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Non-technical Summary

Financial institutions must be careful of expected losses in their credit portfolio. They should develop a methodology for estimating the percentage p of a loan of value X that will not be paid back, given some debtor's and operation's characteristics. The main purpose is to constitute a provision of value pX so that the default on this credit operation does not bring major negative impact on the financial institution's capital.

When it comes to debtors with more than one credit type (for instance, real estate finance and credit card), an important question arises when they become defaulted on one of these categories. While some approaches advocate that such an event will not affect the default risk of the overall non-past due credit types, others sustain the opposite view, considering that there is a "risk contagion" among different credit types. In this latter vein, it is possible, for instance, that a debtor borrows a personal loan in order to pay real estate financing in arrears, avoiding foreclosure, but becoming delinquent in personal credit.

Notwithstanding, to our knowledge there is no empirical study supporting either of these approaches. The purpose of this article is to fill this gap. Relying on two micro data sources (SCR and RAIS) and studying six credit types (payroll-deducted personal loans, non-payroll-deducted personal credit, overdraft, credit card, vehicle financing, and real estate financing), we assess the impact of defaulting on one given type of credit on future default on other credit types.

Our conclusion is that risk contagion among different credit types is significant in Brazil. Financing credit types (vehicle and real estate financing) are those whose default brings more risk to the other credit types: defaulting debtors will resort to other credit types in order to avoid the loss of the financed good. Moreover, riskier credit types (overdraft, non-payroll-deducted personal credit, and credit card) are more affected by defaults on other categories, which is explained by the fact that defaulting individuals have limited access to less risky credit types (such as payroll-deducted loan).

Sumário Não Técnico

As instituições financeiras devem se precaver contra perdas futuras esperadas em suas carteiras de crédito. Elas devem desenvolver uma metodologia para estimar qual a porcentagem p de um empréstimo realizado de valor X não será paga de volta, dadas as características do devedor e da própria operação. O propósito principal é realizar uma provisão de valor próximo a pX, de modo que o advento da inadimplência não traga maiores danos ao patrimônio da instituição financeira.

Em se tratando de clientes com empréstimos em mais de uma modalidade (p. ex., financiamento imobiliário e cartão de crédito), uma questão importante emerge quando o cliente começa a atrasar seus pagamentos em relação a uma dessas modalidades. Enquanto algumas abordagens advogam que isso não aumenta o risco de inadimplência das modalidades que ainda estão em dia, outras defendem o contrário, considerando que há um "contágio de risco" entre diferentes modalidades de crédito. Dentro dessa segunda visão, é possível, por exemplo, que um cliente contraia um crédito pessoal para pagar suas parcelas em atraso em seu financiamento imobiliário para evitar a perda de seu imóvel, vindo a inadimplir porém no crédito pessoal.

Não há, no entanto, dentro do nosso conhecimento nenhum estudo empírico que corrobore alguma dessas visões. O objetivo deste estudo é preencher esta lacuna. Usando micro dados do SCR e do RAIS e trabalhando com seis modalidade de crédito (consignado, não-consignado, veículos, imobiliário, cartão de crédito e cheque especial), estimamos o impacto da inadimplência atual de uma dada modalidade de crédito na inadimplência futura das demais.

Nossa conclusão é que o contágio do risco de crédito é significativo no Brasil. As modalidades de financiamento (veículos e imobiliário) são aquelas cuja inadimplência mais traz risco às outras modalidades: clientes inadimplentes nas mesmas recorrerão a outros empréstimos para evitar a perda do bem financiado. Por outro lado, as modalidades de maior risco (não-consignado, cartão de crédito e cheque especial) são as mais afetadas pelo atraso em outras modalidades, já que clientes inadimplentes têm acesso limitado a modalidades de crédito de menor risco (como o consignado).

Default Contagion among Credit Types: evidence from Brazilian data

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Abstract

The aim of this paper is to assess the impact of defaulting on one personal credit type on future default on other types of loan. Using Brazilian micro data, we run a logistic regression to estimate the probability of default on a given credit type, by including personal overdue exposure in the other debt types among the explanatory variables. Our results show that this effect is positive and significant, although quantitatively heterogeneous. We also discuss the rationale behind these results. Specifically, it was found that financing credit types (vehicle and real estate financing) contaminate the other credit types more, as defaulting may cause the debtor to lose the financed good. Moreover, riskier loan types (overdraft, non-payroll-deducted personal credit, and credit card) are more contaminated by defaults on other credit types, which is explained by the fact that defaulting individuals have limited access to less risky debt types.

Keywords: Credit default contagion, debtor approach, transaction approach, Brazilian credit market
JEL Classification: C58; G17; G28

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1. Introduction

One branch of the literature on default behavior is devoted to studying the pecking order of default. It considers the case of debtors holding multiple types of debts whose payment ability has been negatively affected and so they can service some but not all their obligations. The concern is with identifying the priorities of defaulting on these debt obligations; that is, the credit types that the debtor will choose to default on.

