Personal Experiences in the Labor Market and Household Credit Behavior*

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Abstract

Do personal negative experiences in the labor market shape individuals' willingness to take credit? In this paper, we explore the relationship between credit and labor market. Benefiting from individually matched microdata of the Brazilian credit register and labor force activity, we uncover evidence of how being fired in an unexpected recession impacts the credit behavior of individuals. Using a difference-in-difference methodology, we find evidence that being fired in the 2008-2009 recession negatively impacts both the probability of taking credit and the volume of credit. Although these effects seem to be fading over time, they remain active until 2013.

Keywords: Credit behavior; household finance; Job market; Risk-taking;
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*The views expressed are those of the authors and do not necessarily reflect those of the Banco Central do Brasil

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1 Introduction

Do personal negative experiences in the labor market shape individuals' willingness to take credit? Or in a broader sense, do personal negative experiences of economic fluctuations shape individuals' willingness to take risk? Standard financial models assume that risk preferences and attitudes are not influenced by personal experiences, but would take into account all public information available. However, psychology literature highlights the importance of personal experiences - especially the most recent - when making decisions about risk prospects (Hertwig et al. (2005) and Hertwig et al. (2004)). In this way, there is a growing economic literature on the effects of personal experiences on financial decision making. For instance, one person's past inflation experiences will influence future prospects as documented by Malmendier and Nagel (2015), Ehrmann and Tzamourani (2012) and Fajardo and Dantas (2018). Moreover, risk taking behavior can be influenced by past stock returns (Malmendier and Nagel (2011)) or labor market conditions (Knüpfer et al. (2017)).

This article contributes to the understanding of household financial decision making after a negative experience in the labor market, through an analysis of the Brazilian workers' credit patterns after being fired during a recession. Experiencing a job loss can lead individuals to be more pessimistic, reduce their appetite for risk, and thus to be less likely to take credit. We build our sample by linking two microdata datasets: credit registry (SCR) from the Central Bank of Brazil and Employee-Employer administrative records (RAIS) from the Ministry of Economy. We are able to match these datasets using workers' tax identifier number. With the 18-million observations of this combined dataset, we evaluate how being unexpectedly fired during a recession affects future credit patterns, using a difference-in-difference (diff-in-diff) methodology. Our results show that, after being fired during a recession, workers have a lower probability when compared with those not fired, and this can be attributable to both bank supply and worker demand for credit. We find a similar result for the amount of credit, but in this case, workers' credit behavior seems to be the relevant factor.

Our identification strategy is based on the information given by the employer, about which employees were fired during the recession at the discretion of the employer. We do not consider employees that asked to quit the job or that were fired because of unappropriated behavior. This is an advantage when compared to the data of Knüpfer et al. (2017), which relies on self-reported unemployed, regardless of the motivation. Thus, we believe to have a genuine exogenous negative shock. This unexpected unemployment is likely an important part of the formative experience of the worker. Moreover, the origins of the 2008-2009 recession in Brazil are external, coming from the global liquidity shortage following the Lehman Brothers failure.

Our treated (fired workers) and control groups have markedly different characteristics. During the recession, unskilled workers with lower wages and lower tenure in the job have a higher probability of being fired than skilled workers with higher wages and that with more time in the job [1]. Moreover, SCR credit registry has only loans above a threshold (around US$ 1250 at current exchange rate), which creates an under-reporting bias. Therefore, workers with lower wages - which are more likely to get credit under the threshold - will have a higher under-reporting bias.

In order to cope with differences in our treated and control groups, we use a series of control variables and fixed effects, including not only wages and tenure in the job, but also geographic region, age, gender, race, among others. Besides the traditional use of control variables, we also use a Propensity Score Matching, where each observation of the treated group is matched with one in the control group, based on its main characteristics.

Our traditional regression results show that, when compared with the control group, those fired during the 2008-2009 recession had a statistically significant decrease in the probability of taking credit from 2007 to 2010 of around 2.4 p.p., controlling for pre-recession variables. This is an economic relevant effect since it represents around 22% of the mean probability of taking credit in 2007, before the recession. When also controlling for employee characteristics after the recession (in 2010), this estimates decrease to 1.3 p.p. or 12% of the mean probability of taking credit in 2007.

Regarding the interpretation of our results, we might have loan demand and supply side explanations. From the loan demand side, we can interpret as a change of behavior by fired workers, after a negative recent personal experience. These workers would have a lower perception of job stability after the negative past experience, and thus reduce their appetite to take credit when compared with the control group. From the loan supply side, interpretation could come from the fact that, after a job loss, individuals will have a lower tenure on the job, and possibly a lower salary. As banks might prefer to lend to borrowers who have more time in the current job, those who were fired will mechanically have less tenure in the job and will have less access to credit. When controlling for both pre- and post-recession characteristics - including wage and tenure in the job - we can

[1]This is because skilled workers are harder to replace. Moreover, Brazilian Labor legislation makes the turnover of experienced workers very costly

exclude most of the influences coming from the loan supply side, leaving mainly demand side behavior. Therefore, the estimates of 2.4 p.p. - controlling only for pre-recession - would come from both demand and supply behavior, while the 1.3 p.p. - controlling for both pre- and post-recession - would come mainly from the demand side.

