Default contagion among credit modalities: evidence from Brazilian data

Alexandre, Michel and Antônio Silva Brito, Giovani and Cotrim Martins, Theo

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Default contagion among credit modalities: evidence from Brazilian data[*]

Michel Alexandre[†]

Giovani Antônio Silva Brito[‡]

Theo Cotrim Martins[§]

Abstract:

The aim of this paper is to assess the impact of the default of some personal credit modality in the future default of the other modalities. Using Brazilian microdata, we run a logistic regression to estimate the probability of default in a given credit modality, including among the explanatory variables the personal overdue exposure in the other credit modalities. Our results show that such effect is positive and significant, although quantitatively heterogeneous. We also discuss the rationale behind these results. Specifically, it was found that financing credit modalities (vehicle and real estate financing) contaminate more the other credit modalities, as their default may bring to the debtor the loss of the financed good. Moreover, riskier loan categories (overdraft, non-payroll-deducted personal credit and credit card) are more contaminated by the default of other modalities, what is explained by the fact that defaulted individuals have a limited access to less risky credit modalities.

Keywords: Credit default contagion; debtor approach; transaction approach.

JEL Classification: C58; G17; G28.

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[†] Financial System Monitoring Department, Central Bank of Brazil. Av. Paulista, 1804, São Paulo, Brazil. Fone: +55 (11) 3491-6856. E-mail: michel.alexandre@bcb.gov.br.

[‡] Financial System Monitoring Department, Central Bank of Brazil. Av. Paulista, 1804, São Paulo, Brazil. Fone: +55 (11) 3491-6889. E-mail: giovani.brito@bcb.gov.br.

[§] Financial System Monitoring Department, Central Bank of Brazil. Av. Paulista, 1804, São Paulo, Brazil. Fone: +55 (11) 3491-6693. E-mail: theo.martins@bcb.gov.br.

1 Introduction

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 impaired, all the other transactions of the same debtor should be assigned to the same category. If the “transaction approach” is taken instead, any single exposure is categorized regardless the status of the other loans to the debtor.

Financial regulators outline criterions 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 “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 modalities. While the debtor approach assumes that the default in a single exposure will make the other debtor loans eventually become non-performing, the individual transaction approach hypothesizes that such contagion is weak or inexistent. Notwithstanding, as far as we know, there is not some empirical study supporting any of these approaches.

The purpose of this paper is helping to fill this gap. Relying on two Brazilian datasets (the Central Bank of Brazil’s Credit Risk Bureau System and the Annual Social Information Survey, as we will clarify later), we assess the impact of the default of some credit modality in the future default of the other modalities. We study six personal loan modalities, chosen by their relevance in the Brazilian credit market: payroll-deducted personal loan, non-payroll-deducted personal credit, overdraft, credit card, vehicles financing and real estate financing.

This study is also related to the literature on credit risk modeling. A wide range of models have been developed aiming the estimation of probability of default in credit transactions. Logistic regression has been the technique traditionally employed to this task (Thomas et al 2002), 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 specific different credit modalities, as credit card loans (Leow and Crook 2016) and personal loans (Stepanova and Thomas 2002). For the Brazilian case, Correa et al (2014) used microdata to study the credit default in consumer credit and vehicles financing, with particular emphasis on the influence of the business cycles. Among the explanatory variables used in these studies, there are borrower-related variables as age, gender and income; transaction-related variables (e.g., operation rating); and macroeconomic indicators, as inflation and unemployment rate. Notwithstanding, the impact of the default of other credit modalities has never been analyzed yet, as we are going to do in this study.

Beside this introduction, this paper has more four sections. The next section draws an overall panorama of the Brazilian credit market. Section 3 describes the methodology and the dataset. The fourth section presents the results. Concluding remarks take the last section.

2 The Brazilian credit market

The Brazilian total credit stock reached R$ 3.2 billion in December 2015, an amount 6.7% higher than that of December 2014. It corresponded to 54.5% of the Brazilian GDP, against 53.1% in December 2014. Almost half of this amount came from earmarked resources – i.e., those ruled by the government earmarking allocation regulation. Non-financial corporations had a slightly higher share in the total credit. The main credit modalities granted to non-financial corporations are BNDES[1] 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.

