to forbearance. Both results are consistent among models. The negative estimates of the coefficient of number of periods shows that the probability of forbearance decreases by approximately 0.86 percentage points for each 10% increase in the number of months in which it is not forborne or paid back, consistent with our previous evidence that forbearance is usually made in the first months of non-accrual status. Concerning loan values, estimates of the coefficient show that, the greater the value of the loan, the greater the probability of forbearance. In other words, results indicate that forbearance is usually made in loans with higher values and in a few months after they become non-accrual.

Although the estimates of the coefficients of *has performing*, *mortgage*, and *previous forbearances* are significant at 1.9%, 2.9%, and 5.4% respectively, in unreported results of specification (5) with robust errors clustered by firm or clustered by loan shows that all coefficients for the main variables are significant at 0.1%.

4.2 Robustness Tests

One could argue that the definition used to build the variable *has performing* (six months after the loan becomes non-accrual) is rather arbitrary. To check the robustness of our results, we re-build the same variable considering alternative periods of three months and one month after the loan becomes non-accrual. The results using these alternative definitions (for the specification with the municipality-month, industry-month, and bank-month fixed effects) are reported in columns (2) and (3) of Table 3.

Although there is a decrease in statistical significance from models (1) to (3), the estimates of different measures of *Has Performing Loans* has the same sign and slightly diminishing values, varying from 1.0 to 0.6 percentage points. Considering that the errors are clustered at the bank level (which is conservative), we argue that the result is robust to different definitions of the variable. The estimates of all other variables of interest do not change materially across models (1) to (3).

*Table 3 - OLS regression of the probability of forbearance. Column (1) is the basic model with loan controls (modality, risk category, currency, maturity, and value past due), firm controls (size, type of controllership, and industry sector), log of days of relationship, and fixed effects for municipality-month, industry-month, and bank-month. Columns (2) and (3) presents the same set of controls and fixed effects, but different measures for Has Performing Loans. All regressions are estimated with clustered errors at the bank level. Standard errors are shown in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.*

	Forborne Status		
	(1)	(2)	(3)
Has Performing Loan 6M	0.0102 **		
	(0.0044)		
Has Performing Loan 3M		0.0094 **	
		(0.0047)	
Has Performing Loan 1M			0.0060
			(0.0052)
Guarantee Type			
Lien	-	-	-
	-	-	-
Mortgage	0.0362 **	0.0362 **	0.0362 **
	(0.0165)	(0.0165)	(0.0165)
Other	0.0360 ***	0.0360 ***	0.0360 ***
	(0.0114)	(0.0114)	(0.0114)
Prev. Forb. (# Months)	0.0084 *	0.0084 *	0.0084 *
	(0.0044)	(0.0044)	(0.0043)
Ln(Number of Periods)	-0.0858 ***	-0.0857 ***	-0.0856 ***
	(0.0090)	(0.0090)	(0.0091)
Ln(Loan Value + 1)	0.0166 ***	0.0166 ***	0.0166 ***
	(0.0035)	(0.0036)	(0.0036)
Bank-Month FE	Yes	Yes	Yes
Industry-Month FE	Yes	Yes	Yes
Municipality-Month FE	Yes	Yes	Yes
Error Clustering	Bank	Bank	Bank
Observations	12,776,251	12,776,251	12,776,251
Adj. R-Sq	0.1538	0.1538	0.1537
Adj. Within R-Sq	0.0852	0.0852	0.0851

One can say that the decision to forbear loans to state-owned firms or granted by development banks may face political pressure. If these firms take particular types of loans that are correlated to the probability of forbearance, then our results could be mostly driven by such pressures. To further check if the results are not biased or driven by these loans, we run a regression excluding loans made by development banks and loans taken by governmental firms from the sample. Results are shown in column 2 of Table 4.

*Table 4 - OLS regression of the probability of forbearance. Column (1) is the basic model with loan controls (modality, risk category, currency, maturity, and value past due), firm controls (size, type of controllership, and industry sector), log of days of relationship, and fixed effects for municipality-month, industry-month, and bank-month. Column (2) presents the same set of controls and fixed effects, but observations on loans to state-owned firms or granted by development banks were excluded. All regressions are estimated with clustered errors at the bank level. Standard errors are shown in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.*