We also analyze changes in the volume of credit taken. Our traditional regression results show that, when compared with control group, those fired during the 2008-2009 recession had a statistically significant decrease on the amount of taken credit from 2007 to 2010 of around 0.265 monthly wages, if controlling for pre-recession variables, and 0.247 if controlling for pre- and post- recession variables. Thus, controlling for the supply behavior of banks has little importance for the volume of credit. These estimates are economically relevant, since they represent around 20% of the mean value of the volume of credit taken in 2007.

These effects - for both probability of taking credit and volume - decrease with time. The same regression with pre- and post- recession control variables considering the end-year of 2013 have coefficients much lower, roughly around half of the 2010 estimates. This is an evidence that effects on the worker's behavior may be fading over time.

An alternative approach is the use of propensity score matching (PSM) to cope with ex-ante and ex-post differences between treated (fired workers) and control groups. We build two types of control groups using PSM. One considers a series of variables ex-ante and ex-post, but excludes the tenure in the job after the recession, since workers fired during the recession will have their tenure in the job naturally lower. The second control group considers post-recession tenure in the job as an additional matching variable, imposing a cap on the job tenure of the control group to the maximum possible tenure of those in the treated group. In this way, this control group will have only workers that changed their job after the recession. In both cases, the lower propensity to take credit of workers fired during the recession persists. However, the fading effect is less pronounced. Nevertheless, even with PSM approach, the evidence is that workers changed their credit behavior and became more reluctant int taking credit after the negative experience of being fired.

Our paper is related to Knüpfer et al. (2017), who analyzes portfolio choice by Finnish workers that experienced adverse labor market conditions after a recession. Both papers analyze the risk-taking behavior of workers adversely affected by a recession. While they find a lower share in risky assets by affected workers, we find a lower probability and amount of credit. Another related paper is Malmendier and Nagel (2011) that analyzes if risk-taking behavior of investors is influenced by past stock and bond returns. Past negative experiences with these asset classes make investors less likely to hold them in the future. As in our case, there is a fading effect, with more recent experiences having stronger effects. Van Der Cruijsen et al. (2012) evaluates household's decision on bank deposit instead of credit. Their empirical analysis found that Dutch households who were clients of distressed banks during the 2008 crisis became more likely to spread their investments across several banks. Overall, these three papers, together with our paper, portraits a scenario where bad experience may lead to higher risk aversion in the future, and this might have policy implications.

For policymakers, it is important to understand if and how negative experiences with unemployment affect individuals' credit behavior. In the recovering of a recession, individuals might avoid taking credit even if income and employment levels have returned to original levels, and this phenomenon might spread to consumption. For instance, fiscal and monetary stimulus after a recession may be less effective if households have a ower willingness to take credit.

The paper is organized as follows, in Section 2 we describe the sample and variables construction. Section 3 outlines the methodology and show the main results for the traditional approach using control variables. Section 4 uses the propensity score matching method to re-estimate the results in a more robust way. Section 5 concludes the paper.

2 Sample

2.1 Data Sources

Our analysis combines two different data sources: (i) credit registry from the Brazilian Central Bank (BCB), (ii) employee data from the Brazilian Ministry of Economy. In this section, we discuss the main characteristics of each dataset.

Credit Registry. The BCB collects and maintains data on loans made to individuals in Brazil using a credit registry called SCR (*Sistema de Informações de Crédito*). The unit of observation is a loan. The information is reported monthly by banks to the BCB and must match bank's reported accounting figures. Up to 2012, all loans above BRL 5,000 (≈ US$ 1250 at current exchange rate) must be included in SCR. Although this threshold decreased over time, we kept the original threshold for consistency. We observe each borrower tax code identifier, which is used to link with the employee dataset. Our data is aggregated by borrower. We extract new loans above the BRL 5000 threshold for each borrower in a given year, obtaining the tax code identifier, the volume of the loan and a dummy that identifies

whether the borrower has loans in arrears above 90 days.
Employee Data. We use the employee data from RAIS (*Relação Anual de Informações*) collected by the Brazilian Ministry of Economy, which contains labor market data for the universe of formal workers. Brazilian Economy has a considerable level of informality, including the labor sector. The informality in the labor market is either because firms not registered with tax authorities or because firms have workers off the books. From the employee data, collect the following information at the end of each year:

- A dummy variable equal to one if the employee was fired at the discretion of the employer during the recession of 2008 / 2009 in Brazil. The period of this recession was the last quarter of 2008 and the first quarter of 2009;
- Wages of employees at the end of each year;
- Tenure of employees in their current job;
- Employee's Birthday;
- Occupation of the employee according to the Brazilian occupation classification - CBO (Classificação Brasileira de Ocupações) of 2002. This is based on the International Standard Classification of Occupations (ISCO);
- Educational level of the employee. We consider only three levels: high-school, below high-school and above high school. There are 2,344 different occupations in the sample;
- Gender. Binary variable with either female or male;
- Race. There are five different races. Missing values are considered a different category;
- Employer tax identification code. There are about 1 million different employers considered in the sample;
- Economic activity classification of the employer. We consider the highest level (sector) of CNAE (Classificação Nacional de Atividades Econômicas). There are 21 different economic activities.
- Municipality of the employer. There are about 5450 different municipalities in the sample.

2.2 Sample Construction

We start building the sample with the workers with a formal job at the end of 2007. We then collect loan information from these individuals in 2007, 2010, 2011, 2012, and 2013. We also collect information about their jobs in the years after 2007. We exclude from the sample those who were not formally employed at the end of the regression period (2010 to 2013, depending on the specification). The idea is that they may not have access to credit because of lacking of formal income. Therefore, the sample includes only employees with a formal job in the beginning and at the end of each regression period. Our treated group is composed of employees that were fired at the discretion of the employer during the 2008/2009 recession. Our control group is composed of employees who were not fired during the recession. Thus, we do not consider in the sample employees that asked to quit the job or that were fired because of unappropriated behavior. We also exclude public servants because they have significant job stability since they only can be fired at the discretion of the employer in very specific situations. In this way, this kind of employee is somewhat immune to getting fired due to overall bad economic conditions.

2.3 Dependent Variables Construction

We start by defining the variable $Credit_{y,i}$, which is equal to one if individual i got credit in the year of y. We then define the differential probability of individual i taking credit in the initial year IY (always 2007) and final year FY (either 2010, 2011, 2012 and 2013) as:

$$\Delta\mathbb{P}[Credit_i] = \mathbb{P}[Credit_{FY,i}] - \mathbb{P}[Credit_{IY,i}]. \tag{1}$$

Thus $\Delta\mathbb{P}[Credit_i]$ is our first dependent variable and is intended to analyze the issue in the extensive margin. Our main analysis compares the years of 2007 and 2010. However, we also perform a long-term analysis substituting 2010 by the years of 2011, 2012 and 2013.

Our second dependent variable is based on $V_{Y,i}$, which is the amount of credit taken by individual i in the year of Y divided by his/her monthly wages at year-end. So this is the amount of credit taken by the worker in a given year in terms of monthly wages. The variation $\Delta V_{Y,i}$ from final year FY to initial year IY (always 2007) is:

$$\Delta V_i = V_{FY,i} - V_{IY,i} \tag{2}$$

Thus ΔV_i is our second dependent variable and is intended to analyze the issue in the intensive margin.

2.4 Summary Statistics

The summary statistics of our sample are shown in Table 1, which has four columns. The first column shows summary statistics for the sample with data of 2007 and 2010. This sample is composed of workers with a formal job at the end of 2007 that were also employed at the end of 2010. The second column has statistics for workers with a formal job at the end of 2007, but that were also employed at the end of 2011. Third and fourth columns have the equivalent for the years of 2012 and 2013.

The first two variables show the probability of taking credit in a given year $\mathbb{P}[Credit]$. This probability is biased down since loans below the threshold are not considered. This bias should be stronger for workers with lower wages since their loans are more likely to be under the BRL 5,000 threshold. Thus, our regressions use the log of wages as a control variable. Furthermore, Section 4 uses a propensity score matching considering the wage level (among other variables), in order to tackle this issue.

The probability of taking credit ranges from 10 to 17%, and increased from 2007 to 2013. Part of this increase is may be attributable to the increase in the wages, also shown in Table 1. As only loans above the threshold are reported, the probability of taking credit may mechanically increase due to SCR reporting procedure. We use a differences-in-differences (diff-in-diff) approach that should mitigate this mechanical increase issue.

Our first dependent variable is the difference between the probability of taking credit $\Delta\mathbb{P}[Credit]$ in 2010 and 2007, which has an average of 3,77 percentage points (p.p.). This difference increases to around 5 and 6 p.p. in the years of 2011 to 2013. Our second dependent variable is based on the volume of new credit the households have taken in a given year, and has the same bias down of the probability of taking credit. We normalize this variable by dividing it by the monthly wage of the worker. Thus, in 2007 the average credit taken represents 1.31 times the monthly wage. In the following years, there was an increase to a level of 1.8. Thus, the difference in the volume of new credit from 2007 to the following years ranges between 0.54 and 0.62. Our treated variable is a dummy indicating whether the individual was fired during the recession. We see that less than 10% of the individuals in the sample were fired during the recession. These individuals are considered our "treated" group in the diff-in-diff methodology.