[1] National Bank of Social and Economic Development, the main Brazilian development bank.

There was a general worsening in the ratio of non-performing loans (NPL)[2] 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 higher proportional increase. Among the main modalities, the only one in which a decrease of the NPL ratio was observed was the payroll-deducted personal credit. NPL is more severe in the private national segment. NPL growth was more modest among the foreign private financial institutions and greater in the state-owned financial institutions, despite the latter presents the smaller NPL ratio.

Table 1: Brazilian financial system credit – stock by modality (in R$ million)

	December 2014	December 2015
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
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
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: CBB (2015).
(1): Household loan is the expression used in CBB (2015) for personal loan, term we opted to adopt throughout this paper.

[2] For the purpose of this study, loans past due more than 90 days are considered as non-performing loans (NPL).

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

	December 2014	December 2015
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
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
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: CBB (2015).
(1): Household loan is the expression used in CBB (2015) for personal loan, term we opted to adopt throughout this paper.

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 R$ 200 or above[3]. It brings, on each operation, data 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 the formal sector employees, as well as about their employers. Workers information includes earnings, gender, age and educational level.

As a first step, we generated a uniform random sample of individuals over 18 years-old from the SCR data set. This sample contains 299,369 borrowers, about 0.5% SCR's total. Then we collect information on these individuals from SCR and RAIS, as will be specified later.

[3] As we will specify later, we assessed data from December 2012, December 2013 and December 2014, when such lower bound was R$ 1,000.

After that we run the following logistic regression:

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

The dependent variable $y_{i,t,m}$ assumes the value 1 if the debtor had an exposure past due more than 90 days in the credit modality m in at least one month between t+1 and t+Δ. We consider just overdue exposures greater than a materiality threshold of R$ 100. The time horizon commonly used to assess credit default is 12 months (Jarrow and Turnbull 2000), then we used this value of Δ[4]. Time is discrete and measured in months. $X_{i,t}$ and $C_{i,t,m}$ are vectors of individual- and time-dependent variables, but the latter is also related to the set of credit modalities M, which includes all modalities except m; β and γ are vectors of parameters, while $\varepsilon_{i,t,m}$ is the usual error term. Regarding the explanatory variables, as well as the dependent one, it was considered just loans from banks. The description of the variables is in Table 3.

At t, we consider just the individuals which have no overdue exposure in the credit modality m and that appear in at least one month in the following 12 months. The fraction of debtors that does not appear in the subsequent months is never above 4%, as can be seen in Table 4. We assessed three reference dates: December 2012, December 2013 and December 2014.

In Table 5, 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 modality is the payroll-deducted personal loan (almost 40% of debtors with exposures in this modality), while 10% were granted real estate financing. More than 6% of debtors in the sample have overdue exposure in the credit card loan; regarding the real estate financing, this ratio is 0.2%.

[4] We performed tests using other values of Δ, obtaining very similar results.

Table 3: Variables

Variable	Description	Abbreviation
Gender	Dummy variable equal to 1 if male	gen
Age	Age in years	age
Occupational variables[1]		
Private sector[2]	Dummy variable equal to 1 if the individual belongs to this occupational category	pri
Public sector[3]		pub
Informal sector		inf
Firm-owner[4]		cap
Retired		ret
Income[5]		
3-5 minimum wages (mw)	Dummy variable equal to 1 if the individual has a monthly income between this range	ig1
5-10 minimum wages (mw)		ig2
Above 10 minimum wages (mw)		ig3
Geographic region[6]		
South	Dummy variable equal to 1 if the individual lives in this Brazilian geographic region	sth
North		nth
Northeast		nst
Midwest		mst
Employment	Dummy variable equal to 1 if the individual is employed	emp
Data base[7]		
December 2013	Dummy variable equal to 1 if the information reports to this data base	db13
December 2014		db14
Credit modalities		
Payroll-deducted personal loan	Dummy variable equal to 1 if the individual has exposure in this modality	pay
Non-payroll-deducted personal credit		npr
Vehicles financing		veh
Real estate financing		rsf
Credit card[8]		cre
Overdraft		ovr
Credit modalities – ratio		
Payroll-deducted personal loan	Exposure in the modality to total exposure ratio	pay_c
Non-payroll-deducted personal credit		npr_c
Vehicles financing		veh_c
Real estate financing		rsf_c
Credit card[8]		cre_c
Overdraft		ovr_c
Default		
Payroll-deducted personal loan	Dummy variable equal to 1 if the individual has exposure past due more than 90 days in this credit modality	pay_d
Non-payroll-deducted personal credit		npr_d
Vehicles financing		veh_d
Real estate financing		rsf_d
Credit card		cre_d
Overdraft		ovr_d

