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ESSAYS ON CREDIT POLICIES

ESSAYS ON CREDIT POLICIES

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Campo de Conhecimento: Políticas de Crédito

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Resumo

Esta tese de doutorado engloba três ensaios relacionados à políticas de crédito específicas no Brasil. Em se tratando de um país continental, políticas públicas podem ter impactos diversos nas regiões brasileiras. No último século, a legislação referente ao mercado de crédito brasileiro sofreu variadas mudanças e que agora podem ser melhor avaliadas. Todos os ensaios utilizam o Sistema de Informações de Crédito (SCR) do Banco Central do Brasil como parte da base de dados, integrando-o com outras informações.

O primeiro ensaio da tese verifica o impacto da mudança local do valor máximo do imóvel elegível para crédito subsidiado do Sistema Financeiro da Habitação, no contexto de medidas macroprudenciais relacionadas ao mercado imobiliário que tiveram maior relevância após a crise de 2008. Desde Setembro de 2013, este teto passou de R$ 500 mil para R$ 750 mil para os Estados de São Paulo, Minas Gerais e Rio de Janeiro, e o Distrito Federal, enquanto que para os demais Estados o teto passou de R$ 500 mil para R$ 650 mil, criando uma descontinuidade geográfica entre tais regiões. Nesse sentido, comparamos através de Regressão com Descontinuidade municípios ao redor de 75 quilômetros da fronteira entre as regiões com limites distintos.

Notamos que houve uma diferença temporária de 15% dos valores das garantias dos financiamentos imobiliários, que são o preço dos próprios imóveis financiados, entre municípios vizinhos que passaram a ter tetos distintos de imóveis elegíveis a este financiamento após seis meses da primeira mudança. Esta diferença permanece após variados testes de falsificação. Por outro lado, a maturidade do crédito imobiliário torna-se mais elevada na região com maior teto. Já em 2016, em um período de crise econômica, a alteração do limite máximo do preço dos imóveis de R$ 750 mil para R$ 950 mil nas Unidades de Federação citadas e de R$ 650 mil para R$ 800 mil nas demais regiões parece impactar menos o preço de imóveis. Quando consideramos as capitais e regiões metropolitanas com tetos distintos, vimos que a diferença entre preços de imóveis se torna maior e permanente ao longo do tempo, através de análises por diferenças em diferenças.

Verificamos que tal medida propiciou maior arrecadação de IPTU aos municípios na região com teto maior de eligibilidade do SFH após 2012. Por fim, avaliamos a distorção gerada pela imposição do limite de preços gerada da distribuição dos valores do colateral do financiamento imobiliário. A distorção gerada pelo teto do preço até 2013 ocasionou mudanças da distribuição do preço de imóveis, de forma que a elasticidade da demanda em relação ao preço diminui quatro vezes ao redor dos R$ 500 mil.

O segundo ensaio analisa a relação entre crédito e consumo após as mudanças do mercado bancário brasileiro como a alienação fiduciária, a criação do crédito consignado e a lei das falências. sob o nível da chamada área de ponderação, unidade de observação igual ou menor que o município, construída a partir do Censo populacional de 2000 e de 2010. Como variável instrumental do crédito local, medimos a menor distância entre o centróide do CEP de cada região e variados canais físicos bancários georreferenciados: a agência bancária, os postos de atendimento e correspondentes bancários. Utilizamos este crédito instrumentalizado para avaliar seu impacto sobre o consumo local de bens duráveis, através uma cesta de

bens como televisão, máquina de lavar, computador e geladeira mensurado pelo questionário amostral do Censo.
Encontramos evidência que o aumento de um ponto percentual do crédito em uma área de ponderação pode levar ao aumento de 1.4% na cesta de consumo de bens duráveis local. Já a proximidade física de uma agência bancária ou de um posto de atendimento está relacionado com maior crédito na área compreendida por aquele CEP. Vemos ainda evidências de efeito espacial do crédito, que pode ser neutralizado por modelos espaciais. Os efeitos diferem conforme a região do país e o tamanho das áreas de ponderação, o que evidencia a importância da questão regional do crédito.

Por sua vez, o terceiro ensaio avalia o possível efeito riqueza oriundo da obtenção do imóvel sobre consumo através do programa Minha Casa Minha Vida. Na Faixa 1 desde programa, que abrange familias de até três salários mínimos, são realizados sorteios quando o número de inscritos supera o número de unidades habitacionais disponíveis. Em particular, este artigo identifica o efeito do indivíduo da família de baixa renda ser sorteado para receber um imóvel subsidiado no Rio de Janeiro, onde o sorteio foi feito de forma aleatorizada, em comparação com o indivíduo que participou do sorteio e não foi contemplado, em variáveis de crédito relacionadas com consumo. Foram avaliados seis sorteios entre 2011 e 2013, abrangendo cerca de 500 mil pessoas.
As estimações foram feitas pelo método de Análise de Covariância, comparando o sorteado com o não sorteado, e por variáveis instrumentais, comparando o efetivo beneficiário do programa com o não contemplado. Encontramos efeito nulo ou até negativo do tratamento no montante de crédito realizado nos primeiros sorteios, mas os resultados dos últimos sorteios sugerem forte efeito riqueza do novo imóvel através do Crédito Consignado e do Cartão de Crédito. Por outro lado, há evidências do efeito do sorteio no aumento financiamento de bens relacionado ao programa Minha Casa Melhor e na inclusão financeira através da exposição inicial a algum tipo de crédito em todos os sorteios. Ainda notamos que a exposição ao crédito ofertado pelo Minha Casa Melhor nos primeiros sorteios avaliados pode levar a um aumento da inadimplência ao beneficiário do programa, o que pode piorar seu bem estar ao longo prazo.

Palavras-chave: crédito; políticas públicas; financiamento habitacional; consumo; economia regional.

Abstract

This thesis encompasses three essays related to specific credit policies in Brazil. Brazil is a continental country where public policies can have diverse impacts in the Brazilian regions. In the last century, the legislation regarding the Brazilian credit market has undergone several changes and can now be better evaluated. All the essays consider the Credit Registry Data (SCR) of the Central Bank of Brazil as part of the database, integrating it with other information.

The first essay examines the impact of the local change in the maximum value of the property eligible for subsidized credit from the Housing Finance System (SFH), in the context of macroprudential measures that became relevant after 2008 Crisis. Since September 2013, this eligible-limit went from BRL 500,000 to BRL 750,000 for the states of São Paulo, Minas Gerais and Rio de Janeiro, and the Federal District, while for the other States the limit changed from BRL 500,000 to BRL 650,000, creating a geographical discontinuity between such regions. In this sense, we compare the municipalities around 75 kilometers from the border between regions with distinct eligible limits using the RDD procedure.

We note that there was a temporary difference of 15 % of the values of the housing financing collaterals, which are the price of the real estate financed, between neighboring municipalities that had different ceilings of real estate eligible for this financing after six months of the first change. This difference remains after various falsification tests. On the other hand, the maturity of real estate credit becomes higher in the region with the highest limit. However, the change in the limit in 2016 (in a period of economic crisis), when the eligible-limit came from BRL 750,000 to BRL 950,000 in the main states and BRL 650,000 to BRL 800,000 in other regions, seems to have a lower impact on real estate prices. Considering only housing loans from capitals and metropolitan regions with distinct limits, there is an evidence that the difference between real estate prices becomes larger and permanent over time, through differences-in-differences analysis.

We verify that such a change led to a higher property-tax collection to the municipalities in the region with the highest SFH limit after 2012. Finally, we evaluate the distortion generated by the imposition of this limit generated from the distribution of collateral values of real estate financing. The distortion generated by the upper-bound limit until 2013 caused changes in the distribution of real estate prices, so that the elasticity of demand in relation to the housing price decreases four times around the BRL 500,000 value.

The second essay analyzes the relationship between credit and consumption following changes in the Brazilian banking market such as fiduciary alienation, creation of the payroll credit and the bankruptcy law, considering the weighting area, an observation unit equal or smaller than a municipality measured in Census. As the instrumental variable of local credit, we measured the smallest distance between the zip code's centroid of each region and georeferenced physical banking channels: the bank branch, the bank branches-like and correspondent banks. We used this instrumented credit to evaluate its impact on local consumption of durable goods through a basket of durable goods such as television, washing machine, computer and refrigerator.

We found evidence that increasing one percentage of credit in a weighting area may lead to a 1.4 % increase of the local consumer basket. The physical proximity of a bank branch or a bank branch-like is related to higher amount of credit in the area covered by that zip code. We also see evidence of the spatial effect of credit, which can be neutralized by spatial models. The effects differ according to the region of the country and the size of the weighting areas, which highlights the importance of the regional credit issue.
The third essay evaluates the possible wealth effect derived from obtaining the property over consumption through a Brazilian housing (My House My Life) program. For the households with less than three minimum wages, there are lotteries when the demand exceeds the number of housing units available in the city. In particular, this article identifies the effect of being a lottery winner or a effective beneficiary of a subsidized property in Rio de Janeiro, where the lottery was randomized, over consumer-related credit outcomes. Six lotteries were evaluated between 2011 and 2013, covering about 500,000 individuals.
The estimates consider the covariance analysis method, comparing lottery winners with non-winners, and the instrumental variables, comparing the effective beneficiary of the program with the non-beneficiary. There is not an evidence of positive effects of the treatment on the amount of credit on the first lotteries, but the results of the last draws suggest a strong wealth effect of the new property through Payroll Credit and Credit Card. On the other hand, there is an evidence of winning the lottery on the increase in the durable goods financing related to the My House Better program and on the financial inclusion through the initial exposure to some type of credit. We also note that exposure to the credit offered by My House Better on the first lotteries may lead to an increase in the credit default rates of the beneficiaries of the program, which can worsen their long-term well-being.