Information about arrears in current loans is also important for borrowing and lending decisions. Table 1 has variables with the percentage of individuals with loans in arrears (above 90 days). The increase of arrears over time may be partially explained as a consequence of the increase of access to credit. Table 1 also shows the average age in 2007 and the average tenure in the job. It is important to highlight that, as we anchor the sample in the individuals with a formal job in 2007, the tenure in the job naturally increases from 2007 to the following years.

Table 1: Summary Statistics

	(1) 2010 mean	(2) 2011 mean	(3) 2012 mean	(4) 2013 mean
Fired during Recession 2008-2009	.09299	.09622	.09797	.09905
$\mathbb{P}$[Credit] 2007	.1064	.1056	.1048	.1041
$\mathbb{P}$[Credit] final year	.1441	.1695	.1588	.1663
$\Delta\mathbb{P}$[Credit]	.0377	.06387	.05401	.0622
Credit Volume / Wage in 2007	1.312	1.295	1.284	1.279
Credit Volume / Wage in final year	1.863	1.846	1.833	1.894
Δ (Credit Volume / Wage)	.5447	.5425	.5515	.6184
Arrears in 2007	.00805	.00803	.00802	.00799
Arrears in final year	.01848	.02228	.03157	.03025
Job Tenure in 2007	46.31	45.68	45.11	44.56
Job Tenure final year	58.77	59.56	62.28	64.54
Monthly Wage 2007 (BRL)	1,306	1,296	1,286	1,275
Monthly Wage final year (BRL)	1,855	2,078	2,317	2,570
Number of Observations	1.86e+07	1.82e+07	1.77e+07	1.72e+07

Table 2 shows summary statistics for the 2007-2010 sample conditional on our treated variable. The first column shows mean values for those individuals who were not fired and the second for those who were fired during the recession. Those who were fired have lower wages and lower tenure in the job. This is a characteristic of the Brazilian labor market as a consequence of the legislation that imposes fines for firing workers with high tenure. The lower wages for the fired group is likely the driver of the lower probability of taking credit and the volume of credit to wage ratio seen in Table 1.

Regarding arrears probability, fired workers have higher values, but the differences are small. It is worth noting that these probabilities are not conditional on having credit. The idea of using these variables as controls is that fired individuals might experience an increase in arrears, and this is likely to reduce the supply of credit for them. As in some specifications we want to control for supply factors, this variable is an important control.

In order to tackle these differences between treated and non-treated individuals, we take two approaches: i) on section 3, we use control variables; ii) on section 4 we use a propensity matching score method to eliminate control variables differences between treated and non-treated groups.

Table 2: Conditional Summary Statistics

	(1) Not Fired mean	(2) Fired mean
$\mathbb{P}$[Credit] 2007	.1089	.08183
$\mathbb{P}$[Credit] 2010	.1488	.09822
$\Delta\mathbb{P}$[Credit]	.03989	.01639
Credit Volume/ Wage in 2007	1.331	1.120
Credit Volume/ Wage in 2010	1.909	1.422
Δ(Credit Volume / Wage)	.5695	.3033
Arrears 2007	.008011	.008388
Arrears 2010	.01842	.01909
Job Tenure in 2007	48.59	24.08
Job Tenure in 2010	63.47	12.94
Monthly Wage 2007 (BRL)	1,345	927
Monthly Wage 2010 (BRL)	1,914	1,280
Number of Observations	1.69e+07	1.73e+07

3 Credit after being Fired

In this section, we compare the credit behavior of households before and after being fired during a recession, using a diff-in-diff methodology. We consider two approaches to measure credit: the probability of taking credit and the amount of credit taken.

3.1 Probability of taking credit

The first measurement approach considers the probability of taking credit before and after the recession. The full specification (3) uses the variation of the probability of taking credit $\Delta\mathbb{P}[C_i]$ from 2007 to 2010 as the dependent variable, and a dummy variable indicating whether the individual has been fired during the 2008 / 2009 recession $Fired_i$ as our main independent variable:

$$\Delta\mathbb{P}[C_i] = \alpha Fired_i + \beta\mathbf{\Phi_i} + \mathbf{\Psi} + \varepsilon_i, \tag{3}$$

where:

- $Fired_i$ is equal to one if the individual was fired at the discretion of the employer during the recession of 2008 / 2009;
- Φ_i is a set of control variables of individual i: wages; tenure in the job, and age;
- $\boldsymbol{\Psi}$ is a set of dummy variables for the municipality of the job place, occupation, educational level, existence of loan in arrears, gender, race and employer.

In order to be in this sample the individual must:

- have a formal job in December 2007, and
- have a formal job in December 2010, and
- either have a formal job during the recession of 2008/2009 or have been fired at the discretion of the employer during the recession of 2008 / 2009.