	Forborne Status		
	(1)	(2)	(3)
Has Performing Loan 6M	0.0102 **	0.0102 **	0.0112 **
	(0.0044)	(0.0044)	(0.0045)
Guarantee Type			
Lien	-	-	-
	-	-	-
Mortgage	0.0362 **	0.0351 **	0.0372 **
	(0.0165)	(0.0172)	(0.0164)
Other	0.0360 ***	0.0360 ***	0.0344 ***
	(0.0114)	(0.0114)	(0.0110)
Prev. Forb. (# Months)	0.0084 *	0.0084 *	0.0080 **
	(0.0044)	(0.0044)	(0.0039)
Ln(Number of Periods)	-0.0858 ***	-0.0860 ***	-0.0870 ***
	(0.0090)	(0.0090)	(0.0093)
Ln(Loan Value)	0.0166 ***	0.0166 ***	0.0158 ***
	(0.0035)	(0.0036)	(0.0034)
State-owned Firms and Development Banks	Yes	No	Yes
Exclude last 12 Months	No	No	Yes
Bank-Month FE	Yes	Yes	Yes
Industry-Month FE	Yes	Yes	Yes
Municipality-Month FE	Yes	Yes	Yes
Error Clustering	Bank	Bank	Bank
Observations	12,776,251	12,746,946	11,947,695
Adj. R-Sq	0.1538	0.1540	0.1526
Adj. Within R-Sq	0.0852	0.0854	0.0877

Another possible concern is a selection bias on the loans that entered into the non-accrual status in the last months of the sample period, as one could argue that the forborne loans were more likely to enter the sample. This is because loans that were not forborne last longer than the sample period and were excluded. To test this hypothesis, we run a regression excluding all loans that entered into non-accrual status in the last twelve months of the sample. Results are reported on column (3) of Table 4.

The estimates of all variables across the three specifications of Table 4 remain almost unchanged relative to our baseline results. This shows that the results are not biased by the presence of loans to state-owned firms nor by development banks, and neither by a selection bias of forborne loans at the end of the sample period.

5 Conclusion

This work uses novel and rich microdata on loan forbearance that includes nearly all loans to non-financial firms in Brazil. To the best of our knowledge this is the first study on the topic to use a dataset that covers nearly all loans to firms in the banking system of any given country.

We analyze almost 13 million non-accrual loans (i.e. loans that are past due for more than 60 days), granted by more than a thousand banks for more than 2 million firms. The results show that loans with greater value are more prone to be forborne. In addition, the decision to forbear a loan is usually made quickly, as more than 80% of forbearances occur in the first four months after a loan becomes non-accrual.

We also study the effect of different types of guarantees on forbearance. Results of the regression analysis tell us that the difficulty to seize and sell collateral creates incentives to forbear a loan. More specifically, the probability to forbear a loan with fiduciary lien (that present the least costly procedure for seizing the collateral) is 3.6 percentage points smaller than the probability to forbear a loan with mortgage or other types of collaterals, controlling for other features.

We also find that forbearance by a bank to a given firm is a recurrent phenomenon. Previous forbearances increase the probability of another forbearance. This may indicate the occurrence of successive "bad" forbearances (i.e., loan evergreening), that, in an economy with limited resources, causes misallocation of credit.

Finally, provisioning rules give an incentive for banks to forbear a loan if the firm has another loan in performing status with the same bank. When the bank holds more than one loan to a firm, it must constitute provision considering the risk category of the riskiest loan. According to our results, this seems to be a bad regulatory incentive for banks to forbear a loan even when the bank does not expect the new agreement to be fulfilled.

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Appendix A

This appendix has the full list of categories and corresponding two-digit CNAE codes considered in this work.

Category	Two-digit CNAE code	Description
A	01 - 03	Agriculture, Livestock, Forestry and Fishing
B	05 - 09	Mining
C	10 - 33	Processing Industry
D	35 - 35	Electric and Gas
E	36 - 39	Sanitary Services
F	41 - 43	Construction
G	45 - 47	Retail Trade
H	49 - 53	Transportation, Warehousing and Delivery
I	55 - 56	Lodging and Food
J	58 - 63	Communications
K	64 - 66	Financial Services, Insurance
L	68 - 68	Real Estate
M	69 - 75	Professional, Scientific and Technical Activities
N	77 - 82	Administrative Activities and Complementary Services
O	84 - 84	Public Administrations, Defense, Social Security
P	85 - 85	Education
Q	86 - 88	Human Health and Social Services
R	90 - 93	Arts, Culture, Sports and Recreation
S	94 - 96	Other Services
T	97 - 97	Domestic Services
U	99 - 99	International Organizations