The seminal studies on "selective default" (Grieb et al 2001; Agarwal and Liu 2003) report that, when they experience difficulty making payments (after, for instance, losing their job), individuals choose to default on credit card loans before defaulting on other credit types. The recent crisis in the U.S. real estate market has aroused interest in assessing the choice between defaulting on mortgage loans or on some other loan type (usually, credit card). Andersson et al (2013) found an important change in priority of defaulting for nonprime borrowers holding both a mortgage and at least one credit card. The probability of default on a credit card was eight times greater than that on mortgage debt but, at the end of 2008, they became virtually equal. Some authors (Guiso et al 2009; Bhutta et al 2010; Elul et al 2010) point out that this change in the pecking order of default is due to the bursting of the U.S. real estate bubble. It caused a decline in house prices, creating more incentives for mortgage delinquency. It is important to stress that, even when making monthly mortgage payments is still an option, some debtors may rationally choose not to pay their mortgage obligations because their home values have become significantly lower than their mortgage debts, giving rise to so-called "strategic default".

Other studies argue that the willingness to preserve liquidity is also an important driver in the pecking order of default. According to this view, debtors may prioritize the monthly payment of debt obligations related to sources of liquidity (e.g., credit card or home equity lines of credit), to the detriment of other types of debt (e.g., mortgage debt), in order to maintain their access to credit for consumption. Cohen-Colen and Morse (2010) found that debtors are more likely to keep their credit card account current than honor their mortgage debt commitments due to liquidity concerns. Assessing two types of mortgage debt (home equity loan and home equity lines of credit), Jagtiani and Lang (2011) concluded that debtors are more likely to default on the former as they try to maintain their liquidity.

The above-mentioned studies have assessed the *unconditional* priority of defaulting. It was not appraised how the pecking order of default is affected by the previous occurrence of delinquency on some credit type. Our goal is to go one step ahead in this discussion by asking the following questions, not addressed so far: what is the probable sequence of default *given that default has already occurred on a specific credit type*? Is the "original" priority of defaulting affected by delinquency in a given type of loan? More specifically, we ask if there is some degree of default contagion among credit types, understood as the effect of defaulting on one loan type on delinquency with regards to other debt obligations.

The purpose of this paper is to answer these questions. Relying on two Brazilian datasets (the Banco Central do Brasil's Credit Risk Bureau System and the Annual Social Information Survey, which we will explain later), we assess the impact of defaulting on one credit type on future default on other debt types. We study six personal types of loan, chosen for their relevance in the Brazilian credit market: payroll-deducted personal loans, non-payroll-deducted personal credit, overdraft, credit card, vehicle financing, and real estate financing.

Beside this empirical contribution, we also hope to shed some light on an important practical issue. There is an ongoing discussion on how different loans to the same debtor should be categorized for the purposes of regulatory requirements, credit risk management, and accounting reports. According to the so-called "debtor approach", if the debtor has a single material exposure categorized as non-performing, defaulted, or credit impaired, all the other transactions of the same debtor should be assigned to the same category. If the "transaction approach" is used instead, any single exposure is categorized regardless of the status of the other loans to the debtor.

Financial regulators outline criteria for applying one approach or another. According to the Basel Committee on Banking Supervision (BCBS), the categorization of credit exposures as performing or non-performing should be based on the "transaction approach" for retail portfolios and the "debtor approach" for non-retail portfolios (BCBS 2016). Other institutions define more quantitative thresholds. For instance, the European Banking Authority (EBA) establishes the following: "When a debtor has exposures past due more than 90 days representing 20% of all its exposures, or when the past-due amounts for this debtor represent 5% of its total exposures, all on- and off-balance sheet exposures to this debtor shall be considered as non-performing" (EBA 2013: 13).

Each approach implicitly makes different assumptions regarding the risk contagion among credit types. While the debtor approach assumes that default on a single exposure will eventually make the debtor's other loans become non-performing as well, the individual transaction approach hypothesizes that such contagion is weak or inexistent. Notwithstanding, as far as we know, there is no empirical study supporting either of these approaches.

Finally, this study is also related to the literature on credit risk modeling. A wide range of models have been developed aiming to estimate the probability of default in credit transactions. Logistic regression has been the technique traditionally employed for this task (Thomas et al 2002; Nguyen 2015), but survival analysis models have been gaining space more recently (e.g., Bellotti and Crook 2009, 2014; Tong et al 2012). They have been applied to different specific credit types, such as credit card loans (Leow and Crook 2016), personal loans (Stepanova and Thomas 2002), and auto loans (Nguyen 2015). For the Brazilian case, Correa et al (2014) used micro data to study consumer credit default and car loan default, with particular emphasis on the influence of business cycles. The explanatory variables used in these studies include borrower-related variables such as age, gender, and income; transaction-related variables (e.g., operation rating); and macroeconomic indicators, such as inflation and unemployment rate. Notwithstanding, the impact of default on other credit types has not yet been analyzed, which we are going to do in this study.

Beside this introduction, this paper has four more sections. The next section provides an overview of the Brazilian credit market. Section 3 describes the methodology and the dataset. The fourth section presents the results. The last section features our concluding remarks.

2. The Brazilian credit market

The total Brazilian credit stock reached BRL 3.2 billion in December 2015, an amount 6.7% higher than that of December 2014 (Table 1)[1]. It corresponded to 54.5% of

[1] All the tables of this paper are presented in the Annex.

Brazilian GDP, against 53.1% in December 2014. Almost half of this amount came from earmarked resources – i.e., those covered by government earmarking regulation. Non-financial corporations had a slightly higher share of total credit. The main credit types granted to non-financial corporations are BNDES[2] funds (earmarked resources) and working capital (non-earmarked resources). Personal loans are granted mainly as real estate financing, personal credit – most of which is payroll-deducted – and credit card. More than half of Brazilian credit came from state-owned financial institutions.