Table 3 shows only the α estimated coefficients, i.e., those for the *Fired* variable. Column 1 includes control variables and fixed effects only for the year of 2007, while columns 2 and 3 includes for both 2007 and 2010. Column 3 is the most saturated because it includes fixed effects for the employer, while columns 1 and 2 do not.

Column 1 of Table 3 has the results of the specification with controls and fixed effects only from 2007. It shows that those fired during the recession had a decrease on the probability of taking credit from 2007 to 2010 of 2.37 p.p. when compared to those who kept the job. The magnitude of the α coefficient represents around 22% of the mean probability of taking credit $\mathbb{P}$[Credit] from 2007 (see Table 1), so it is an economically relevant effect. Regarding the interpretation, as we do not have in this specification controls from 2010, we can not distinguish this effect from loan demand or supply. Therefore, the effect may be coming from both workers and banks.

Column 2 of Table 3 has the results of the specification with controls and fixed effects from both 2007 and 2010, with an α coefficient of 1.26 pp, which is lower than column 1 and represents around 12% of the mean probability of taking credit in 2007. The inclusion of 2010 controls is an attempt to exclude the loan supply effects. Given the diff-in-diff approach, explanations from the loan supply side must be attached to job loss.

One possible explanation using the supply side is that banks prefer to lend to borrowers with certain characteristics like higher wages, more time in the current job, no loan arrears, etc. Therefore, as our treated group has lower wages and less tenure in the job than the control group also in 2010, they may have less access to credit. When controlling for wages, tenure in the job, and other control variables also in 2010, we equalize the main characteristics used by banks to analyze credit offering. Although there might be other aspects considered by banks, we believe that this specification has essentially effects from the loan demand side. Therefore, our interpretation for the finding in column 2 is a change of behavior by fired workers. Thus, when we compare the 2.37 p.p. coefficient on column 1 and the 1.26 p.p. coefficient in column 2, a significant part of the effect could be attributable to worker credit behavior.

Column 3 has results for the most saturated specification which includes employer fixed effects from 2007 and 2010 (approximately 1 million each), which is able to cope with unobservable heterogeneity across employers. The α coefficient is very similar to specification 2.

In order to further tackle ex-ante and ex-post differences between treated and control groups, we use the propensity score matching methodology in section 4. Given the robustness of results to these additional control procedures, supply-side explanations seem less plausible.

Table 3: Recession and Probability of Taking Credit (2010-2007)

	(1)	(2)	(3)
	$\Delta\mathbb{P}$[Credit]	$\Delta\mathbb{P}$[Credit]	$\Delta\mathbb{P}$[Credit]
Fired	-0.0237***	-0.0126***	-0.0129***
	(-21.45)	(-16.37)	(-18.91)
Gender FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Municipality FE	Pre	Pre/Post	Pre/Post
Job Occupation FE	Pre	Pre/Post	Pre/Post
Education FE	Pre	Pre/Post	Pre/Post
Employer FE	No	No	Yes
Controls	Pre	Pre/Post	Pre/Post
# Observations	1.84e+07	1.79e+07	1.69e+07
Adj R2	0.00468	0.01018	-0.01006

3.2 Amount of credit

We turn now to the second credit measurement approach, which uses the variation in the amount of credit taken as a dependent variable. The specifications in this subsection are also (3), with a change of the dependent variable, which now is ΔV_i (variation in the amount of credit taken) instead of $\Delta\mathbb{P}[C_i]$ (variation in the probability of taking credit). The independent variable is the same: a dummy variable indicating whether the individual has been fired during the 2008 / 2009 recession.

Coefficients in Table 4 are Those who were fired during the recession had a statistically significant reduction on the volume of credit taken from 2007 to 2010, ranging from 0.24 to 0.27 monthly wages when compared to those who kept the job. This represents around 20% of the mean value of the volume of credit taken in 2007. Coefficients are similar in columns 1 and 2, indicating that controlling for the supply behavior of banks has little importance for the differential volume of credit. Controlling for employer FE (column 3) does not materially change results.

Table 4: Recession and Credit Volume (2010-2007)

	(1)	(2)	(3)
	ΔCredit	ΔCredit	ΔCredit
Fired	-0.2654***	-0.2467***	-0.2732***
	(-24.13)	(-15.32)	(-15.79)
Gender FE	Yes	Yes	Yes
Race FE	Yes	Yes	Yes
Municipality FE	Pre	Pre/Post	Pre/Post
Job Occupation FE	Pre	Pre/Post	Pre/Post
Education FE	Pre	Pre/Post	Pre/Post
Employer FE	No	No	Yes
Controls	Pre	Pre/Post	Pre/Post
# Observations	1.83e+07	1.79e+07	1.69e+07
Adj R2	0.00063	0.00178	-0.03219