Keywords: credit; policies; housing; consumption; regional economics.

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[1] The views expressed in this work are those of the author and do not necessarily reflect those of the Central Bank of Brazil or its members.

1.1 Introduction

After the Great Recession, numerous financial instruments have been used for financial regulation, named macroprudential tools. Some of these tools involve loan criteria in the housing market, such as the maximum allowable loan-to-value (LTV), loan-to-income (LTI) ratios, or thresholds for conforming loans. Those housing policies have been implemented in various countries, such as Ireland (HALLISSEY et al., 2014), Canada (ALLEN et al., 2017), India (CAMPBELL; RAMADORAI; RANISH, 2015) or even in Brazil (ARAUJO et al., 2016). The impact on real state prices are not always clear (KUTTNER; SHIM et al., 2012). However, the relationship between credit and house price booms is strong in most countries (CERUTTI; DAGHER; DELL'ARICCIA, 2017).

The housing market is one of most important environments for redistribution policies. A house can be the most important asset for many households. Having this physical asset may be essential to meet the basic needs of living. In addition, there is a huge relevance of the mortgage loan (using house as a collateral) in several countries, improving consumption at a local level after changing housing prices ((MIAN; RAO; SUFI, 2013), (MIAN; SUFI, 2014) and (IACOVIELLO; MINETTI, 2008)).

In contrast, regional macroprudential policies are more common only in currency unions (like the European Union), although it is clear that booms and busts can be (and have been) regional (CLAESSENS, 2015). Nevertheless, if labor and other factors markets are not sufficiently flexible to allow a satisfactory reallocation of resources, such as the housing market in developing and large countries, it allows the operation of macroprudential policies at a regional level.

Conforming housing loans in Brazil, a continental, developing country, have significant subsidies on their interest rates. The most important subsidized credit facility is the SFH (Brazilian Housing Finance System), which finances housing for middle-income households. The eligibility criteria for SFH are also related to a maximum housing price. This article evaluates the impact of changing the limit of an eligible SFH loan asymmetrically across Brazilian states on housing prices observed in September 2013 and November 2016. In the United States, houses that become eligible for financing with a conforming loan show an increased value (ADELINO; SCHOAR; SEVERINO, 2012).

For this study, we consider real estate loans from 925 municipalities at the frontier of eight Brazilian States and the Federal District with different upper-bound limits for the SFH loan, using a two-dimensional (latitude and longitude) Regression Discontinuity design. Those loans have housing price as collateral, which is our main variable of interest.

We find evidence that this policy affects local real estate prices in the short run. Municipalities around the boundary with higher limits to assume a subsidized housing loan can increment more than 10% of the real estate price evaluated by the financial institutions in comparison to municipalities with a lower limit six months after the first regional change (September of 2013). Almost one year after this temporal change in housing prices, we still find differences in the Loan-to-Value (7.5% smaller for the higher-limit region). We do not notice any other variable changes between those regions except this loan-limit value. We find evidence of differences in housing prices between those municipalities after the second regional change (November 2016), but in an opposite manner and with a lower magnitude. Demand for housing seems to be affected distinctly beyond those regions only for this second change. However, economic crises between 2014 and 2016 affected the number of SFH loan contracts in both regions.

The results are consistent with the literature. In England, raising the housing price threshold for a transaction tax reduced the after-tax sale price (BESLEY; MEADS; SURICO, 2014) over the short-term. Our estimations suggest that the long-term impact only occurs in Brazilian main cities and in Metropolitan Areas, probably due to an extensive marginal response, which is also evident in the example in England (BEST; KLEVEN, 2017).

This paper is organized as follows. Section 2 explains the history of Housing Finance in Brazil and recent institutional framework. Section 3 presents the data and Section 4 presents the empirical strategy. Section 5, lays out the main results of this paper. Section 6 evaluates robustness checks of previous results with counterfactual estimations, effects on bigger cities and local tax revenues and bunching implications. Finally, Section 7 concludes.

1.2 Housing Finance in Brazil

Long-term lending has historically been very scarce in Brazil due to several episodes of high inflation (HADDAD; MEYER, 2011). The Brazilian Housing Finance System (SFH) was created in 1964 (Law 4,380) due to financial reforms that occurred at the beginning of the military dictatorship. SFH implemented a monetary correction for inflation in contracted loans and improved long-term credit.

SFH funding has two sources: i) a compulsory fund, Employees Guarantee Fund (FGTS), which is compounded from an 8 % tax collected on all private sector wages, providing unemployment insurance and low-income housing; and ii) a voluntary fund, SBPE (Savings and Loans Brazilian System), a free income-tax investment for middle-income families that provides funds based on savings deposits in banks. The saving deposits in SBPE received a basic remuneration, the TR (a floating and partial inflationary correction) and an additional remuneration (a fixed 0.5% monthly interest rate). Currently, if the Brazilian interest rate (SELIC) is equal or below 8.5%, that fixed remuneration is replaced with a 70% SELIC interest rate [2]. 65% of the total SPBE invested in financial institutions fund must finance Brazilian housing credit.

At least 80% of this credit supported by SBPE should go to the Brazilian Housing Financial System (SFH), which is the most important conforming housing loan with subsidized interest rates, while the other part is allowed for a housing loan in the free market.

After the Real Plan (1994), the Brazilian economy has been stabilized with lower inflation and reorganization of the financial industry. Law 9,514 (1997) created the Real Estate Financing System (*Sistema Financeiro Imobiliário*, or SFI) and allowed the retention of title as a collateral for financing real estate property acquisitions, facilitating the recovery of the property (which remains in the name of the lender until repayment) by the financial institution if the loan defaults. Fiduciary property law (Law 10,931 of 2004) improved that type of credit (MARTINS; LUNDBERG; TAKEDA, 2011), creating the legal figure of the fiduciary assignment (trust deed arrangement) in Brazil.

[2] If SELIC rate is above 8.5%, the TR + 0.5% monthly keeps unchanged.

In Figure 1 we can see the impact of those changes in the Brazilian housing market. The Extended National Consumer Price Index (IPCA) is the official measure of inflation, and the Collateral Value Index (IVG-R) measures the long-term trend of the household's houses in Brazil. This index is calculated by the Central Bank of Brazil using the evaluation data for housing loans that are granted to natural persons and collateralized by financed real estate in main Brazilian metropolitan regions. We can clearly see that housing prices grew much faster than other prices, even considering a national economic crisis after 2013. Concurrently, housing loans became representative in Brazil, increasing from 1.5% to 9% of GDP in ten years, but remaining low in comparison to other emerging countries.

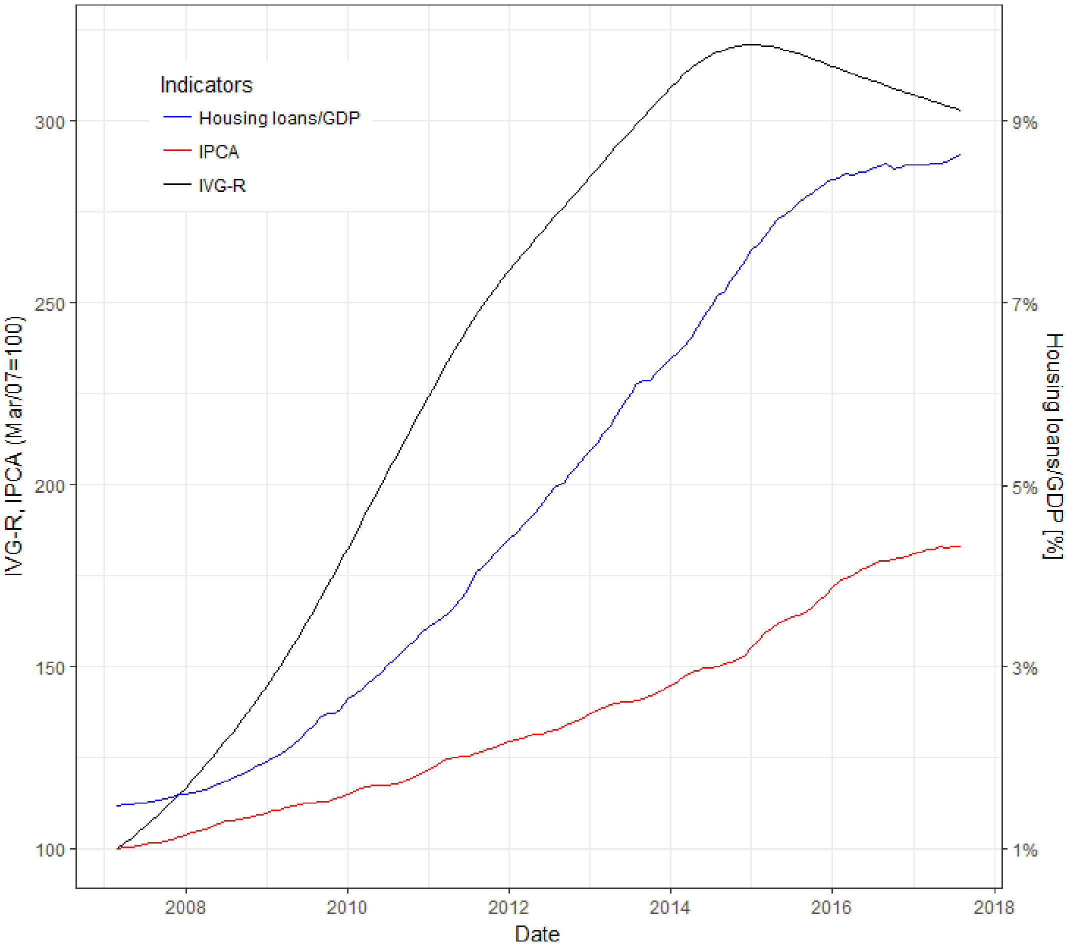


Figure 1 – Housing indicators over time
Source: Central Bank of Brazil. IVG-R and IPCA rates were transformed to index prices. March 2007= 100. Black and red line refers to the IVG-R and the IPCA index, respectively. Blue line is the proportion between the whole amount of Housing Financing and Gross Domestic Product.

