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Article

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Permanent income hypothesis in emerging markets: Some Brazilian evidence

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Abstract

This paper uses a dataset from one of the largest credit card issuers in Brazil to investigate the extent of credit constraints for one of the world's largest emerging market economies. In order to deal with the endogeneity problem from an observational dataset, an identification strategy based on the issuer actual policies was used to better identify the long run effects of a credit card limit increase on debt. The results point to a long run effect of credit limit on credit card debts of 0.1144, a similar size to the ones found in Gross and Souleles (2001). This value indicates the Permanent Income Hypothesis is rejected for this sample, and some evidence supporting a variation of buffer stock behavior is found. Furthermore, results indicate the degree of heterogeneity in effects is much higher than similar results for developed countries, lending credence to the conclusion credit constraints are much stronger for lower income groups. This conclusion is in line to previous studies in Brazil, such as de Lucinda and Vieira (2014).

JEL classification: D12; D19; D91

Keywords: Permanent income hypothesis; Credit constraints; Credit Demand; Credit Card

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1. Introduction

It is well documented that there are several credit constraints affecting households in less developed countries, but the extent of such constraints in large emerging markets is still not well understood. Even though it is expected lower income households in such countries to be as constrained as in even less developed countries, the existence of a large share of medium and high income families raises questions about if the marginal household is credit constrained in equilibrium or not.

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We are using a dataset from one of the largest Brazilian credit card companies to investigate whether the Permanent Income Hypothesis is valid or not. Apart from the sheer size of the dataset, one of our advantages is using information on the issuer's credit policy to identify the sensitivity of credit card debt to changes in credit card limit.

This question has theoretical and policy relevant implications. As for the theoretical implications, the extent of credit constraints implies models in which such constraints are non-existent are less relevant for understanding macroeconomics in these countries. Policy relevant questions whose answers depend on the extent of credit constraints households face are the level of competition on the credit market, the effects of microcredit among others.

The present paper also ties into a large empirical literature about liquidity constrained consumer behavior. Papers such as [Ausubel \(1991\)](#) and [Ausubel \(1999\)](#) try to point out causes of household inability to borrow at market equilibrium rates. Our approach here is more in line with [Gross and Souleles \(2001\)](#). In this paper, the authors use a dataset from a large credit card issuer to investigate whether the Permanent Income Hypothesis holds for U.S. households.

They find such households are credit constrained. Besides, they also find an increase in credit leads to increased indebtedness for all individuals – those that already used a lot of their credit limit as well as those who used a small share of their limit. They conclude this behavior could be related to buffer stock saving theories, as in [Deaton \(1989\)](#) and [Ludvigson \(1999\)](#). According to these theories, people are willing to keep some credit lines unused for precautionary reasons. With an exogenous increase in the credit volume above the desired level, they would direct at least part of the additional credit to consumption – thus increasing indebtedness.

In 2013, 76.1% of Brazilian population had at least one credit or debit cards, with a transactions volume of BRL 853 million, BRL 553 million of which were accounted for in credit cards. Taking into account only those who have access to electronic means of payment, the share of debit and credit cards in household consumption is 57%, as noted by [Associação Brasileira das Empresas de Cartões de Crédito e Serviços \(2014\)](#).

As mentioned before, credit cards can also work as an additional source of credit, since the balance owed can be paid across several periods. Still according to [Associação Brasileira das Empresas de Cartões de Crédito e Serviços \(2014\)](#), 31% of Brazilians have at least one did not pay the full outstanding balance at the time the bill is due.

The paper is composed of four sections, with the present introduction being the first one. On the next section we will describe the dataset used, and the third will be focused on the main analysis. The fourth one concludes.

2. Data and methodology

It was used for this paper a random sample of cardholders from one of the largest financial institution which serves more than 40% of credit card users in Brazil. There were approximately 60 thousand cardholders in the first time period of the panel, May 2013. Some cardholders were dropped from the base due to one of the following reasons:

- Lack of activities – no purchases throughout the period.
- The cardholder requested the card to be canceled.
- The cardholder was unable to repay its debts and it was considered as delinquent.

In the last time period of the panel, April 2015, 70.46% of the original 60 thousand cardholders were still active. Thus, we have an unbalanced panel dataset. For each cardholder, we had available the info in the credit card bill sent monthly to the cardholder:

- Balance Outstanding.
- Interest rate in case the balance is not paid in full.
- Amount of the last payment.