There was a general worsening in the ratio of non-performing loans (NPL)[3] between December 2014 and December 2015, reflecting the downturn of the Brazilian economy during this period. The total NPL ratio jumped from 2.7% to 3.4%. Although still smaller, the NPL ratio of earmarked resources granted to non-financial corporations suffered the highest proportional increase. Among the main types of credit, the only one in which a decrease in the NPL ratio was observed was in payroll-deducted personal credit. NPLs are more severe in the domestic private sector. NPL growth was more modest among foreign private financial institutions and greater in the state-owned financial institutions, despite the latter presenting the smallest NPL ratio.

3. Methodology and dataset

We examine two data sets in this study: the Central Bank of Brazil's Credit Risk Bureau System (SCR) and the Annual Social Information Survey (RAIS). SCR is a very thorough data set which records every single credit operation within the Brazilian financial system worth BRL 200 or more.[4] It provides data on each operation such as financial institution and debtor identification, amount, type of loan, interest rate, and risk classification. RAIS is managed by the Brazilian Ministry of Labor and contains information about formal sector employees, as well as their employers. Worker information includes earnings, gender, age, and occupation.

As a first step, we generated a random uniform sample of debtors over 18 years old from the SCR data set. This sample contains 299,369 debtors, about 0.5% of the SCR

[2] National Bank of Social and Economic Development, the main Brazilian development bank.
[3] For the purpose of this study, loans past due more than 90 days are considered as non-performing loans (NPL).
[4] As we will specify later, we assessed data from December 2012, December 2013, and December 2014, when this lower limit was BRL 1,000.

total. For these debtors in the SCR dataset, we then collected their exposures (total and overdue) in the six credit types we are assessing. Before proceeding, it is important to stress two points: i) all exposures refer to debt stock and ii) by overdue exposure we mean, throughout this paper, exposures past due more than 90 days greater than a materiality threshold of BRL 100.

Secondly, we used the RAIS dataset in order to obtain, for our sample debtors, all information available that can be useful for predicting their likelihood of credit default: age, gender, income level, geographic region, employment status, and occupation. We assessed data from December 2012, December 2013, and December 2014. The list of explanatory variables is presented in Table 3.

Finally, we checked the future exposures of these debtors in the SCR in order to construct the dependent variable $y_{i,t,m}$, in which t is equal to December 2012, December 2013, and December 2014. It assumes the value 1 if debtor i had a positive overdue exposure in credit type m in at least one month between $t+1$ and $t+12$, and zero otherwise.[5] For instance, when t = December 2012, we measured debtors' exposures between January and December 2013. Notice that each debtor has six values of $y_{i,t,m}$, one for each credit type. If the debtor disappeared from the SCR dataset (i.e., if they no longer had any credit exposure) before $t+12$, we assigned the value to $y_{i,t,m}$ considering this narrower time period. If they had no overdue exposures within this period, we assumed they paid all their debt obligations and assigned the value zero to $y_{i,t,m}$.

In Table 4, we present some sample statistics. Nearly half of the individuals in our sample are men and most of them earn less than three minimum wages and live in the Southeast Region. The most widespread loan type is the payroll-deducted personal loan (almost 40% of debtors with exposures in this type of credit), while 10% were granted real estate financing. More than 6% of debtors in the sample have overdue exposure in credit card loans; for real estate financing, this ratio is 0.2%.

Most of the debtors in our sample, almost 80%, have exposure in one or two credit types, while around 2.5% have exposures in five or more loan types. Considering only those who have overdue exposures, nearly 70% have overdue exposure in just one debt

[5] We adopted the time horizon commonly used to assess credit default (Jarrow and Turnbull 2000). We performed tests using other time horizon values, obtaining very similar results.

type (Table 5). There is a significant overlap between some types of credit, as can be seen in Table 6. For instance, more than 64% of the debtors in our sample with non-payroll deducted loans also have exposure in overdraft.

Table 7 shows the fraction of debtors without overdue exposures in a given credit type at *t* that default on this loan type between *t+1* and *t+12*, according to their exposures in the other credit types. Consider, for instance, the debtors with exposures in real estate finance and credit card at *t*, but without overdue exposures in the latter type. More than 32% of the debtors with overdue exposures in real estate financing default on credit card within the following 12 months, while this ratio is 18% for those without overdue exposures in real estate financing. In general, debtors with overdue exposures in a given credit type proved to be more prone to defaulting on the other loan types. Moreover, if the debtor defaulted on a given loan type within this timeframe, it happened faster (i.e., with a smaller average time of first default) if they had overdue exposure in another credit type (Table 8).

4. Results

4.1. General results

For each credit type *m*, we ran the following regression:

$$y_{i,t,m} = \beta X_{i,t,m} + \varepsilon_{i,t,m} \qquad (1).$$

In the equation above, $X_{i,t}$ is the vector of the variables listed in Table 3, β is the vector of parameters, and $\varepsilon_{i,t,m}$ is the usual error term. We only included the debtors that held not-overdue exposures in credit type *m* at *t*. The explanatory variables concerning credit exposure and default (the last three groups of variables in Table 3) relative to loan type *m* are obviously excluded from the regression. We also excluded the debtors that did not appear in any of the subsequent twelve months. This fraction is never above 4%, as can be seen in Table 9.

The results are presented in Table 10. Some of the results correspond to what is intuitively expected. Employed individuals (especially those in the private and public sector) and individuals in higher income brackets present a smaller propensity to default.