At the end of 2016, housing finance loans aggregated 534 billion BRL (164 USD billions). The Federal Savings Bank (*Caixa Econômica Federal*, which is the financial agent of FGTS), had 73% of this market share and the five biggest banks have 98.5%. Those loans are all denominated in local currency (BRL).

Approximately 85% of these loans go to SFH with earmarked rates.

SFH loans are available to prospective borrowers of their first house who are not already homeowners in that city. For this purpose, an upper bound limit for a housing price has been established to be eligible for an SFH loan. In recent decades, this limit has changed in relation to the indicators presented in the Figure 1, mainly inflation.

Those changes are shown in Figure 2. Resolution 3,706 (National Monetary Council, 2009) established the eligible limit to SFH loans was 500,000 *reais* (BRL) across the country. However, Resolution 4,271 (National Monetary Council, 2013) changed this limit regionally. For the states of São Paulo, Rio de Janeiro, Minas Gerais (the largest ones considering population) and for the Federal District, the limit had been modified to 750,000 BRL, while the other states had a new limit of 650,000 BRL. Subsequently, Resolution 4,537 (National Monetary Council, 2016) adjusted those limits to 950,000 BRL and 800,000 BRL, respectively. Those policies also changed the loan-to-value ratios uniformly in the country (ARAUJO et al., 2016). We explore these changes in our identification strategy.

In July 2013, Rio de Janeiro, São Paulo and Brasilia (capital of State of Rio de Janeiro, São Paulo and the unique city of Federal District, respectively) had the largest average housing prices[3], which remains unchanged today.

There are distinct credit types for housing in addition to SFH, which constitutes approximately 70% of the total housing credit. Regular real estate loans called SFI (*Sistema de Financiamento Imobiliário*) apply to all types of housing with market rates and represent less than 5% of housing credit contracts and less than 15% of the total amount of housing loans. FGTS itself also provides housing loans for lower-income households by government programs with even smaller rates that represent 25% of the total housing credit. The upper-bound limit for a house to be eligible for this loan also changes across time, borrower's income and region, but it was always equal to or less than 190,000 BRL (before October 2015) or 225,000 BRL (before January 2017). We explore credit types for middle-income real estate (SFH and SFI) and lower-income real estate (FGTS) in estimations since they have distinct purposes.

Households have incentives to demand an SFH loan if the house is eligible. Figure 3 compares the subsidized interest rates from SFH and FGTS with market real estate loan rates (SFI) and the basic interest rate defined by the government (Selic) monthly over time. All these rates are on an annual basis. We notice that average market housing loan rates are between 50% and 100% higher than average SFH/FGTS loan rates until 2016. In addition, for almost all periods, average loan rates are lower than Selic rates. SFH loans have a maximum effective cost of 12% annually, with limited administration fees (25 BRL per month) and a limited cost of a housing insurance contract.

1.3 Data

We use loan-level information about real estate loans in the Brazilian Credit Registry System (*Sistema de Informações de Crédito*, or SCR), a database from the Central Bank of Brazil on a quarterly basis from December of 2012 to September of 2017. SCR has information for all loans of citizens or companies

[3] According to FipeZap Index. Website www.fipe.org.br/pt-br/indices/fipezap. Accessed on 8th December 2017.

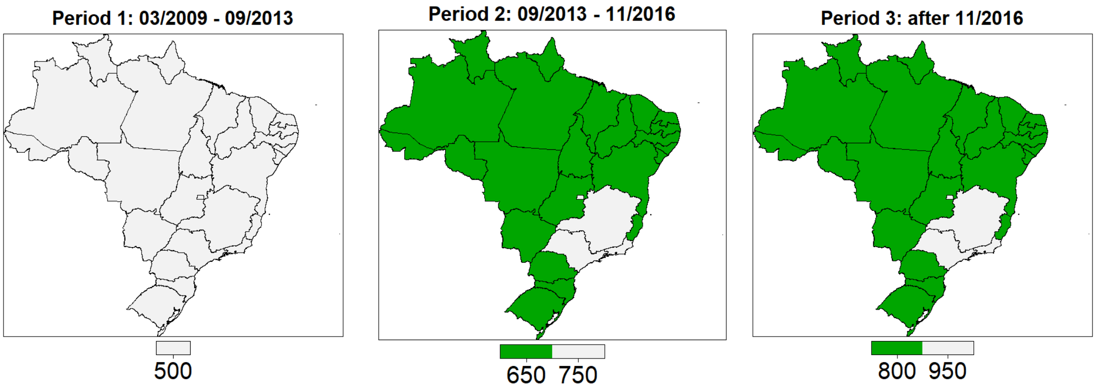
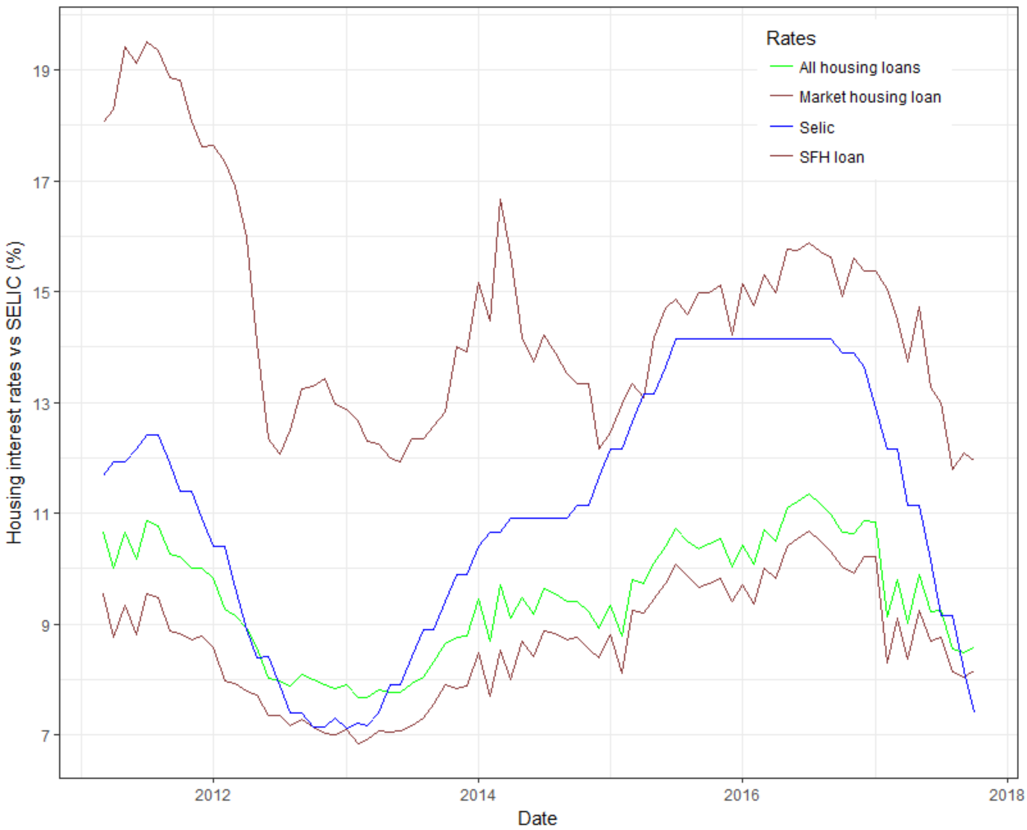


Figure 2 – SFH's limit (BRL 1,000) over time



Source: Central Bank of Brazil. Rates are in a year basis and are plotted monthly in the graph.

Figure 3 – Average Loan rates over time

whose total obligations issued by financial institutions operating in the country are above 5,000 Brazilian *Reais* (BRL) until 2012 and subsequently above 1,000 BRL. All housing loans are above those thresholds. Credit Registry System has information about the borrower (such as the city where he lives), the debt contract identification, the source of funding, and collateral information, such as type and value.

The main information for this study is the value of the loan's collateral evaluated at the beginning of the credit contract. In a real state credit by fiduciary alienation (the most important source of housing financing in Brazil), the collateral is the subject of the loan; in that case, it is the proper house. Financial institutions evaluate the real estate value, usually visiting the place before authorizing the loan. Other characteristics of the contract, such as the maturity, the loan-to-value-ratio and the municipality of the borrower, are considered herein.

Here, we consider only new contracts in each trimester since the evaluation of real estate value is mandatory at the beginning of a loan contract. To construct the housing price index of determined regions, we apply the same methodology of the Collateral Value Index (IVG-R) illustrated in Figure 1, including only loans for households and collateralized by financed real estate and first-degree mortgage (any loan collateralized by a real estate). We evaluate the period of the first change (3rd quarter of 2013) and the second change (4th quarter of 2016). We also distinguish loans by lower-income households (FGTS) and middle-income and higher-income households (SFH and SFI) that may be affected by that change of law.