3.3 Long-term Effects

Previous subsection's findings provide empirical support to lower willingness to take credit by workers after being fired, with a window of a couple of years. In this section, we evaluate whether this effect is persistent over time, or fades in the long term. In order to do this analysis, we keep the initial year in 2007 but replace data from the year of 2010 by data from the following years of 2011, 2012 and 2013. The regression specification is that of column 2 of Tables 3 and 4, i.e., using pre- and post-recession controls and fixed effects, except for employer fixed effects. Table 5 shows results for the probability of taking credit. Column 1 of table 5 repeats the result of column 2 of Table 3, for comparison. Column 2 provides the estimates of a sample with workers who were employed at the end of 2007 and at the end of 2011. Columns 3 and 4 show the equivalent considering 2007 as initial year and 2012 and 2013 as final years, respectively. All coefficients on Table

5 are still significant at 1% level. However, the magnitude decreases, especially when looking to the years on 2012 and 2013. The coefficient for 2013 (column 4) is around half of the coefficient for 2010 (column 1). This is an evidence that the negative experience effects are fading over time.

Table 5: Recession and Probability of Taking Credit - Long-term Effects

	(1) $\Delta\mathbb{P}$[Credit] (2010-2007)	(2) $\Delta\mathbb{P}$[Credit] (2011-2007)	(3) $\Delta\mathbb{P}$[Credit] (2012-2007)	(4) $\Delta\mathbb{P}$[Credit] (2013-2007)
Fired	-0.0126***	-0.0117***	-0.0086***	-0.0064***
	(-16.37)	(-15.20)	(-13.44)	(-9.21)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	1.79e+07	1.75e+07	1.70e+07	1.65e+07
Adj R2	0.01018	0.01765	0.02049	0.02271

Table 6 shows long-term results for the volume of credit taken. Column 1 repeat the result of Table 4, column 2, for comparison. Again, all coefficients are still significant at 1% level and are decreasing over time, with the coefficient for 2013 being less than half of the coefficient for 2010. This corroborates the evidence of negative experiences effects fading over time, now at the intensive margin.

Table 6: Recession and Volume of Credit: Long-term Effects

	(1) ΔCredit (2010-2007)	(2) ΔCredit (2011-2007)	(3) ΔCredit (2012-2007)	(4) ΔCredit (2013-2007)
Fired	-0.2467***	-0.2030***	-0.1580***	-0.1135***
	(-15.32)	(-11.58)	(-8.80)	(-5.58)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	1.79e+07	1.75e+07	1.70e+07	1.65e+07
Adj R2	0.00178	0.00270	0.00359	0.00456

4 Results using Propensity Score Matching

Given the differences in the control variables from fired and non-fired groups, in this section, we use the propensity-score matching (PSM) method as an alternative to simply use control variables.

We use implementation approaches for the PSM. In the first approach, we match each treated individual with a similar individual in the control group (with replacement), based on a propensity score, and then perform the long-term regressions with the matched control group. This score is based on personal characteristics (race, age, gender, and educational level), job characteristics (job tenure, wage, and 3-digit occupation code), mesoregion of the employer, and existence of arrears. We match these variables for both pre-recession (2007) and post-recession end-years (2010 to 2013), except for the tenure in the job, which is used only for 2007.

Recall that the tenure in the job the end-year of fired workers is capped by construction[2], and this is a problem for the execution of the PSM method straight away.

In order to overcome this issue, in our second approach, we perform the propensity score matching using a control group composed of workers with a job tenure limited to the maximum possible tenure of a fired worker [3]. This means these workers of the control group also changed their jobs after the recession in some way, either asking to quit of being fired outside recession times. In this second approach, all variables are also matched for post-recession characteristics, including tenure in the job.

It is important to mention that the two matching procedures differ mainly on the tenure on the job. While in the first PSM approach, we may have in the control group workers that are in the same job since 2007, in the second PSM approach, workers in the control group necessarily changed their jobs after 2007.

Subsection 4.1 present results of the first approach, and subsection 4.2 for the second approach.

4.1 First PSM Approach: no control for post-recession tenure

In this first approach, we match all control variables and fixed effects of pre- and post-recession periods, except for the tenure in the job after the recession. Table 7

[2]Employees that did not lose their jobs during the crisis can reach certain values for tenure in their current job that those who were fired could not reach. This creates an asymmetry for this variable when we compare treated and control groups.

[3]For instance, a worker fired in January 2009 would have a maximum tenure in the job of 24 months at the end of 2010.

shows summary statistics for treated and control groups of the PSM sample, for the end-years of 2010 and 2013. We see that fired and non-fired groups have very similar mean statistics for the control variables, except for tenure in the job post-recession. The difference in the means of fired and non-fired is usually below 2%. The probability of taking credit and credit volume in the baseline year (2007) also have similar values. Using this matched sample allows us to exclude most credit supply effects so that results would uncover the workers' demand for credit.