We also corroborate some findings from other studies. For instance, as in Correa et al (2014), we find that women and older borrowers have a lower probability of default. In most cases, the influence of having exposure in other debt types on future default is positive, but holding a high relative exposure in other credit types decreases the chance of default in a given type of debt. This is particularly observed when the dependent variable is default in the riskier credit types (non-payroll deducted loan, credit card, and overdraft). A greater relative exposure in overdraft raises the probability of default in the other credit types (except credit card loan), probably due to their high interest rate. The area under the ROC curve (AUC) ranges between 0.63 (payroll-deducted loans) and 0.75 (overdraft).

4.2. Risk contagion

As expected, there is risk contagion among different credit types. In most situations, the probability of a debtor having overdue exposure in a loan type is positively impacted by their current overdue exposures in other type of credit. In order to assess this impact properly, we estimated the marginal effects following the two approaches discussed in the literature: the average effect over all individual observations, the average marginal effects (hereafter abbreviated as AME), and the effect at mean values of independent variables, the marginal effects at the mean (MEM) (Long 1997). These results are presented in Tables 11 and 12, respectively. For the sake of summarization, in Table 13 we provide the in- and out-degree of contagion, which are, respectively, the column and row mean values of the marginal effect for each credit type.

The dimension of this influence varies according to the loan types involved. The credit types whose default has the strongest impact on other types' overdue exposure are the financing loans: vehicle financing and real estate financing. These credit types have an out-degree of contagion of around 12%. In these loan types, the good that was purchased is collateral for the credit operation so the financial institution may take it back in the case of default. To avoid this situation, the debtor will borrow through other loan types in order to pay the overdue debt in the financing credit. However, even if debtors prefer to stay current in other debt types, they cannot resort to financing loans with this aim; hence, they are weakly contaminated by default in other types of credit.

The credit types with the highest in-degree of contagion are overdraft, non-payroll-deducted personal credit, and the credit card loans. Debtors with overdue exposures have more restricted access to the credit market, and are only granted risky, high interest rate loan types. They will thus transfer their credit risk to these debt types. In fact, the aforementioned credit types are among the most expensive in Brazil (Table 14). In contrast, payroll-deducted personal credit, whose interest rate is significantly lower, is much less contaminated by other credit types.

5. Concluding remarks

In this paper, we used a Brazilian data set to assess the risk contagion among different personal loan types. It was observed that such default is relevant; that is, default on a given type of debt positively depends on the existence of past overdue exposures in other credit types.

Moreover, our results showed that the dimension of these effects varies according to the credit types involved – i.e., which credit type is contaminating and which one is being contaminated – and we discussed the rationale behind these findings. Specifically, the types of loan whose default is very disadvantageous to the debtor due to collateral costs (vehicle and real estate financing) contaminate the other credit types more. Debtors with overdue exposures in these credit types will resort to other sources of credit in order to honor their debt obligations and avoid losing the financed good. As they are already in default, they will be granted credit mainly from high risk credit types (non-payroll-deducted personal credit and overdraft). Therefore, the risk of default is transferred to these credit types, explaining why they are the most contaminated ones. Conversely, debtors cannot resort to financing credit in order to stay current in other credit types: hence, financing credit types are weakly contaminated by default in other types of debt.

Our study contributes to the ongoing debate involving the "debtor approach" and the "transaction approach", in the sense that it provides elements to be taken into consideration when deciding which methodology should be adopted. Our results suggest that when the debtor has a relevant overdue exposure in credit types with a high out-degree of contagion (vehicle and real estate financing), their exposures in highly contaminated types of loan (non-payroll-deducted personal credit and overdraft) should be of concern to financial institutions.

There is certainly much more to be done in order to create a reasonable criterion for classifying an exposure as non-performing or not, but we have shed some light on this issue. Specifically, we have found that the interaction between the marginal effects of credit types (as reported in Tables 11 and 12) and the past due exposures in these debt types with a debtor's total past due exposures is something to be taken into account.

Finally, we added new insights to the literature concerning credit risk. By our findings, overdue exposures in other credit types is an important explanatory variable to be included in models aiming to forecast default in credit operations.

References

Agarwal, S., and Liu, C. (2003). Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors. Journal of Economics and Finance 27 (1), 75-84. DOI: 10.1007/BF02751591.

Andersson, F., Chomsisengphet, S., Glennon, D., and Li, F. (2013). The changing pecking order of consumer defaults. Journal of Money, Credit and Banking 45(2-3), 251-275. DOI: 10.1111/jmcb.12001.

Banco Central do Brasil (BCB) (2015). Press releases. Accessed in http://www.bcb.gov.br/en/#!/n/PRESS. December 2015.

Basel Committee on Banking Supervision (BCBS) (2016). Prudential treatment of problem assets – definitions of non-performing exposures and forbearance. Issued for comments by July 15th, 2016.

Bellotti, T., and Crook, J. N. (2009). Credit Scoring with Macroeconomic Variables Using Survival Analysis. Journal of the Operational Research Society 60 (12), 1699-1707. DOI: 10.1057/jors.2008.130.

Bellotti, T., and Crook, J. N. (2014). Retail Credit Stress Testing using a Discrete Hazard Model with Macroeconomic Factors. Journal of the Operational Research Society 65 (3), 340-350. DOI: 10.1057/jors.2013.91.