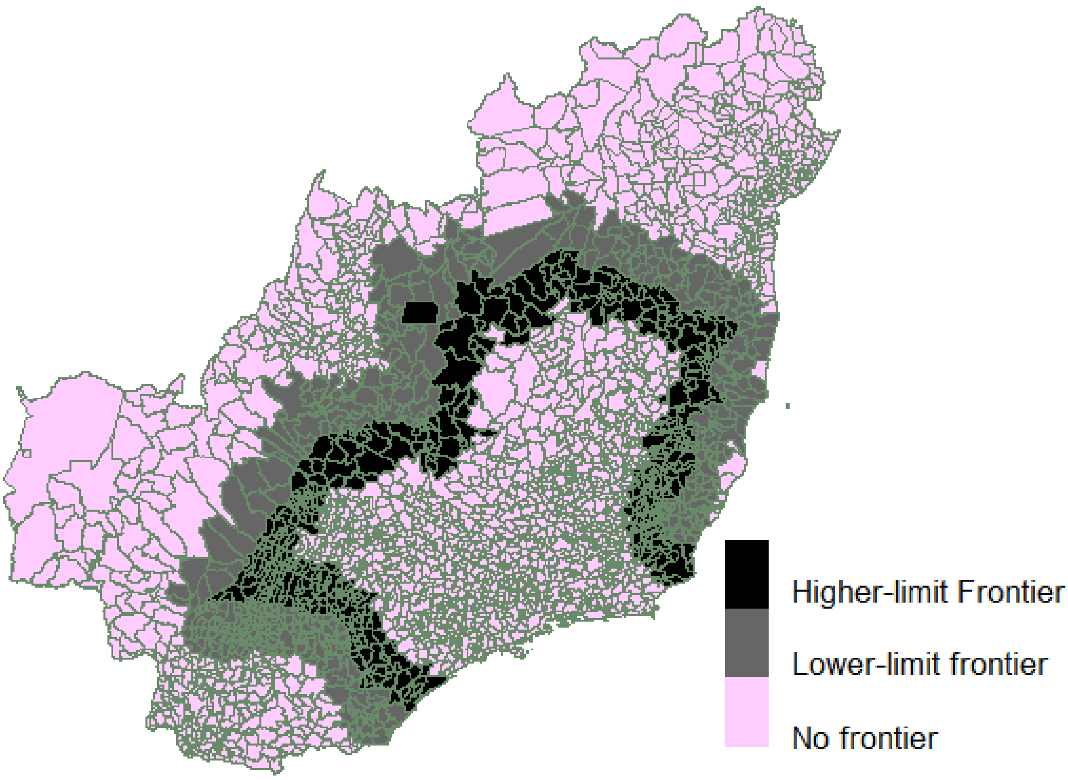
1.4 Empirical Strategy

Similar to Campbell, Ramadorai e Ranish (2015), we propose a regression discontinuity design approach to measure the impact of the change in the SFH limit regionally. We used the so-called Geographic Regression Discontinuity Design (KEELE; TITIUNIK, 2014), where the border of the States' frontier is a sharp discontinuity, and the treatment is deterministic by law.

Our goal herein consists of isolating the treatment. We are concerned about multiple treatments that may affect housing prices or another financial outcomes, such as particular features of each state. Thus, we restrict the analysis to areas around the border of Brazilian states with distinct upper bound limits for eligibility for SFH loans. Then, we consider real estate loans only from those municipalities around that boundary. The geographic location of a municipality m that contains a house financed by an SFH loan is given by two coordinates such as latitude and longitude, $S_m = (S_{m1}, S_{m2})$. $\mathcal{F}$ is the set that collects the locations of all frontier points around a 75km-radius, and $f = (S_1, S_2) \in \mathcal{F}$ is a single point on this frontier.

Let A^t be the treated region ("higher limit frontier" in Figure 2) that received a larger change in the SFH limit in 2013 and 2016, and let A^c be the "non-treated" region ("lower limit frontier") that also shows a change, albeit smaller, in SFH limit. The treatment is then a function of location of the real estate municipality: $T_i = T(S_i)$. Hence, in set $L \subset A^c$, there are 451 municipalities with a lower SFH limit (from the States of Bahia, Espírito Santo, Goiás, Mato Grosso do Sul and Paraná) with an Euclidean distance of 75 kilometers or less from the frontier with states with another SFH limit, where $T(s) = 0$. In contrast, there are 473 municipalities in subset $H \subset A^t$ with a higher SFH limit from the States of Minas

Gerais, Rio de Janeiro, São Paulo and Federal District (which includes Brasilia) that are 75 km closer to this frontier, where $T(s) = 1$. We then have $L + H = B$. Figure 4 shows those municipalities in a map, where the discontinuity is the frontier between the States.



Lower-limit region		Higher-limit region	
State	Municipalities	State	Municipalities
Bahia	82	Distrito Federal	1
Espírito Santo	69	Minas Gerais	240
Goiás	90	Rio de Janeiro	22
Mato Grosso do Sul	14	São Paulo	211
Paraná	196		
Total	451	Total	474

Figure 4 – Municipalities' discontinuity and regions of comparison

An analysis of distribution in housing prices suggests that this policy may affect only the top tail of the distribution. Figure 5 shows that most of the housing financing collateral has considered real estate prices under 200,000 BRL in the period of the first change in the SFH limit between regions. This distribution is similar for both groups (see Appendix 1.A.1). Thus, we investigate the effect of policy not only on the *average* housing prices in each municipality ($\sum_{i=1}^{n} \frac{Y_{nt}^{m}}{n}$, where Y is the housing price and n is the number of contracts in period t and municipality m) but also the *median*, a value representative of 50 percent of the housing prices evaluated with lower or equal values, or $P\left(Y_{nt}^{m} \leq med\left(Y_{t}^{m}\right)\right) = \frac{1}{2}$), the *thirth-quartile* $q_{Y_{mt}}$ (where $P\left(Y_{nt}^{m} \leq q_{Y_t^m}\left(0.75\right)\right) = 0.75$) and the 90%-*quantile* (where $P\left(Y_{nt}^{m} \leq q_{Y_t^m}\left(0.9\right)\right) = 0.9$) to evaluate changes in the hole distribution.

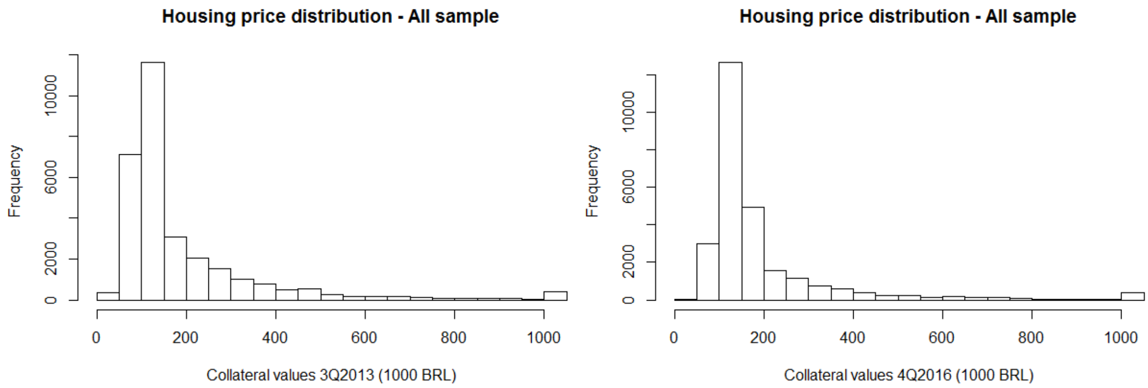


Figure 5 – Housing prices distribution during SFH's limit changes
Obs: each graph represents the distribution of one quarter, considering all the sample. Bin selection was 50,000 BRL.

This distribution also occurs even when we distinguish collaterals of SFH or SFI loans from loans provided only by FGTS during the first period of the change. Even when we consider only collaterals of nonsubsidized or SFH loans (Figure 6a), most of the housing prices are below the limit. Nevertheless, there is some evidence of discontinuity of housing prices beyond the limit of 500,000 BRL until the end of 2013 (a real estate loan process usually takes 3 months, therefore the change in limit in September 2013 can still impact prices for a while). Hence, this eligible limit becomes binding for that period. In contrast, we can see a new discontinuity of housing prices through each region with distinct limits after this period (Appendix 1.A.2 shows the distribution of housing prices for regions L and H). Naturally, loans provided only by FGTS (Figure 6b) concentrated houses with lower prices.