Besides credit card bill data we also had information on the past relationship of the cardholder with the bank:

- Maximum credit limit.
- Whether the limit was changed by the bank or by request of the cardholder.
- Credit Card type.
- Credit Score.

- Demographics – age and region.

Accurate information on the cardholder's income was not available, but it is common practice in the industry different cards are targeted at different income levels, and the lender from which the data comes from is not an exception. Thus, four groups of cards were created, and named *low*, *medium low*, *medium high* and *high*.

The empirical analysis is similar to the one in [Gross and Souleles \(2001\)](#). Our variables of interest are the amount of debts, $D_{i,t}$, the credit limit $L_{i,t}$ and the interest rate $r_{i,t}$. The subscripts i and t are the cardholder and time period, respectively. The first model to be presented, for investigating the cumulative effect on debts from an increase in credit card limit, is:

$$\Delta D_{i,t} = \beta_0 \Delta L_{i,t} + \dots + \beta_s \Delta L_{i,t-s} + \Omega' X_{i,t} + \varepsilon_{i,t} \quad (1)$$

In which $\Delta D_{i,t}$ is the change in debts from time period $t - 1$ to time period t , and $\Delta L_{i,t}$ is the change in the credit limit between the same time periods. The $X_{i,t}$ are control variables, β_0, \dots, β_s the effects from each time period lagged difference and $\Omega_{i,t}$ is a coefficient vector for all controls. We are interested in the cumulative effect of a change in credit card limit, so the relevant statistic is $b_s = \sum_{j=0}^s \beta_j$. We used a maximum lag of 10 periods, somewhat smaller than the 12 month period used by [Gross and Souleles \(2001\)](#).³ The resulting dataset still have about 450 thousand observations.

The following variables were used as controls for the $X_{i,t}$ vector:

- Monthly Time dummies.
- Account age.
- Credit Score of the cardholder.⁴
- Credit Card type.
- Monthly expenses.
- Dummy variable of whether the limit change was initiated by the cardholder. This presumably is a first step on controlling for the reverse causality effect.

Another control for the reverse causality was using the strategy of [Gross and Souleles \(2001\)](#), by using a variable indicating how many months have passed since the last credit card change limit as an instrument. Our issuer had a policy at that time of automatically increase the credit card limit only after a specific amount of time since the last limit change. Thus, a card with an earlier limit change has a higher probability to have its limit changed this month, with everything else held constant. Finally, the last instrument used for the credit card limit change was an indicator created from the internal credit policies of the bank.

3. Results

The first step on the analysis was determining the maximum lag to be used for the credit card limit to identify its effects on the credit card debt. [Fig. 1](#) plots the size of the estimated cumulative effect of changes in the credit card limit for various lag limits. The effects seem to level off after two lags.⁵

The effect size is not independent of whether the change was initiated by the cardholder or the issuer. The cumulative effects for those cardholders who actually asked for a change in credit card limit. For those cardholders, for each additional BRL in credit card limit the cumulative effect was 0.112 BRL, significant both statistically and economically. [Fig. 2](#) presents this result.

On the other hand, for those cardholders who did not ask for a credit limit the unconditional long run effects on debts are equal to zero, both in statistical and economic terms. For each additional BRL of automatic change in credit card limit, the cumulative effect on debts was 0.0012 BRL, as shown in [Fig. 3](#).

³ The results do not change much from changing to 12 periods.

⁴ Outside measures of borrower quality are not widely available. Brazilian law until 2014 forbid the use of default information by credit score bureaus.

⁵ At this point, the results are mostly exploratory, and we did not experiment with the different specifications and controls/instruments.

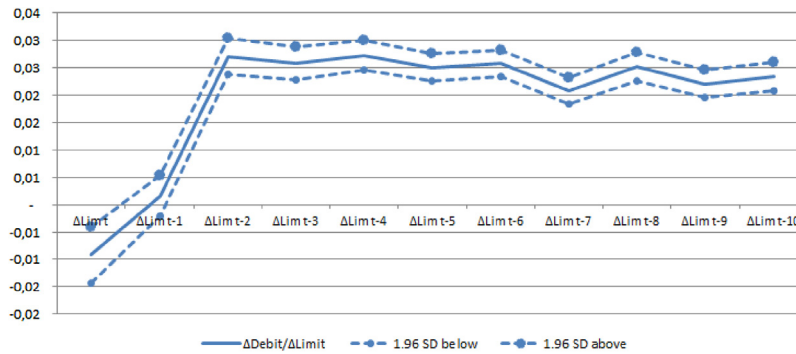


Fig. 1. Cumulative effects on credit card debt of an increase in credit card limit.