Bhutta, N., Dokko, J., and Shan, H. (2010). How Low Will You Go? The Depth of Negative Equity and Mortgage Default Decisions. Finance and Economics Discussion Series 2010-35. Washington: Board of Governors of the Federal Reserve System.

Cohen-Cole, E., and Morse, J. (2010). Your House or Your Credit Card, Which Would You Choose? Personal Delinquency Tradeoffs and Precautionary Liquidity Motives. Federal Reserve Bank of Boston Working Paper No. QAU09-5.

Correa, A. S., Marins, J. T. M., Neves, M. B. E., and Silva, A. C. M. (2014). Credit Default and Business Cycles: An Empirical Investigation of Brazilian Retail Loans. Brazilian Review of Economics 68 (3), 337-362. DOI: http://dx.doi.org/10.1590/S0034-71402014000300003.

Elul, R., Souleles, N., Chomsisengphet, S., Glennon, D., and Hunt, R. (2010). What "Triggers" Mortgage Default? American Economic Review Papers and Proceedings 100: 490-494. DOI: 10.1257/aer.100.2.490.

European Banking Authority (EBA) (2013). Consultation Paper on Draft Implementing Technical Standards on Supervisory reporting on forbearance and non-performing exposures under article 95 of the draft Capital Requirements Regulation. Issued for comments by March 26th, 2013.

Grieb, T., Hegji, C., and Jones, S. T. (2001). Macroeconomic Factors, Consumer Behavior, and Bankcard Default Rates. Journal of Economics and Finance 25 (3), 316-327. DOI: 10.1007/BF02745892.

Guiso, L., Sapienza, P., and Zingales, L. (2009). Moral and Social Constraints to Strategic Default. NBER Working Paper 15145.

Jagtiani, J., and Lang, W. W. (2011). Strategic Defaults on First and Second Lien Mortgages during the Financial Crisis. The Journal of Fixed Income 20 (4), 7-23. DOI: https://doi.org/10.3905/jfi.2011.20.4.007.

Jarrow, R. A., and Turnbull, S. (2000). The Intersection of Market and Credit Risk. Journal of Banking and Finance 24 (1-2), 271–299. DOI: https://doi.org/10.1016/S0378-4266(99)00060-6.

Leow, M., and Crook, J. N. (2016). The Stability of Survival Model Parameter Estimates for Predicting the Probability of Default: Empirical Evidence over the Credit Crisis. European Journal of Operational Research 249 (2), 457-464. DOI: https://doi.org/10.1016/j.ejor.2014.09.005.

Long, J. S. (1997). Regression Models for Categorical and Limited Dependent Variables. Thousand Oaks, CA: Sage.

Nguyen, H-T. (2015). Default predictors in credit scoring: evidence from France's retail banking institution. Journal of Credit Risk 11 (2), 41-66. DOI: 10.21314/JCR.2015.191.

Stepanova, M., and Thomas, L. C. (2002). Survival Analysis Methods for Personal Loan Data. Operations Research 50 (2), 277-289. DOI: http://dx.doi.org/10.1287/opre.50.2.277.426.

Thomas, L.C., Edelman, D.B., and Crook, J.N. (2002). Credit Scoring and its Applications. SIAM Monographs on Mathematical Modeling and Computation. SIAM: Philadelphia, USA.

Tong, E. N. C., Mues, C., and Thomas, L. C. (2012). Mixture cure models in credit scoring: If and when borrowers default. European Journal of Operational Research 218 (1), 132-139. DOI: https://doi.org/10.1016/j.ejor.2011.10.007.

Annex: Tables

Table 1: Brazilian financial system– credit outstanding, by type (in BRL billion)

	December 2014	December 2015
Households[1]	1,412.1	1,512.2
Non-earmarked	782.8	805.3
Personal credit	353.1	380.0
Payroll-deducted	252.2	273.9
Vehicles financing	184.1	161.1
Credit card	160.8	172.7
Earmarked	629.3	706.9
Real estate financing	431.6	499.6
Non-financial corporations	1,605.4	1,707.2
Non-earmarked	793.4	832.0
Working capital	392.4	378.7
Earmarked	812.0	875.3
BNDES funds	595.2	633.4
Total	3,017.5	3,219.4
% GDP	53.1	54.5
Total earmarked	1,441.3	1,582.2
Total non-earmarked	1,576.2	1,637.3
By capital control		
State-owned financial institutions	1,623.1	1,796.7
National private financial institutions	953.2	948.0
Foreign financial institutions	441.2	474.7

Source: BCB (2015).

(1): Household loan is the expression used in BCB (2015) for personal loan, term we opted to adopt throughout this paper.

Table 2: Brazilian financial system credit – NPL (in %)

	December 2014	December 2015
Households[1]	3.7	4.2
Non-earmarked	5.3	6.2
Personal credit	3.8	4.3
Payroll-deducted	2.4	2.3
Vehicles financing	3.9	4.2
Credit card	6.6	8.1
Earmarked	1.6	2.0
Real estate financing	1.4	1.8
Non-financial corporations	1.9	2.6
Non-earmarked	3.4	4.5
Working capital	3.9	4.6
Earmarked	0.5	0.9
BNDES funds	0.4	0.8
Total	2.7	3.4
Total earmarked	1.0	1.4
Total non-earmarked	4.3	5.3
By capital control		
State-owned financial institutions	2.0	2.7
National private financial institutions	3.7	4.6
Foreign financial institutions	3.3	3.5

Source: BCB (2015).