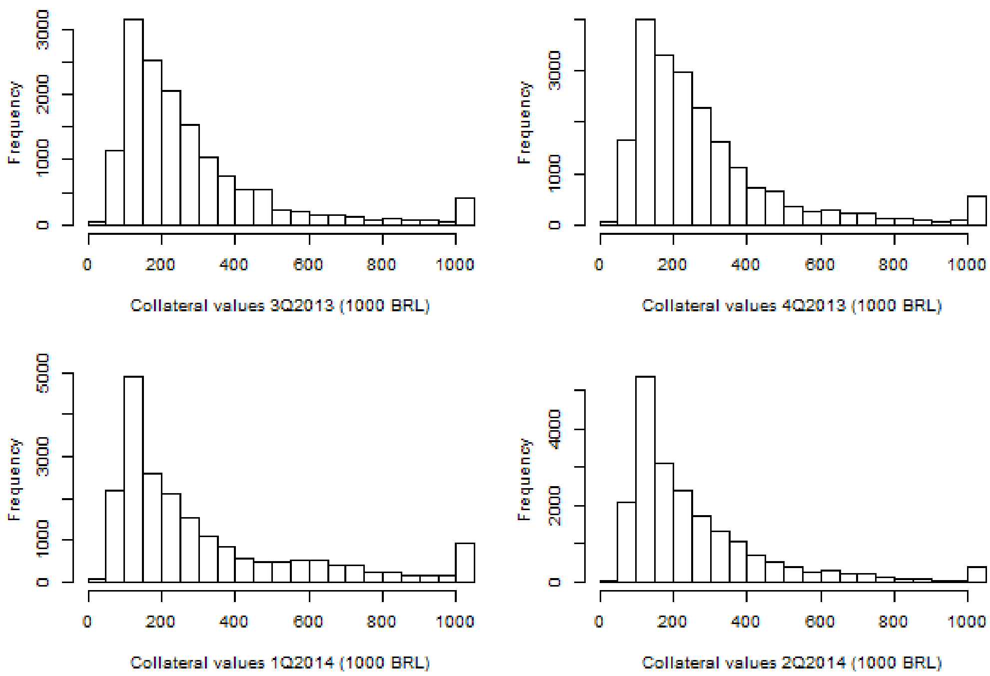
We are then concerned about the average causal effect of the treatment at the discontinuity point (the frontier) for each dimension (latitude and longitude) between a distinct eligible limit of a housing to take an SFH loan, that is, the sharp conditional treatment effect at every point in the boundary set $\mathcal{F}$:

$$\tau_{SRD} = \mathbb{E}(Y_m|Z_m, T = 1) - \mathbb{E}(Y_m|Z_m, T = 0) \tag{1.1}$$

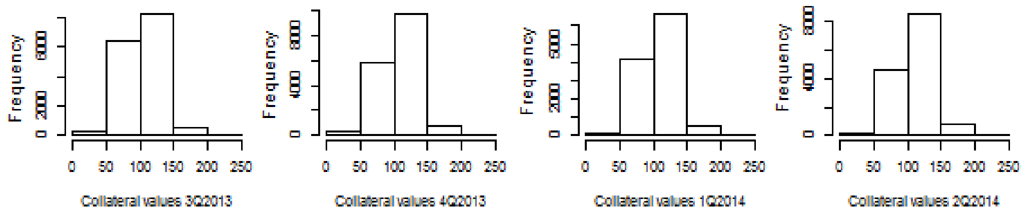
, where Z represents covariates, Y is the value of interest for each municipality $m \in \mathcal{F}$ and $\mathcal{F}$ is a set of possibilities of points in the frontier with 75km-radius, $T = 1$ if the municipality is on the higher-limit frontier, $T = 0$ if the municipality belongs to the lower-limit frontier. To construct Y, we consider three samples: one including all data, one including only SFH and SFI loans, and another including only FGTS loans. Due to a few data of non-subsidized loans we joined SFI with the SFH sample.

[3] A municipality level was chosen instead a weighting area level to reach a certain number of observations

Figure 6 – Housing price distribution by credit type (1,000 BRL)



(a) SFH and SFI



(b) FGTS

Obs: each graph represents the distribution of one quarter. Bin selection was 50,000 BRL.

We are concerned about three variables of interest per municipality: housing collateral (mean, median and quantiles of housing prices), LTV (loan-to-value) and payment maturity (in months). As covariates, we use the local Gross Domestic Product per capita, number of bank branches and Infant Mortality Rate (number of deaths below one year of age in that year divided by the number of births in that municipality). The running variable is the distance from the boundary (negative if it belongs to the lower-limit region and positive if it belongs to the higher-limit region).

Following Hahn, Todd e Klaauw (2001), Keele e Titiunik (2014) and Imbens e Zajonc (2011), we assume two hypothesis to estimate this discontinuity design approach with two thresholds (latitude and longitude). One assumption is related to the Continuity of Conditional Distribution Functions: for all $s \in \mathcal{F}$, the marginal density of S_i, $f(S)$, is positive in a neighborhood of $\mathcal{F}$ and $F(S)$ is continuous in this region. Both treated and non-treated regions belong to a continental area; therefore, both the latitude and longitude of each municipality that belong to $\mathcal{F}$ are continuous.

Another assumption is about the Continuity of the Conditional Regression Function: the conditional regression function $E[(Y_m(D=1) - Y_m(D=0)]$ must be continuous in for all $s \in \mathcal{F}$, i.e., variables in the neighborhood of the SFH boundary should have comparable potential outcomes. To certify this assumption, we establish only municipalities less than 75 km away from the boundary to make both regions (with lower and higher limit) comparable. Table 1 compares banking and economic outcomes from municipalities in each region by an average test. The gross domestic product (2013), population (2013), Infant Mortality rate (2015), total credit (2013), number of bank branches or number of bank branches-like are similar between municipalities in both groups. Only the area for each municipality is larger in the higher-limit region, which provides evidence that Assumption 2 may be still valid within a 75-kilometers boundary.

We also suppose that inflation is similar on both regions and does not distinctly influence housing prices. The Brazilian Institute of Geography and Statistics (*IBGE*) collects monthly CPIs from the largest cities. Inflation in the capitals of those States varied only from 30.3% (Belo Horizonte) to 34.2% (Rio de Janeiro) between 2013 and 2016. Those cities are 450 km away from each other. Hence, it is supposed that this inflation difference can vanish throughout the boundary.

Variable	GDP (BRL million)	Population	Area (km^2)	IMR (1,000 births)	Total Credit (BRL million)	Bank branches	Bank branches like
Lower limit region	818.5	30759.2	979.0	12.67	40.54	4.940	1.373
Higher limit region	882.9	24973.5	750.4	12.76	42.18	4.799	1.386
T-test	-0.147	0.742	2.897	-0.103	-0.043	0.079	-0.023
P-value	0.884	0.459	0.004	0.918	0.965	0.937	0.982

Source: IBGE, DataSUS, Estban.

Table 1 – Comparison between regions

Municipalities in those boundary regions are usually smaller (in population and in area), so we are less concerned about the measurement error of distance (DONG, 2015) in this geographical RDD. Even if we exclude the largest cities in each group (Brasilia and Curitiba, capitals of the Federal District and the state of Paraná, respectively), covariates from both regions remain similar. Since a real estate loan process is particularly rigid and middle-income households usually use their own FGTS fund (applied only for that city where a household works) to pay the loan, we are not concerned with migration from a lower-limit region to higher-limit region.

Table 2 provides details about the contract loans used in this paper. It also evaluates demand for a real estate loan: until 2014, we had an average of 35,000 housing contracts for each quarter. The number of contracts from FGTS and SFH funds were similar. After 2014, housing contracts for middle-income loans (SFH) dropped more than 50% due to an economic crisis and higher interest rates (as indicated in Figure 3) but contracts for lower income did not greatly change. Number of non-subsidized (SFI) contracts are relatively low for all quarters. Again, we note the similarity between both regions, since there is not much difference between the number of contracts, and the variation across time are equivalent.

Region	All	Lower-limit region		Higher-limit region		All Contracts
Period	SFI	SFH	FGTS	SFH	FGTS	
3Q2013	38	9,072	12,519	9,182	8,270	39,081
4Q2013	44	8,998	8,894	8,851	5,962	32,749
1Q2014	83	9,767	7,464	11,567	5,116	33,997
2Q2014	96	10,568	9,730	10,435	5,716	36,545
3Q2014	964	8,220	13,073	7,648	9,031	38,936
4Q2014	487	8,509	12,209	8,172	9,267	38,644
1Q2015	270	6,723	10,506	6,531	7,415	31,445
2Q2015	233	5,217	11,403	5,000	8,947	30,800
3Q2015	374	3,295	13,021	2,881	9,661	29,232
4Q2015	105	3,590	13,947	3,355	10,840	31,837
1Q2016	101	3,565	12,071	4,330	12,198	32,265
2Q2016	225	2,405	12,257	2,204	13,052	30,143
3Q2016	201	2,437	10,853	2,443	9,575	25,509
4Q2016	169	2,976	14,820	2,418	9,565	29,948
1Q2017	115	1,954	9,314	1,901	8,432	21,716
2Q2017	109	2,147	11,221	1,877	9,633	24,987
3Q2017	116	2,324	10,733	2,170	8,911	24,254
All	3,730	91,767	194,035	90,965	151,591	532,088

Table 2 – Number of contracts per period and fund of loan

Note: Column SFI (*Sistema de Financiamento Imobiliário*) represents regular housing loan contracts. SFH (Housing Financing System) columns represents subsidized housing loan contracts for middle-income families. FGTS (Employees Guarantee Fund) columns represents highly subsidized housing loan contracts for lower-income households.