Table 7: Conditional Summary Statistics - PSM - First Approach

	(1) Not Fired 2010	(2) Fired 2010	(3) Not Fired 2013	(4) Fired 2013
$\mathbb{P}$[Credit] 2007	.07895	.08202	.07797	.08105
$\mathbb{P}$[Credit] end-year	.1145	.09861	.1385	.0914
$\Delta\mathbb{P}$[Credit]	.03555	.01658	.06055	.01035
Credit Volume/ Wage in 2007	1.121	1.129	1.115	1.113
Credit Volume/ Wage in end-year	1.805	1.449	1.797	1.607
Δ(Credit Volume / Wage)	.6833	.3207	.6816	.4935
Arreas 2007	.008348	.008333	.008364	.008217
Arreas end-year	.0192	.01898	.03021	.03029
Job Tenure in 2007	24.33	24.12	24.54	24.35
Job Tenure in end-year	38.07	12.77	44.46	24.25
Age in 2007	31.22	31.3	30.99	31.05
Monthly Wage 2007 (BRL)	929.4	937.9	928.2	934.1
Monthly Wage end-year (BRL)	1,312	1,309	1,960	1,956

We replicate results of long-term effects regressions using PSM. Tables 8 and 9 show results for long-term effects for Probability of Credit and Volume of Credit, respectively. The coefficient estimates are still statistically significant and with a decreasing pattern, but have lower values than those of tables 5 and 6.

The $\Delta\mathbb{P}$[Credit] from 2010 to 2007 is -0.0079 (column 1 of table 8) which is around 7.5% of the mean probability of taking credit in 2007. However, it has a steep decrease over time, so that coefficient in 2010 (column 4) is less than one-quarter of the 2010 coefficient.

The volume of credit (table 9) shows a similar pattern: lower and decreasing estimates, but still statistically significant. The -0.1252 coefficient of Column 1 is roughly half of the equivalent in table 6, but still represents around 10% of the initial credit volume / wage in 2007. The coefficient for 2013 (column 4) is around half of those for 2010. Thus, the analysis with PSM confirms the evidence that adverse experience effects are fading over time.

Table 8: Recession and Probability of Taking Credit - First PSM Approach

	(1) $\Delta\mathbb{P}$[Credit] (2010-2007)	(2) $\Delta\mathbb{P}$[Credit] (2011-2007)	(3) $\Delta\mathbb{P}$[Credit] (2012-2007)	(4) $\Delta\mathbb{P}$[Credit] (2013-2007)
Fired	-0.0079***	-0.0060***	-0.0035***	-0.0018***
	(-11.35)	(-7.66)	(-6.41)	(-2.69)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	3.34e+06	3.37e+06	3.33e+06	3.27e+06
Adj R2	0.01498	0.02350	0.02849	0.03107

Table 9: Recession and Credit Volume - First PSM Approach

	(1) ΔCredit (2010-2007)	(2) ΔCredit (2011-2007)	(3) ΔCredit (2012-2007)	(4) ΔCredit (2013-2007)
Fired	-0.1252***	-0.1306***	-0.0827***	-0.0623***
	(-3.20)	(-7.46)	(-4.69)	(-4.24)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	3.34e+06	3.37e+06	3.33e+06	3.27e+06
Adj R2	0.00578	0.00942	0.00865	-0.00161

4.2 Second PSM Approach: post-recession tenure capped

In the second PSM approach, we also use the post-recession tenure in the matching score. As mentioned before, we do this by excluding from the universe of possible matching observations individuals with a job tenure unreachable by workers fired during the recession. This means exclusion of job tenures of 27, 39, 51 and 63 months for the end-years of 2010, 2011, 2012 and 2013, respectively[4]. In this way, control and treated groups have approximately the same means for the control variables, including job tenure in the post-recession. Table 10 shows these summary statistics.

Table 10: Conditional Summary Statistics - PSM - Second Approach

	(1) Not Fired 2010	(2) Fired 2010	(3) Not Fired 2013	(4) Fired 2013
$\mathbb{P}$[Credit] 2007	.07762	.07964	.07772	.07938
$\mathbb{P}$[Credit] end-year	.1037	.09587	.1346	.1293
$\Delta\mathbb{P}$[Credit]	.0261	.01622	.05686	.04989
Credit Volume/ Wage in 2007	1.026	1.063	1.052	1.069
Credit Volume/ Wage in end-year	1.497	1.378	1.665	1.56
Δ(Credit Volume / Wage)	.4713	.3147	.613	.4904
Arreas 2007	.00820	.00812	.00813	.00809
Arreas end-year	.01869	.01872	.03034	.03018
Job Tenure in 2007	23.13	23.37	23.78	23.78
Job Tenure in end-year	11.37	11.35	22.93	23.00
Age in 2007	31.13	31.2	30.95	30.97
Monthly Wage 2007 (BRL)	926.9	927.8	932.7	926.3
Monthly Wage end-year (BRL)	1,298	1,292	1,970	1,939