(1): Household loan is the expression used in BCB (2015) for personal loan, term we opted to adopt throughout this paper.

Table 3: Explanatory variables

Variable	Description
Gender	Dummy variable equal to 1 if male
Age	Age in years
Occupational variables[1] Private sector[2] Public sector[3] Informal sector Firm-owner[4] Retired	Dummy variable equal to 1 if the individual belongs to this occupational category
Income[5] 3-5 minimum wages (mw) 5-10 minimum wages (mw) Above 10 minimum wages (mw)	Dummy variable equal to 1 if the individual has a monthly income between this range
Geographic region[6] South North Northeast Midwest	Dummy variable equal to 1 if the individual lives in this Brazilian geographic region
Employment[7]	Dummy variable equal to 1 if the individual is employed
Reference date[8] December 2013 December 2014	Dummy variable equal to 1 if the information reports to this reference date
Other credit types Payroll-deducted personal loan Non-payroll-deducted personal credit Vehicles financing Real estate financing Credit card[9] Overdraft	Dummy variable equal to 1 if the individual has exposure in this credit type at t
Other credit types – ratio Payroll-deducted personal loan Non-payroll-deducted personal credit Vehicles financing Real estate financing Credit card[9] Overdraft	Exposure in the credit type to total exposure ratio at t
Default other credit types Payroll-deducted personal loan Non-payroll-deducted personal credit Vehicles financing Real estate financing Credit card[9] Overdraft	Dummy variable equal to 1 if the individual has exposure past due more than 90 days in this credit type at t

(1): Control group: unemployed/other occupational categories.
(2): Exclude financial sector employers.
(3): Include militaries.
(4): Include landlords.
(5): Control group: below 3 m.w.
(6): Control group: Southeast Region.
(7): Considers only the employment status in the formal sector.
(8): Control group: December 2012.
(9): Exclude interest free transactions, associated with an instalment plan or not.

Table 4: Sample statistics

Variable	December 2012	December 2013	December 2014
Sample size			
Number of debtors	204,662	216,531	222,654
Number of operations	364,783	386,463	394,406
Men – % debtors	52.8	52.2	51.8
Age – average	46.0	46.2	46.5
Employed – % debtors	40.3	40.1	39.5
Income – % debtors			
Below 3 minimum wages	58.1	60.8	63.1
3-5 minimum wages (mw)	15.5	14.9	14.6
5-10 minimum wages (mw)	12.2	12.3	12.1
Above 10 minimum wages (mw)	8.0	8.2	7.7
Occupation – % debtors			
Private sector	8.3	8.0	7.8
Public sector	7.9	7.5	7.3
Informal sector	4.4	4.3	4.2
Firm-owner	6.8	6.6	6.5
Retired	4.1	3.8	3.6
Geographic region – % debtors			
South	16.1	15.9	15.9
Northeast	22.7	23.2	23.2
North	5.9	6.0	6.0
Midwest	8.2	8.2	8.2
Southeast	47.2	46.7	46.6
Credit type – % debtors			
Payroll-deducted personal loan	39.0 (1.5)	39.3 (1.6)	39.1 (1.4)
Non-payroll-deducted personal credit	27.6 (4.0)	26.1 (3.2)	25.2 (3.1)
Vehicles financing	19.9 (1.4)	19.2 (1.2)	17.6 (0.9)
Real estate financing	8.0 (0.1)	9.0 (0.1)	10.0 (0.2)
Credit card	33.9 (6.5)	34.3 (6.0)	36.4 (6.3)
Overdraft	27.9 (3.0)	27.8 (2.5)	27.0 (2.2)
Credit type – average ratio			
Payroll-deducted personal loan	31.2	31.6	31.7
Non-payroll-deducted personal credit	13.4	12.5	11.8
Vehicles financing	15.3	14.3	12.8
Real estate financing	6.8	7.7	8.8
Credit card	14.4	14.8	16.3
Overdraft	5.6	5.5	5.3

(1): In parenthesis: % of debtors in the whole sample with overdue exposure in the credit type.

Table 5: Number of credit types (% of debtors)

N. of credit types	Dec/12	Dec/13	Dec/14
All exposures:			
1 type	54.5	54.5	54.8
2 types	24.1	24.1	24.2
3 types	13.1	13.0	12.9
4 types	5.8	5.8	5.7
5 or more types	2.4	2.6	2.4
Only overdue exposures:			
1 type	70.7	72.4	73.9
2 types	19.3	18.8	18.2
3 types	8.1	7.1	6.6
4 or more types	1.8	1.7	1.3
% debtors without overdue exposures	85.7	86.9	87.2

Table 6: Overlap between credit types

Types*	PAY	NPR	VEH	RSF	CRE	OVR
PAY	-	37.4	15.4	6.5	39.2	38.9
NPR	44.5	-	22.5	9.3	57.0	64.1
VEH	28.2	34.6	-	13.1	48.8	43.6
RSF	27.4	32.8	30.1	-	48.7	60.6
CRE	35.9	43.8	24.4	10.6	-	48.8
OVR	42.6	59.1	26.1	15.8	58.5	-

x(i,j) = % of debtors holding the row type that also have exposures in the column type.
(*): PAY = payroll-deducted personal loans, NPR = non-payroll-deducted personal credit, VEH = vehicle financing, RSF = real estate financing, CRE = credit card, OVR = overdraft.