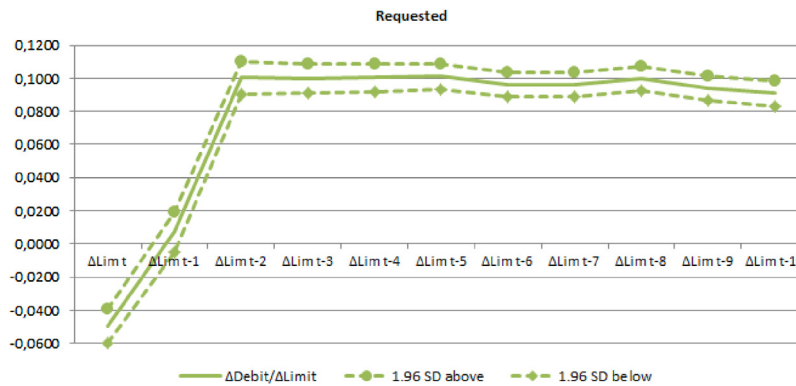


Fig. 2. Cumulative effects on credit card debt of a requested increase in credit card limit.

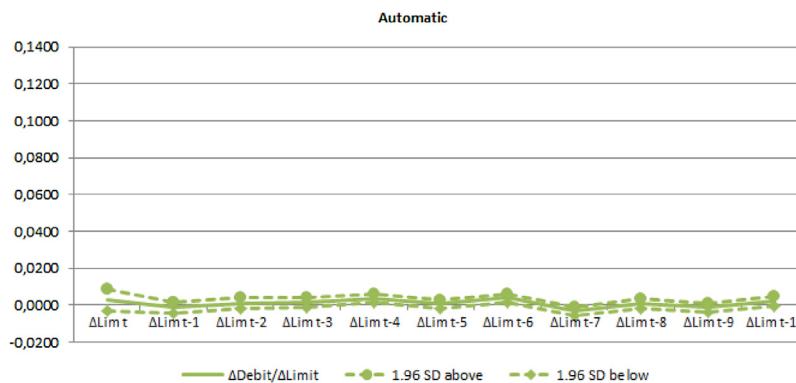


Fig. 3. Cumulative effects on credit card debt of an automatic increase in credit card limit.

We would like to caution this is not an indication of an absence of effect of debt increase from changes in credit card limit; other issues such as attention problems could be happening to explain these results, such as reported by Ferman (2012).

Since there is a *prima facie* case for the results for the subsample composed of individuals who actually asked for credit limit increases to be the result of reverse causality, our analysis will be focused on the subsample of cardholders who did not ask for a credit limit increase. The results for several specifications, for both groups, are presented in Table 1.

Different columns in this table shed light on how the addition of controls and different identifying assumptions on the unobserved component of the regression models could lead to better identification of the long-run effect of credit

Table 1
Long run effects of debts of credit limit changes.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Long run effect	0.0271 (9.3448)***	0.0234 (5.3182)***	0.0012 (0.4781)	0.1003 (11.6832)***	0.0024 (0.5855)	0.0908 (7.1762)	−0.006 (0.5752)	0.006 (4.7581)***	0.0336 (6.5395)***	0.0339 (6.5851)***
Lags	2	10	2	2	10	10	10	10	10	10
Type of change	All	All	Aut.	Req.	Aut.	Req.	Aut.	Aut.	Aut.	Aut.
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	No	No	Yes	No	No	No
Credit score	No	No	No	No	No	No	No	Yes	Yes	Yes
Outstanding balance	No	No	No	No	No	No	No	No	Yes	Yes
Account age	No	No	No	No	No	No	No	No	Yes	Yes
Age + Region	No	No	No	No	No	No	No	No	No	Yes
Card type	No	No	No	No	No	No	No	No	No	No
Observations	874,059	492,567	781,133	92,926	436,820	55,747	426,820	436,820	427,281	497,923

Asy *t* statistics in parentheses. ****P*-value < 0.05. Type of change: Aut. – Automatic; Req. – Requested.