(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): Control group: December 2012.
(8): Exclude interest free transactions, associated with an instalment plan or not.

Table 4: Debtors that does 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 5: Sample statistics

Variable	December 2012	December 2013	December 2014
Sample size	204,662	216,531	222,654
Men – % individuals	52.8	52.2	51.8
Age – average	46.0	46.2	46.5
Employed – % individuals	40.3	40.1	39.5
Income – % individuals			
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 – % individuals			
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 – % individuals			
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 modality – % individuals[1]			
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 modality – 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 with NPE in the modality.

Table 6 brings the fraction of debtors without overdue exposures in a given credit modality in t that default on this loan modality between t+1 and t+12, according to their exposures in the other modalities. It can be seen, for instance, that 10.5% of debtors with overdue exposures in real estate financing and without overdue exposures in credit card loan default on this latter modality within the next 12 months. In general, debtors with overdue exposures in a given credit modality proved to be more prone to default on the other loan modalities. Moreover, given that the debtor defaulted on a given loan modality within this time window, it happens faster (i.e., with a smaller average time of first default) if she has overdue exposure in other credit modality (Table 7).

Table 6: Default migration

Credit modality		PAY	NPR	VEH	RSF	CRE	OVR
PAY	(1)	-	3.91	1.05	0.43	6.21	4.98
	(2)	-	2.29	0.75	0.28	5.58	2.02
NPR	(1)	2.23	-	2.11	0.77	9.92	11.84
	(2)	2.22	-	1.37	0.48	12.43	7.22
VEH	(1)	1.75	2.74	-	0.86	7.04	3.87
	(2)	0.76	2.57	-	0.41	6.41	2.96
RSF	(1)	1.95	4.77	2.89	-	10.5	8.21
	(2)	0.79	2.46	0.98	-	6.53	3.94
CRE	(1)	2.38	5.82	2.38	1	-	7.54
	(2)	1.62	5.22	1.35	0.51	-	5.19
OVR	(1)	1.77	5.25	2.07	1.33	11.47	-
	(2)	2.07	7.89	1.46	0.76	11.92	-

x(i,j) = fraction of debtors with exposure in the row modality and without overdue exposure in the column modality in t that default on the column modality between t+1 and t+12 (t = December 2012, December 2013 and December 2014).

(1): with overdue exposures in the row modality.

(2): without overdue exposures in the row modality.

Table 7: Average time of first default (in months)

Credit modality		PAY	NPR	VEH	RSF	CRE	OVR
PAY	(1)	-	4.63	5.49	5.63	5.52	4.33
	(2)	-	6.46	6.01	6.2	6.34	6.85
NPR	(1)	5.4	-	4.97	5.3	4.22	3.62
	(2)	6.38	-	6.33	6.54	6.08	6.49
VEH	(1)	6.59	5.53	-	5.68	5.05	5.28
	(2)	6.37	6.47	-	6.26	6.43	6.7
RSF	(1)	6.06	6	5.48	-	6.31	5.49
	(2)	6.14	6.3	6.21	-	6.21	6.68
CRE	(1)	5.49	4.34	5.31	5.55	-	4.53
	(2)	6.39	6.02	6.3	6.44	-	6.41
OVR	(1)	5.28	3.17	4.99	5.61	4.08	-
	(2)	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 modality and without overdue exposure in the column modality in t, given that this debtor defaulted on the column modality between t+1 and t+12 (t = December 2012, December 2013 and December 2014).
(1): with overdue exposures in the row modality.
(2): without overdue exposures in the row modality.