Table 3 provides descriptive statistics of variables used here at a municipality level. Half of these municipalities are less than 30 kilometers from the boundary between States and one quarter of them are cities that share this boundary. The loan-to-value indicator (ratio between the total amount of the loan and the value of collateral) is 73% (75% for middle-class loans), which indicates that households borrow to finance their homes an amount approximately 75% of the value of real estate. LTV data are available only from the third quarter of 2013. Usually, a housing debt contract has a 28 years-duration and does not differ by loan type. Approximately 15% of municipalities do not have a new housing loan for each quarter. There is no evidence of bias of missing data across time (Appendix 1.A.6). Although the ratio of municipalities without housing loan contracts is larger for the higher limit region, the number of municipalities with data is similar in both regions.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Higher-limit region	925	0.512	0.500	0	0	1	1	1
Distance to frontier	925	30.262	24.271	0	0	29.895	49.404	74.906
2015 IMR	925	0.013	0.014	0	0	0.011	0.018	0.167
Area	925	861.9	1,196.1	34.2	228.7	455.9	1,004.1	10,206.9
2015 Bank branches	925	2.211	3.667	0	0	1	4	90
2015 Housing Financing (1000 BRL)	925	93,304	1,145,065	0	0	315,6	19,365,4	29,628,898
2015 GDP	925	932,814	7,855,909	16,119	72,931	168,703	433,613	215,613,025
2015 GDP per capita	925	21,738	25,537	5,039	11,088	17,037	25,127	513,134
LTV - All sample	13,439	0.730	0.111	0.077	0.685	0.744	0.796	3.996
LTV - FGTS	12,612	0.753	0.113	0.075	0.718	0.769	0.812	3.996
LTV - SFH	8,449	0.682	0.137	0.080	0.600	0.695	0.779	3.530
Maturity	15,659	335.1	44.8	10.0	321.7	349.6	360.0	425.0
Maturity - FGTS	14,514	332.3	46.9	36.0	320.2	353.6	360.0	385.0
Maturity - SFH	10,196	336.3	62.2	10.0	307.7	346.7	371.9	426.0
Housing prices								
4Q2012	724	129,479	61,870	25,499	89,999	115,066	153,759	618,250
1Q2013	720	130,950	60,439	24,999	92,999	117,583	153,013	600,000
2Q2013	776	131,949	57,477	21,499	97,064	120,896	153,076	768,500
3Q2013	761	127,368	55,245	24,999	92,572	116,987	145,977	654,002
4Q2013	829	128,999	50,429	25,005	96,077	117,500	147,024	600,000
1Q2014	775	138,971	58,325	25,013	99,283	125,127	160,602	551,200
2Q2014	808	133,630	56,013	30,018	99,416	121,774	151,156	875,000
3Q2016	771	140,129	58,803	40,102	103,599	127,710	160,642	660,000
4Q2016	783	143,834	72,799	46,271	109,632	132,198	155,000	1,320,000
1Q2017	755	146,414	59,889	67,077	109,738	133,806	163,460	680,027
2Q2017	777	146,441	62,722	70,053	112,000	134,054	165,129	1,181,341
3Q2017	794	147,964	51,955	64,107	116,794	136,483	164,626	450,000
Only FGTS	14,514	105,678	28,546	9,317	89,149	100,344	120,585	698,563
Only SFH	10,196	227,838	123,212	26,913	150,000	200,528	272,776	2,300,000

Table 3 – Descriptive Statistics per municipality

Obs: Variables related to LTV, Maturity and type of sample (SFH or FGTS) include all periods. Quarterly housing prices has less than 925 observations because some municipalities didn't have a housing loan in that quarter.

1.5 Results

1.5.1 First Period

Table 4 presents the results for the RDD estimations for the first period of changes in the upper-bound limit considering housing prices as the variable of interest. Housing prices in both regions are similar conditional upon municipality covariates (Infant Mortality Rate, number of bank branches and Gross Domestic Product per capita) in all quarters of 2013. In the 1st quarter of 2014 (6 months after the change), there is some evidence of different housing prices across the regions. Average housing prices in the higher-limit region seem to be 18,000 BRL (12.9%) larger than average housing prices in the lower-limit region. The 3rd quartile of housing prices is 20,646 BRL (or 29,706 BRL if you do not consider FGTS loans) larger in the region with a higher limit in that period. Housing prices also seem larger in the 2nd quarter of 2014 for that region if you consider only SFH and SFI loans. As expected, there are no evidence of differences in prices when we consider loans provided only by FGTS (columns 4 and 5). We present herein estimations for a third-order polynomial to improve the accuracy of the regression. Nevertheless, in Appendix 1.A.3, there are estimations considering a first order (p = 1) polynomial with similar results: distinct housing prices across the regions six months after the change of the law. The number of bandwidths was chosen by minimizing the mean squared error of the local polynomial estimator in both regions together. Also following the literature (CATTANEO; IDROBO; TITIUNIK, 2018) we used a triangular Kernel function to give more weight to municipalities closer to the boundary. Appendix 1.A.4 provides all the details of this RDD procedure.

	Dependent variable: municipalities' housing prices							
	All sample				SFH and SFI			FGTS
Period	Average	2nd quartile	3rd quartile	90th quantile	1st quartile	Average	3rd quartile	Average
2Q2013	-1763.1	331.0	142.4	-6975.9	15792.1	15925.3	17637.9	-1158.6
	(8362.2)	(7843.9)	(9116.3)	(11936.9)	(10273.6)	(12324.4)	(12723.3)	(2772.8)
3Q2013	6667.5	5680.4	9541.2	9208.9	12136.2	15945.9	16092.5	5089.4
	(5825.5)	(5048.7)	(7384.8)	(11103.0)	(8563.8)	(11587.9)	(14251.5)	(3002.5)
4Q2013	2847.1	5879.4	-302.7	-2856.9	6976.5	4265.5	8639.7	-1597.1
	(6831.9)	(6636.4)	(7967.4)	(10789.9)	(8334.5)	(9944.1)	(12205.2)	(2640.2)
1Q2014	17965.1**	11281.7*	20646.0**	33277.7**	10682.6	23661.2*	29705.7*	-692.4
	(7381.7)	(5999.5)	(9064.2)	(15168.8)	(10316.5)	(14092.9)	(17783.7)	(2762.4)
2Q2014	6571.6	4889.8	3650.2	12296.2	14767.9*	24899.3**	21556.1*	927.0
	(6890.7)	(5570.7)	(8109.4)	(13764.3)	(7866.9)	(10911.2)	(13714.4)	(2782.7)
3Q2014	3203.9	2985.5	2009.9	7020.1	6531.7	16650.8	22444.6	-1009.5
	(7209.2)	(6985.8)	(7940.9)	(11088.3)	(10657.6)	(12266.3)	(14124.0)	(2610.6)
4Q2014	-6474.3	-2942.4	-3604.2	-14465.0	-13543.4	-7039.6	3238.1	277.5
	(6847.7)	(6083.5)	(7680.6)	(12993.4)	(17796.9)	(18098.1)	(19408.3)	(2599.2)
N	925	925	925	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01. Z_m: GDP per capita, number of bank branches, Infant Mortality Rate. Each column represents one regression of Equation 1.1 according to the sample and the measure of housing prices. Standard errors are in parenthesis. Bandwidth selection was the optimal Mean Squared Error. Kernel function was triangular.

Table 4 – First period estimates - Housing Prices

This discontinuity of the boundary can also be investigated graphically. Each point on the graphs shown in Figure 8 corresponds to one bandwidth related to the running variable - distance in kilometers from the boundary of the SFH limit. This bandwidth determines the size of the neighborhood of municipalities around the cutoff where each local polynomial method is applied. On the left side (negative distance from the frontier), there are municipalities in States with a lower limit, the "control" group. On the right side (positive distance), we have municipalities from States with a higher SFH limit, the treatment group. Each graph corresponds to one quarterly period. We saw that for all three measures – the mean (Figure 7a), third quartile (Figure 7b) and 90% percentile (Figure 7c) of the housing price for each municipality- there are differences between both groups in the 2nd quarter of 2014 (third graph at each row) - six months after the law. Despite the difference, both regions suffered a temporal increase in housing prices. In that period, the lower bounds of the bandwidths on the right side of each graph are usually related to the curve of the local polynomial on the left side. Similar graphs occur if we consider the mean (Figure 8a) or the 3rd quantile

(Figure 8b) of SFH loans alone. This is related to the long process of Brazilian Housing loans - usually requiring 3 months from the demand to effectively receive the loan to purchase real estate.