This subsection presents long-term regression results for the second PSM approach, where we limit the tenure of the job. For the probability of taking credit, results of table 11 are still statistically significant, with coefficient estimates higher in magnitude than the previous PSM approach. When comparing with the long-term regressions from table 5, coefficients from years 2010-2012 are lower in magnitude, but the one from 2013 is higher. Thus, the fading effect is considerably less pronounced, going from -0.0092 in 2010 to -0.0068 in 2013. Regarding the credit volume results of table 12, again the coefficients are statistically significant and higher in magnitude than previous PSM approach. When comparing to the traditional approach of table 6, coefficients are higher in magnitude for 2010 and 2011 but have a similar magnitude for 2012-2013. The fading effect is also

[4] A worker fired at the beginning of the recession - October 2008 - would have a tenure in the job of 27 months in December 2010, 39 months in December 2011, and so on.

considerably less pronounced in this second approach when compared to tables 6 and 9.

The interpretation of this subsection's results should consider that all individuals in this sample changed their jobs at some point after the recession, given the tenure in the job cap. In this way, we are comparing individuals fired during an unexpected recession with individuals that changed their jobs in other ways: either asking to quit or fired outside recession period. Therefore, the interpretation would be that being fired during a recession has an impact on credit behavior even compared with a control group with job change experiences.

Table 11: Recession and Probability of Taking Credit - Second PSM Approach

	(1) $\Delta\mathbb{P}$[Credit] (2010-2007)	(2) $\Delta\mathbb{P}$[Credit] (2011-2007)	(3) $\Delta\mathbb{P}$[Credit] (2012-2007)	(4) $\Delta\mathbb{P}$[Credit] (2013-2007)
Fired	-0.0092***	-0.0102***	-0.0077***	-0.0068***
	(-14.10)	(-12.24)	(-13.52)	(-11.06)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	3.28e+06	3.32e+06	3.29e+06	3.23e+06
Adj R2	0.01876	0.02657	0.03142	0.03373

Table 12: Recession and Credit Volume - Second PSM Approach

	(1) ΔCredit (2010-2007)	(2) ΔCredit (2011-2007)	(3) ΔCredit (2012-2007)	(4) ΔCredit (2013-2007)
Fired	-0.1460***	-0.1753***	-0.1545***	-0.1159***
	(-9.53)	(-10.00)	(-11.35)	(-5.04)
Gender FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Municipality FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Job Occupation FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Education FE	Pre/Post	Pre/Post	Pre/Post	Pre/Post
Employer FE	No	No	No	No
Controls	Pre/Post	Pre/Post	Pre/Post	Pre/Post
# Observations	3.28e+06	3.32e+06	3.29e+06	3.23e+06
Adj R2	0.01236	0.01200	0.00974	0.00171

5 Final Remarks

This article provides empirical evidence that, after the negative experience of being fired during a recession, Workers decrease their willingness of taking credit both in the extensive and intensive margins. This evidence is obtained by taking advantage of the Brazilian recession following the global financial crisis in 2008, and microdata from both labor and credit markets. We believe to have a genuine exogenous employment shock for the individual for two reasons. First, our data allows us to identify workers fired at the discretion of the employer. Second, the crisis that leads to the recession was externally induced, and thus largely unexpected to Brazilians firms and workers. Our results suggest some follow-up questions. For instance, if this negative experience would also reduce the willingness of these households to invest in risky assets, or if this would diminish the propensity to consume. If this is the case, policies designed to stimulate consumption and credit concession after a recession may be increasing the risk aversion of households, with consequences in future investment and consumption decisions. Another interesting question is whether the 2014-2016 recession in Brazil produced similar effects. This recession had different characteristics. In particular, it was the longest in Brazilian history. Would this produce a stronger effect on risk taking?

References

Ehrmann, M. and Tzamourani, P. (2012). Memories of high inflation. *European Journal of Political Economy*, 28(2):174–191.

Fajardo, J. and Dantas, M. (2018). Understanding the impact of severe hyperinflation experience on current household investment behavior. *Journal of Behavioral and Experimental Finance*, 17:60 – 67.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological science*, 15(8):534–9.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2005). The role of information sampling in risky choice. In Fiedler, K. and Juslin, P. E., editors, *Information Sampling and Adaptive Cognition*, page 72–91. Cambridge University Press.

Knüpfer, S., Rantapuska, E., and Sarvimäki, M. (2017). Formative experiences and portfolio choice: Evidence from the finnish great depression. *The Journal of Finance*, 72(1):133–166.

Malmendier, U. and Nagel, S. (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? *Quarterly Journal of Economics*, 126(1):373–416.

Malmendier, U. and Nagel, S. (2015). Learning from Inflation Experiences. *The Quarterly Journal of Economics*, 131(1):53–87.

Van Der Cruijsen, C. A., De Haan, J., Jansen, D.-J., and Mosch, R. H. (2012). Households' decisions on savings accounts after negative experiences with banks during the financial crisis. *Journal of Consumer Affairs*, 46(3):436–456.