4 Results

4.1 General results

Here we present the results of the logistic regression specified in equation (1) (Table 8). 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 cohorts present a smaller propensity to default. We also corroborate some findings of other studies. For instance, as in Correa et al (2014), we find that women and older borrowers have a lower probability of default.

The influence of having exposure in other modalities on future default is mixed. In most of the cases, this impact is positive, but holding a high relative exposure in other modalities decreases the chance of default in a given modality. It can be explained by the fact that the existence of other modalities implies that the debtor has less resources to meet the debt commitments of the modality in question. However, if the relative weight of the other modalities is higher, it means that the relative exposure in the modality in question is smaller so its default will be inexistent or negligible. The most notable exception to this general rule is the overdraft. A greater relative exposure in overdraft raises the probability of default in the other modalities (except credit card loan), probably due to its high interest rate.

Table 8: Result of regression

Independent variables	Dependent variable					
	PAY	NPR	VEH	RSF	CRE	OVR
Constant	-1.63(***)	-0.83(***)	-1.55(***)	-2.37(***)	-0.58(***)	-0.84(***)
gen	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(***)
pri	-0.17(***)	-0.28(***)	-0.54(***)	-0.19(***)	-0.34(***)	-0.25(***)
pub	-0.07(**)	-0.45(***)	-0.73(***)	-0.67(***)	-0.53(***)	-0.57(***)
inf	0.16(**)	0.26(***)	0.23(***)	0.33(***)	0.13(***)	0.23(***)
cap	0.02	0.24(***)	0.18(***)	0.42(***)	0.06(**)	0.13(***)
ret	0.20(***)	0.00	-0.18(**)	-0.19	-0.08(**)	-0.09
ig1	-0.18(***)	-0.29(***)	-0.34(***)	-0.10(**)	-0.16(***)	-0.24(***)
ig2	-0.30(***)	-0.41(***)	-0.48(***)	-0.25(***)	-0.29(***)	-0.39(***)
ig3	-0.31(***)	-0.46(***)	-0.72(***)	-0.49(***)	-0.58(***)	-0.54(***)
sth	-0.19(***)	0.03	-0.17(***)	-0.22(***)	-0.02	-0.11(***)
nth	-0.10(***)	0.01	0.14(***)	0.38(***)	0.13(***)	-0.01
nst	0.09(**)	0.07(**)	0.29(***)	0.97(***)	0.22(***)	0.03
mst	0.03	0.09(***)	0.15(***)	0.43(***)	0.10(***)	-0.01
emp	-0.32(***)	-0.42(***)	-0.45(***)	-0.38(***)	-0.31(***)	-0.45(***)
db13	-0.07(***)	0.04(*)	-0.09(***)	0.00	0.06(***)	0.07(***)
db14	-0.09(***)	0.09(***)	-0.17(***)	-0.11(**)	0.22(***)	0.10(***)
pay	-	0.05	0.07	0.11	0.20(***)	0.04
npr	0.26(***)	-	0.25(***)	0.27(***)	0.65(***)	0.50(***)
veh	-0.05	0.11(**)	-	-0.16(*)	0.23(***)	0.15(***)
rsf	-0.12	0.28(***)	-0.08	-	0.10	0.24(**)
cre	0.19(***)	0.51(***)	0.11(***)	0.30(***)	-	0.53(***)
ovr	-0.05(*)	0.23(***)	-0.05	-0.18(***)	0.38(***)	-
pay_c	-	-0.84(***)	0.40(***)	0.84(***)	-0.47(***)	-1.43(***)
npr_c	-0.57(***)	-	-0.08	-0.16	-0.59(***)	-0.77(***)
veh_c	-0.90(***)	-0.83(***)	-	-0.65(*)	-0.93(***)	-1.22(***)
rsf_c	-0.60(***)	-0.91(***)	-0.42(*)	-	-0.66(***)	-1.32(***)
cre_c	-0.25(*)	-0.05	-0.10	0.78	-	-0.43(***)
ovr_c	1.13(***)	1.01(***)	0.89(***)	2.89(***)	-0.33(***)	-
pay_d	-	1.11(***)	0.49(***)	0.28	0.56(***)	1.47(***)
npr_d	0.61(***)	-	0.62(***)	0.13	0.66(***)	1.19(***)
veh_d	0.87(***)	0.79(***)	-	1.39(***)	1.01(***)	0.95(***)
rsf_d	0.66(**)	1.04(***)	1.53(***)	-	0.76(***)	1.32(***)
cre_d	0.59(***)	0.79(***)	1.02(***)	0.96(***)	-	0.80(***)
ovr_d	0.20(***)	1.12(***)	0.22(**)	0.90(***)	0.63(***)	-