Table 2
Long run effects of credit card limit increases – instrumental variables specifications.

	(11)	(12)	(13)	(14)
Long run effect	0.1198 (11.4226)***	0.1144 (36.1111)***	0.1132 (35.7662)***	0.111 (35.1044)***
Lags	10	10	10	10
Type of change	Aut.	Aut.	Aut.	Aut.
Monthly dummies	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No
Credit score	Yes	Yes	Yes	Yes
Outstanding balance	Yes	Yes	Yes	Yes
Account age	Yes	Yes	Yes	Yes
Demographics (Age + Region)	Yes	Yes	Yes	Yes
Card type	Yes	Yes	Yes	Yes
Other card dummy	No	No	Yes	Yes
Other card out. balance	No	No	No	Yes
IV	Months since last change	Months since Last change + Eligibility Dummy	Months since Last change + Eligibility Dummy	Months since Last change + Eligibility Dummy
Observations	426,089	426,089	426,089	426,089

Asy *t* statistics in parentheses. ****P*-value < 0.05.

card limit on debts. The first two columns of [Table 1](#) expand on the conclusion of [Figs. 1–2](#) – that is, after two months the long run effect seems to be about the same.

Models 3 and 4 in [Table 1](#) show the results of the previous figures in the same table just for comparison, while models 5 and 6 indicate the results are quite unaffected by changes in the maximum lag allowed. The seventh model in the same table includes fixed effects per cardholder, resulting in very small cumulative effects. This result is probably due to attenuation bias, since these variables show a high degree of persistence.

When information on the credit behavior of the cardholder is included, as in model 8 of [Table 1](#) with the Credit Score variable, the estimated long run effects more than doubles, from 0.0029 to 0.006. When we expand the set of controls for unobserved characteristics by including the Outstanding Balance and the account age, the long run effects still go up by more than five times, to 0.0339. This result implies an additional BRL in credit limit leads to an increase of 0.0339 BRL in additional credit card debt. This effect does not change much if individual characteristics such as card type and cardholder age and geographical location are included.

This effect is still about a third of the one found by [Gross and Souleles \(2001\)](#). This could be a result of Brazilians being less credit constrained than Americans or a sizable correlation between our credit card limit variable and the part of the unobservables which are not captured by the sets of controls used in [Table 1](#). This endogeneity problem could be due to some omitted factor not controlled for by these variables making the lender to perceive the cardholder as riskier, thus reducing the lenders willingness to increase the credit card limit. Thus, there would be a negative correlation between the error term and the variables indicating limit changes and the coefficients of [Table 1](#) would be biased downward.

Since it is observational data, not experimental ones as in [de Lucinda and Vieira \(2014\)](#), an instrument is required to identify the effects of interest. We used two identification strategies. The first one is based on the number of months since last change in credit card limit, as in [Gross and Souleles \(2001\)](#). Since changes will be made after a minimum amount of time, this rule could be a valid instrument – provided it is correlated enough with the lagged changes in limit and having no effects on credit card debt levels.

The last three lines in [Table 2](#) explore some robustness checks for our main result in the first one. In line (13) a dummy variable indicating whether the cardholder has another credit card with the same bank, and in line 14, instead of the dummy, the outstanding balance in these other cards is included as another continuous variable. The results do

Table 3
Long-run effects on credit card debt of changes in credit card limit for subgroups.

(12)	Main model	Long run effect	T-stat
		0.1144	(36.1111)***
<i>Usage Index</i>			
	Below 25%	0.0835	(7.8037)***
	From 25% to 75%	0.2838	(6.1696)***
	Above 75%	3.1297	(7.3953)***
<i>Score</i>			
	below 25%	0.791	(8.5792)***
	From 25% to 50%	0.0321	(0.9331)
	From 50% to 75%	0.0346	(1.9222)*
<i>Card Types</i>			
	Medium Low	0.1424	(8.4762)***
	Medium High	0.0534	(2.4608)**
	High	0.0762	(3.9278)***

Asy. *T* statistics in parentheses. ****P*-value < 0.01, ***P*-value < 0.05, **P*-value < 0.01.