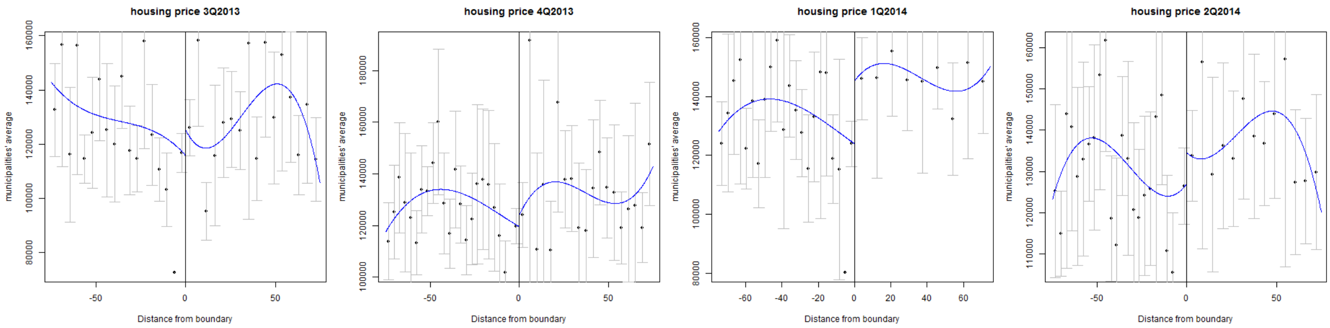


Figure 7a – Municipalities' average housing price over groups and time

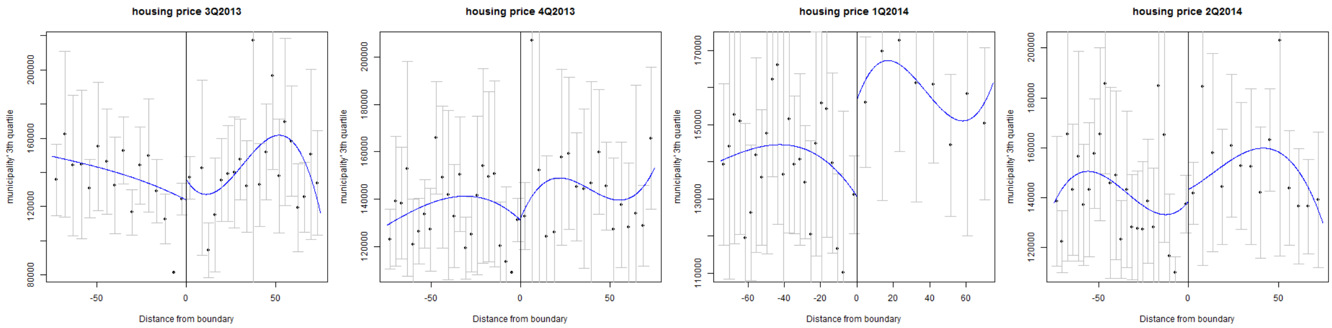


Figure 7b – Municipalities' 3rd quantile housing price over groups and time

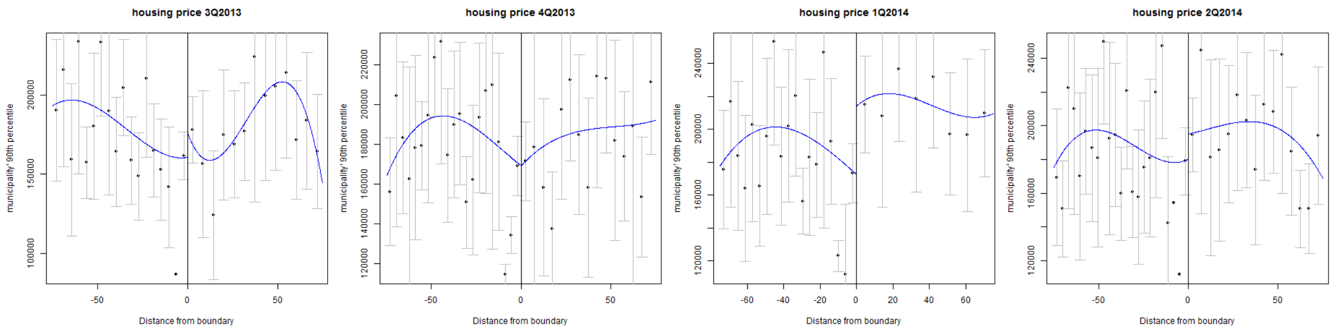


Figure 7c – Municipalities' 90th percentile housing price over groups and time

Obs: Those graphs consider the whole sample. Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.

Table 5 presents the results for the first period of changes in the upper-bound limit considering LTV and maturity as variables of interest. There is no evidence of distinct loan-to-value rates (1 if the amount

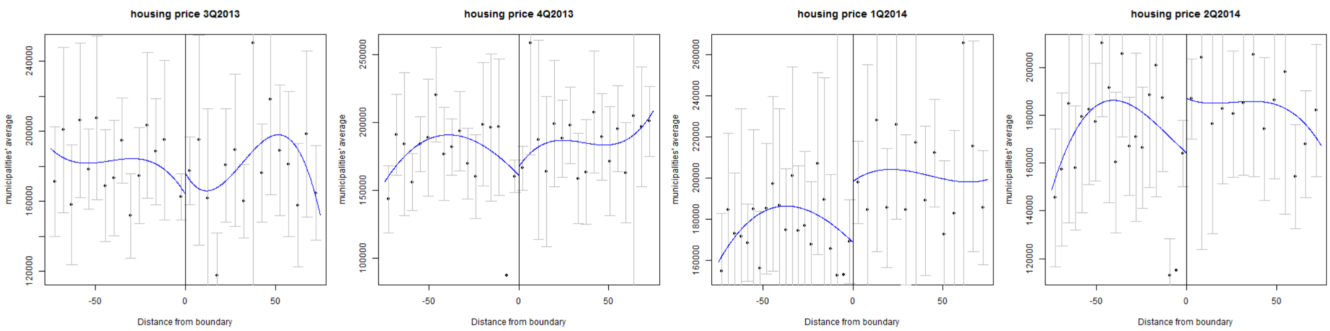


Figure 8a – Municipalities' average housing price over groups and time - SFH

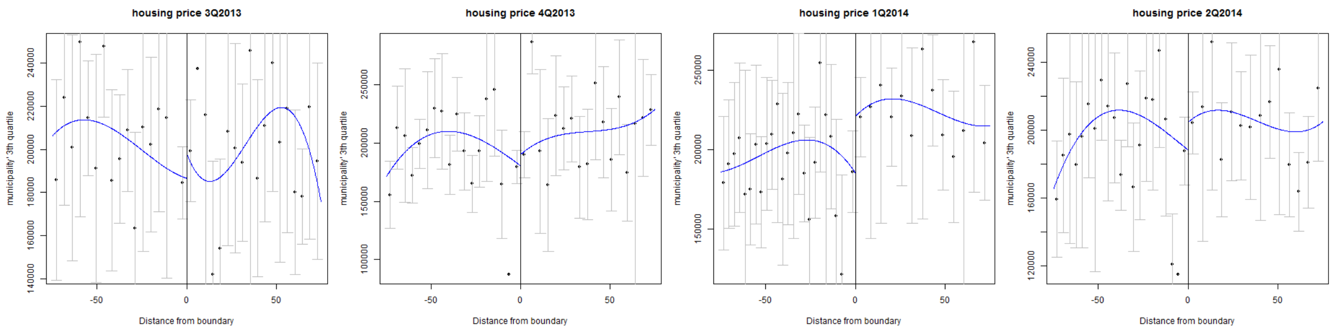


Figure 8b – Municipalities' 3rd quantile housing price over groups and time - SFH

Obs: Those graphs consider measures of only SFH contracts. Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.

of the loan and the value of collateral are equal) between both regions around the change of limits and the end of 2014. However, there is a difference in LTV for SFH loans (column 2) in the first quarter of 2015 - one and a half years after the change of the law and one year after the change in prices. In that period, LTV in the higher-limit region is 7.5% lower than LTV in the lower-limit region. Maturity in the higher-limit region is higher for SFH loans (column 5) even during the law change (3Q2013) and one year after the change of the law (2nd and 3rd quarters of 2014), so the effect of this policy is less clear herein. Nevertheless, differences between region maturity never reach 10% since the average maturity is always longer than 300 months. As expected, there is no evidence of distinct values between both regions for FGTS loans either for LTV (column 3) or maturity (column 6), which suggests that changes of this limit have no effect on lower-income households.

Differences between Loan-to-Value ratios in both regions (Figure 10) are less clear than differences in housing price graphs. Since Resolution n. 4,271/2013 also modifies LTV limits, both regions may be affected in the same way in the short run. The apparent overall reduction observed in the graph is also found in Araujo et al. (2016). However, significant and distinct LTV ratios are found at the beginning of 2015.

	Dependent variable					
	Loan-to-Value (0 to 1)			Maturity (months)		
Period	All sample	SFH	FGTS	All sample	SFH	FGTS
2Q2013				10.472*	13.303*	8.381
				(6.117)	(7.890)	(6.544)
3Q2013	-0.004	-0.013	0.007	4.968	21.352***	-4.438
	(0.015)	(0.017)	(0.017)	(6.330)	(7.679)	(6.200)
4Q2013	-0.012	-0.019	0.015	-8.300	-13.621*	3.213
	(0.013)	(0.017)	(0.014)	(6.525)	(7.810)	(7.224)
1Q2014	-0.007	-0.017	0.002	4.556	14.047*	1.660
	(0.014)	(0.020)	(0.015)	(6.464)	(7.610)	(7.418)
2Q2014	-0.007	0.018	0.001	11.796*	18.690***	2.182
	(0.013)	(0.017)	(0.016)	(6.388)	(7.155)	(7.878)
3Q2014	0.003	0.003	0.002	4.635	26.210***	-1.890
	(0.013)	(0.023)	(0.012)	(6.231)	(9.004)	(6.319)
4Q2014	-0.014	-0.036*	-0.018	-4.541	-9.471	-4.562
	(0.014)	(0.020)	(0.012)	(5.718)	(9.639)	(6.041)
1Q2015	-0.004	-0.075***	0.023	6.414	14.665	1.627
	(0.028)	(0.019)	(0.029)	(6.178)	(9.932)	(6.216)
2Q2015	0.005	-0.027	0.019	3.185	9.539	2.977
	(0.011)	(0.021)	(0.012)	(6.137)	(11.069)	(4.422)
N	925	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01. Z_m: GDP per capita, number of bank branches, Infant Mortality Rate. Each column represents one regression according to outcomes (LTV or maturity) and sample. LTV ratios are available from 3Q2013. Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular.