(*): Significant at the 10% level.
(**): Significant at the 5% level.
(***): Significant at the 1% level.

4.2 Risk contagion

As expected, there is a risk contagion among different credit modalities. In most of situations, the probability of a debtor having overdue exposure in a loan modality is positively impacted by her current overdue exposures in other credit categories. In order to assess such 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 9 and 10, respectively. For the sake of summarization, we provide in Table 11 the in- and out-degree of contagion, which are, respectively, column and row mean value of the marginal effect for each modality.

The dimension of such influence varies according to the loan modalities involved. The modalities whose default has the stronger impact in other modalities overdue exposure are the financing loans: vehicle financing and real estate financing. These categories have an out-degree of contagion around 12%. In these loan categories, the good that was purchased is the collateral of the credit operation so the financial institution may take it back in case of default. To avoid this situation, the debtor will borrow through other loan modalities in order to pay the overdue debt in the financing credit.

Table 9: 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	-

Table 10: 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	-

Table 11: In-degree and out-degree of contagion

Loan modality	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 modalities default in the default of the modality. It measures how much the modality is "contaminated" by the others. Obs.: greatest values are in bold.
(2): Average value of the marginal effects of default of the modality in the default of the other modalities. It measures how much the modality "contaminate" the others. Obs.: greatest values are in bold.

The modalities with the higher in-degree of contagion are the overdraft, non-payroll-deducted personal credit and the credit card loan. Debtors with past due exposures have a narrower access to the credit market, being granted only risky, high interest rate loan modalities. In fact, the above mentioned credit categories are among the most expensive in Brazil (Table 12). In contrast, the payroll-deducted personal credit, whose interest rate is significantly smaller, is much less contaminated by other credit modalities.

Table 12: 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: Central Bank of Brazil.

5 Concluding remarks

In this paper, using a unique Brazilian data set, we assessed the risk contagion among different personal loan modalities. It was observed that such default is relevant, that is, default in a given credit modality depends positively on the existence of past overdue exposures in the other credit modalities.

Moreover, our results showed that the dimension of these effects varies according to the modalities involved – i.e., which credit modality is contaminating and which one is being contaminated – and we discussed the rationale behind these findings. Specifically, modalities whose default is very disadvantageous to the debtor, as it may imply the loss of a financed good (vehicle and real estate financing), contaminate more the other modalities. On the other hand, debtors with overdue exposures will be granted credit mainly from high risk credit modalities (non-payroll-deducted personal credit and overdraft). It explains why these credit modalities are the most contaminated ones.

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 past due exposure in modalities with a high out-degree of contagion (vehicle and real estate financing), her exposures in highly contaminated modalities (non-payroll-deducted personal credit and overdraft) should be a concern to financial institutions.

Certainly there is much more to be done in order to create a reasonable criterion to classify 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 modalities (as reported in Tables 9 and 10) and the past due exposures in these modalities over debtor's total past due exposures is something to be held into account.

Finally, we added on new insights to the literature about credit risk. Overdue exposures in other credit modalities were proved, by our findings, to be important explanatory variables to be included in models aiming to forecast default in credit operations.

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