Table 7: Default migration

Credit type*		PAY	NPR	VEH	RSF	CRE	OVR
PAY	Overdue	-	22.7	18.4	14.8	28.2	30.1
	Not-overdue	-	8.5	7.5	5.6	17.6	6.7
NPR	Overdue	14.5	-	28.5	20.4	46.3	48.1
	Not-overdue	5.5	-	8.4	6.2	24.6	12.9
VEH	Overdue	10.2	24.1	-	23.5	36.6	29.8
	Not-overdue	3.7	11.4	-	4.2	17.0	9.5
RSF	Overdue	8.5	29.4	27.0	-	32.6	31.9
	Not-overdue	3.7	11.9	5.0	-	18.0	8.4
CRE	Overdue	12.0	32.3	25.2	20.7	-	35.4
	Not-overdue	5.5	16.5	7.8	5.9	-	13.7
OVR	Overdue	13.8	47.8	25.3	22.7	45.6	-
	Not-overdue	5.3	16.1	7.5	4.9	23.3	-
Overdue in some other type		12.0	30.6	24.2	19.7	39.8	35.4
Not-overdue in any other type		4.8	13.0	6.8	4.4	20.2	10.1

x(i,j) = fraction of debtors with exposure in the row/column types, but without overdue exposure in the column type, in t that default on the column type between *t+1* and *t+12* (t = December 2012, December 2013 and December 2014).
(*): For the meaning of the abbreviations, see Table 6.

Table 8: Average time of first default (in months)

Credit type*		PAY	NPR	VEH	RSF	CRE	OVR
PAY	Overdue	-	4.63	5.49	5.63	5.52	4.33
	Not-overdue	-	6.46	6.01	6.2	6.34	6.85
NPR	Overdue	5.4	-	4.97	5.3	4.22	3.62
	Not-overdue	6.38	-	6.33	6.54	6.08	6.49
VEH	Overdue	6.59	5.53	-	5.68	5.05	5.28
	Not-overdue	6.37	6.47	-	6.26	6.43	6.7
RSF	Overdue	6.06	6	5.48	-	6.31	5.49
	Not-overdue	6.14	6.3	6.21	-	6.21	6.68
CRE	Overdue	5.49	4.34	5.31	5.55	-	4.53
	Not-overdue	6.39	6.02	6.3	6.44	-	6.41
OVR	Overdue	5.28	3.17	4.99	5.61	4.08	-
	Not-overdue	6.32	5.91	6.24	6.33	6.05	-

x(i,j) = average time of first default, in months, of debtors with exposure in the row type and without overdue exposure in the column type in t, given that this debtor defaulted on the column type between t+1 and t+12 (t = December 2012, December 2013 and December 2014).
(*): For the meaning of the abbreviations, see Table 6.

Table 9: Debtors that do not appear in the following 12 months, in %

Debtors with exposures in	December 2012	December 2013	December 2014
Payroll-deducted personal loan	0.85	0.84	0.93
Non-payroll-deducted personal credit	3.01	3.03	2.60
Vehicles financing	1.71	1.99	2.40
Real estate financing	0.66	0.64	0.41
Credit card	3.94	3.41	3.39
Overdraft	3.29	3.02	3.04