Baseline spec: 10 lags, automatic limit changes, credit score, outstanding balance, acct. age, credit card, demographics. IV: Months since last change and eligibility dummy.

not change noticeably, indicating an effect similar to what is reported by Ponce (2014): cardholders do not change which cards they use in response in changes in the relative credit card rates.⁶

All instrumental variables estimates point to a long run effect of credit limit on debts of almost three times the effects of the last lines of Table 1. This result is similar to the 0.111 effect found by Gross and Souleles (2001). The *F* test for excluded instruments in Appendix at Table A.4 indicates the instruments are, in fact, quite strong. The results of a Hansen Overidentification test in Table A.5 also indicate the identification strategy is effective.

As for the economic significance of the results, the estimates in Table 2 point out that for every additional 100 BRL in credit limit the credit card debt increases in about BRL 11 in until 10 months after the limit increase. This is an indication of credit constraints in the Brazilian financial markets, just as Gross and Souleles (2001) found for the USA.

However, the effects estimated above are only average effects. There is a sizable literature dealing with heterogeneities in the response of borrowers to credit terms. This is the point of the next section.

3.1. Heterogeneity of effects

It is a well documented fact the effects of changes in credit availability on debts are heterogeneous across borrowers. For instance, Gross and Souleles (2001) mention buffer stock effects as an explanation of both a long run effect of credit on debts as well as an heterogeneous effect. Besides, de Lucinda and Vieira (2014), from an empirical point of view, also note an heterogeneous effect of interest rates on credit demand.

Thus, the analysis of the previous section was extended and done for subgroups, defined across three different characteristics:

- Usage level – four different levels.
- Credit score – three different levels.
- Type of credit card – four types.

The results are in Table 3.

The long run effects of different groups of cardholders, grouped according to the percentage of the credit limit actually used, are higher for those who already use higher shares of their credit card limits. For groups with debts of more than 60% of their credit card limit, the relationship becomes one-to-one: an additional BRL in credit has an

⁶ Since data for only one bank was available for this study, we are not able to check whether this effect applies to credit cards from other financial institutions.

increase of one BRL in debts. This result is even stronger than the one in [Gross and Souleles \(2001\)](#) for the groups with higher usage of credit card debt. They reported a long run effect of 0.452 for this group.

For the sample grouped by credit card scores, the results are also consistent with prior evidence. The long run effect for the group with the lowest credit score was 0.8830, much higher than the effect for the groups of lowest credit scores (which are below 0.04). Both this effect and the one described in the prior paragraph are broadly consistent with a setting of severe credit constraints, as in [Gross and Souleles \(2001\)](#).

4. Concluding remarks

This paper uses a dataset from one of the largest credit card issuers in Brazil to investigate the extent of credit constraints for one of the world's largest emerging market economies. In order to deal with the endogeneity problem from an observational dataset, an identification strategy based on the minimum period between credit limit changes was used to better identify the long run effects on debt of a credit card limit increase.

The results point to a long run effect of credit limit on credit card debts of 0.1144, a similar size to the ones found in [Gross and Souleles \(2001\)](#). This value indicate the Permanent Income Hypothesis is rejected for this sample, and some evidence supporting a variation of “buffer stock behavior” is found.

Furthermore, the results indicate the degree of heterogeneity in effects is much higher than similar results for developed countries, lending credence to the conclusion credit constraints are much stronger for lower income groups. This conclusion is in line to previous studies in Brazil, such as [de Lucinda and Vieira \(2014\)](#).

Appendix A. *F* test for excluded instruments

Table A.4

F tests for excluded instruments.

Teste <i>F</i>	
H0: coefficient for excluded instruments equal to 0	
End. variable	<i>F</i> value
ΔLim_t	5831.62
ΔLim_{t-1}	6208.55
ΔLim_{t-2}	6387.01
ΔLim_{t-3}	6399.38
ΔLim_{t-4}	6388.9
ΔLim_{t-5}	6653.47
ΔLim_{t-6}	6970.42
ΔLim_{t-7}	7032.64
ΔLim_{t-8}	7487.08
ΔLim_{t-9}	7508.98
ΔLim_{t-10}	517.56

Table A.5

Hansen test.

Hansen test	
Regression of residuals – Main specification with respect to exogenous and excluded instruments	
R^2	0.0157
N° Variáveis	44

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