Table 10: Results of the regressions

Independent variables	Dependent variable: overdue exposures in the column credit type[1]					
	PAY	NPR	VEH	RSF	CRE	OVR
Constant	-1.63(***)	-0.83(***)	-1.55(***)	-2.37(***)	-0.58(***)	-0.84(***)
Gender	0.33(***)	0.33(***)	0.11(***)	0.20(***)	0.18(***)	0.31(***)
Age	-0.02(***)	-0.03(***)	-0.01(***)	-0.02(***)	-0.02(***)	-0.02(***)
Occupation						
Private s.	-0.17(***)	-0.28(***)	-0.54(***)	-0.19(***)	-0.34(***)	-0.25(***)
Public s.	-0.07(**)	-0.45(***)	-0.73(***)	-0.67(***)	-0.53(***)	-0.57(***)
Informal s.	0.16(**)	0.26(***)	0.23(***)	0.33(***)	0.13(***)	0.23(***)
Firm-owner	0.02	0.24(***)	0.18(***)	0.42(***)	0.06(**)	0.13(***)
Retired	0.20(***)	0.00	-0.18(**)	-0.19	-0.08(**)	-0.09
Income						
3-5 m.w.	-0.18(***)	-0.29(***)	-0.34(***)	-0.10(**)	-0.16(***)	-0.24(***)
5-10 m.w.	-0.30(***)	-0.41(***)	-0.48(***)	-0.25(***)	-0.29(***)	-0.39(***)
> 10 m.w.	-0.31(***)	-0.46(***)	-0.72(***)	-0.49(***)	-0.58(***)	-0.54(***)
Region						
South	-0.19(***)	0.03	-0.17(***)	-0.22(***)	-0.02	-0.11(***)
North	-0.10(***)	0.01	0.14(***)	0.38(***)	0.13(***)	-0.01
Northeast	0.09(**)	0.07(**)	0.29(***)	0.97(***)	0.22(***)	0.03
Midwest	0.03	0.09(***)	0.15(***)	0.43(***)	0.10(***)	-0.01
Employment	-0.32(***)	-0.42(***)	-0.45(***)	-0.38(***)	-0.31(***)	-0.45(***)
Data base						
Dec/13	-0.07(***)	0.04(*)	-0.09(***)	0.00	0.06(***)	0.07(***)
Dec/14	-0.09(***)	0.09(***)	-0.17(***)	-0.11(**)	0.22(***)	0.10(***)
Other cred. type (dummy)						
Payroll loan	0.26(***)	-	0.25(***)	0.27(***)	0.65(***)	0.50(***)
Non-pay. l.	-0.05	0.11(**)	-	-0.16(*)	0.23(***)	0.15(***)
Vehicles fin.	-0.12	0.28(***)	-0.08	-	0.10	0.24(**)
Real est. fin.	0.19(***)	0.51(***)	0.11(***)	0.30(***)	-	0.53(***)
Credit card	-0.05(*)	0.23(***)	-0.05	-0.18(***)	0.38(***)	-
Overdraft	0.26(***)	-	0.25(***)	0.27(***)	0.65(***)	0.50(***)
Other cred. type (ratio)						
Payroll loan	-0.57(***)	-	-0.08	-0.16	-0.59(***)	-0.77(***)
Non-pay. l.	-0.90(***)	-0.83(***)	-	-0.65(*)	-0.93(***)	-1.22(***)
Vehicles. fin.	-0.60(***)	-0.91(***)	-0.42(*)	-	-0.66(***)	-1.32(***)
Real est. fin.	-0.25(*)	-0.05	-0.10	0.78	-	-0.43(***)
Credit card	1.13(***)	1.01(***)	0.89(***)	2.89(***)	-0.33(***)	-
Overdraft	-0.57(***)	-	-0.08	-0.16	-0.59(***)	-0.77(***)
Default other cred. type						
Payroll loan	-	1.11(***)	0.49(***)	0.28	0.56(***)	1.47(***)
Non-pay. l.	0.61(***)	-	0.62(***)	0.13	0.66(***)	1.19(***)
Vehicles. fin.	0.87(***)	0.79(***)	-	1.39(***)	1.01(***)	0.95(***)
Real est. fin.	0.66(**)	1.04(***)	1.53(***)	-	0.76(***)	1.32(***)
Credit card	0.59(***)	0.79(***)	1.02(***)	0.96(***)	-	0.80(***)
Overdraft	0.20(***)	1.12(***)	0.22(**)	0.90(***)	0.63(***)	-
Sample size	240,367	142,865	111,701	56,932	177,816	155,819
AUC	0.6323	0.7183	0.6796	0.7006	0.6639	0.7461

(*): Significant at the 10% level.
(**): Significant at the 5% level.
(***): Significant at the 1% level.
([1]): For the meaning of the abbreviations, see Table 6.

Table 11: Marginal effects, AME(*)

	PAY	NPR	VEH	RSF	CRE	OVR
PAY	-	0.1602	0.0417	0.0159	0.0967	0.2059
NPR	0.0356	-	0.0592	0.0056	0.1163	0.1586
VEH	0.0635	0.1186	-	0.1183	0.1897	0.1213
RSF	0.0198	0.1248	0.1855	-	0.1113	0.1635
CRE	0.0347	0.1094	0.1081	0.0675	-	0.0944
OVR	0.0114	0.1638	0.0179	0.0649	0.1104	-

(*): Impact of the current overdue exposure in the row loan type on the future overdue exposure in the column credit type. For the meaning of the abbreviations, see Table 6.

Table 12: Marginal effects, MEM(*)

	PAY	NPR	VEH	RSF	CRE	OVR
PAY	-	0.161	0.0383	0.0139	0.0986	0.2068
NPR	0.0332	-	0.0548	0.0049	0.1187	0.1533
VEH	0.0596	0.1169	-	0.1099	0.197	0.116
RSF	0.0183	0.1235	0.1804	-	0.1139	0.1607
CRE	0.0324	0.1065	0.1019	0.0614	-	0.0876
OVR	0.0105	0.1646	0.0162	0.0587	0.1126	-

(*): Impact of the current overdue exposure in the row loan type on the future overdue exposure in the column credit type. For the meaning of the abbreviations, see Table 6.

Table 13: In-degree and out-degree of contagion

Credit type*	In-degree[1]		Out-degree[2]	
	AME	MEM	AME	MEM
PAY	0.0330	0.0308	0.1041	0.1037
NPR	**0.1354**	**0.1345**	0.0751	0.0730
VEH	0.0825	0.0783	**0.1223**	**0.1199**
RSF	0.0544	0.0498	**0.1210**	**0.1194**
CRE	**0.1249**	**0.1282**	0.0828	0.0780
OVR	**0.1487**	**0.1449**	0.0737	0.0725

(1): Average value of the marginal effects of other debt types default in the default of the credit type. It measures how much the credit type is “contaminated” by the others. Obs.: greatest values are in bold.
(2): Average value of the marginal effects of default of the debt type in the default of the other credit types. It measures how much the credit type “contaminates” the others. Obs.: greatest values are in bold.
(*): For the meaning of the abbreviations, see Table 6.

Table 14: Interest rates in Brazil, in % per year

	December 2014	December 2015
Overdraft	201.0	287.0
Non-payroll-deducted	101.9	117.7
Payroll-deducted	25.9	28.8
Vehicles	22.3	26.0
Credit card		
Revolving[1]	331.6	431.4
Financing[2]	104.1	136.2
Real estate financing	8.9	10

(1): Include cash withdrawals.
(2): Regular instalments only.
Source: Banco Central do Brasil.