Table 5 – First period estimates - LTV and Maturity

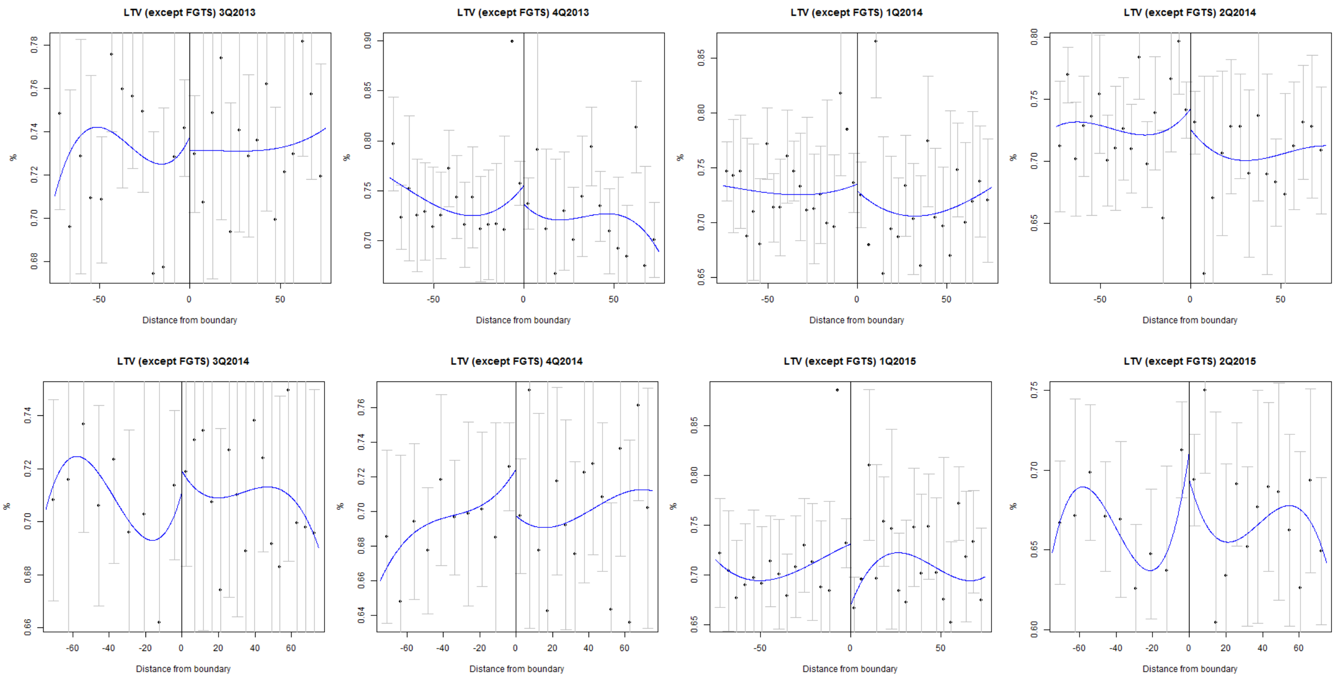


Figure 9 – Municipalities' LTV over groups and time - SFH sample
Obs: Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.

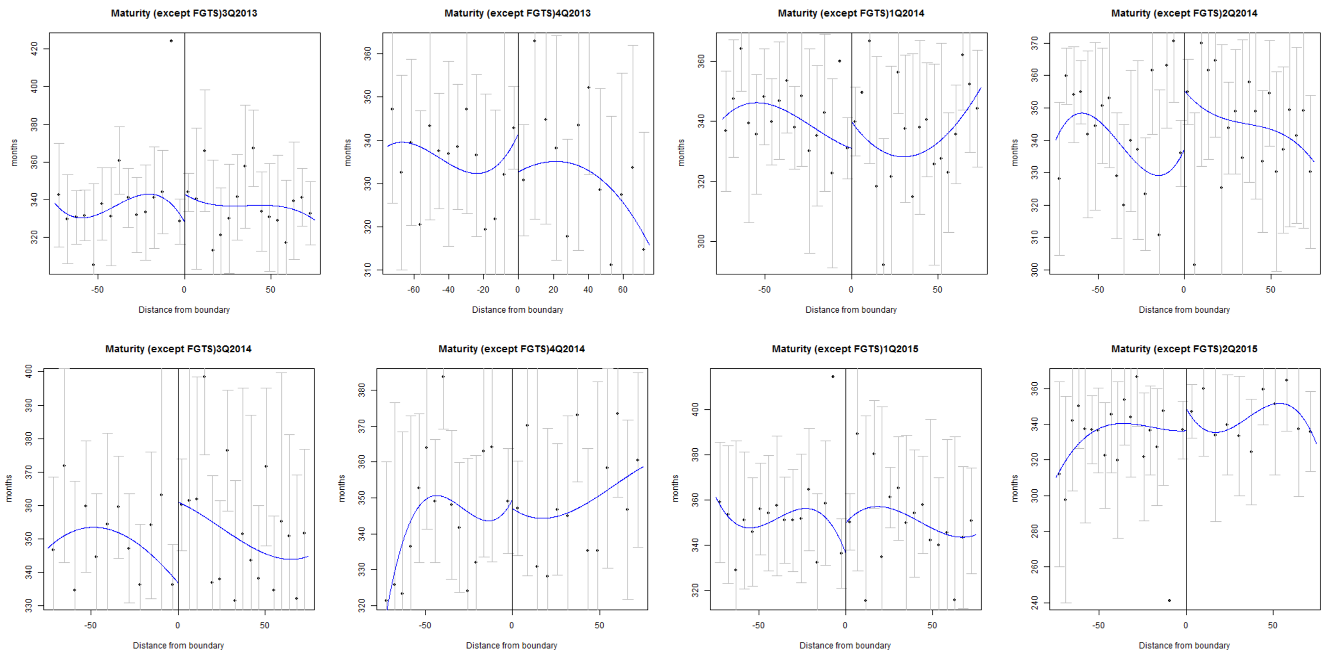


Figure 10 – Municipalities' maturity over groups and time - SFH
Obs: Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.

We also evaluated the demand for housing. The point here is that changes in conforming housing loans can change not only the price of housing but also alter the number of financial housing contracts. Descriptive statistics in Table 2 provide evidence of a temporary increase in demand in the same period of increasing housing prices (1Q 2014) and a large decrease mainly from SFH loans as from 2015. Nevertheless, those effects can be distinct along regions with distinct SFH loan limits.

In addition, we are interested in household behavior: changing the price of real estate can cause a middle-income family to search for cheaper real estate and hence apply for an FGTS instead of an SFH loan. Table 6 considers the following measures of demand: total number of housing contracts in that municipality (column 1); total number of SFH housing contracts (column 2); total number of FGTS housing contracts (column 3); ratio between SFH housing contracts and total housing contracts in each municipality (column 4); ratio between the sum of collaterals from SFH housing contracts and sum of collaterals from all housing contracts (column 5).

There does not seem to be any evidence of a difference between the number of contracts across those regions, even considering all periods (from 2013 to 2017). There is also no difference in the proportion of SFH loans after the first period of changes. However, SFH loans become more relevant in the region with a higher limit after changing the limit from 750,000 BRL to 900,000 BRL (November 2016). The SFH contracts ratio is approximately 7% larger in that region in the 4th quarter of 2016 and at the beginning of 2017 (columns 4 and 5). The ratio of the SFH contracts falls from 50% to 20% in both regions, but this drop seems to be larger for the lower-limit region after the last change in 2016. One possible reason for this finding is a change in higher-income household preferences: applying for an SFH loan instead of buying real estate without a loan due to a drop in housing prices. Another reason is related to the drop in regular interest rates (Selic) which made SFH loans less attractive. With lower housing prices, the migration to an FGTS loan-eligible real estate can be stronger in the lower-limit region.

	Dependent variable				
	Number of contracts			Proportion of SFH (0 to 1)	
Period	All sample	SFH	FGTS	Quantity	Value
2Q2013	46.47	38.04	8.49	-0.002	-0.003
	(61.46)	(43.46)	(18.22)	(0.046)	(0.044)
3Q2013	36.87	28.20	8.67	-0.042	-0.030
	(53.37)	(33.38)	(20.24)	(0.047)	(0.044)
4Q2013	45.70	37.66	8.70	-0.048	-0.051
	(61.37)	(45.61)	(15.97)	(0.042)	(0.040)
1Q2014	50.18	45.53	5.34	-0.068	-0.069
	(63.89)	(54.30)	(9.79)	(0.046)	(0.045)
2Q2014	36.30	31.74	5.41	-0.019	0.004
	(53.03)	(40.95)	(12.21)	(0.045)	(0.043)
3Q2014	41.90	31.63	10.25	0.013	-0.005
	(60.68)	(35.30)	(25.65)	(0.045)	(0.040)
4Q2014	39.54	32.91	6.81	0.016	-0.001
	(56.92)	(36.84)	(20.47)	(0.043)	(0.036)
1Q2015	30.48	26.38	4.86	-0.017	-0.022
	(44.42)	(29.94)	(14.84)	(0.044)	(0.039)
2Q2015	28.71	19.88	9.01	-0.007	-0.014
	(43.69)	(22.44)	(21.49)	(0.041)	(0.032)
3Q2015	23.49	11.18	12.12	-0.020	-0.014
	(33.46)	(11.27)	(22.34)	(0.037)	(0.027)
4Q2015	24.29	11.21	13.18	-0.017	-0.023
	(36.80)	(12.56)	(24.40)	(0.035)	(0.029)
1Q2016	31.23	17.01	14.75	-0.032	-0.023
	(42.35)	(20.07)	(22.40)	(0.045)	(0.039)
2Q2016	26.98	9.01	18.08	-0.005	-0.003
	(37.34)	(10.53)	(26.90)	(0.042)	(0.034)
3Q2016	24.02	10.21	13.80	-0.008	0.013
	(32.83)	(11.63)	(21.36)	(0.042)	(0.036)
4Q2016	25.46	9.48	16.08	0.076^{**}	0.064^{**}
	(37.71)	(11.34)	(26.47)	(0.036)	(0.027)
1Q2017	24.1	7.60	16.63	0.076^{**}	0.071^{**}
	(31.09)	(8.90)	(22.27)	(0.037)	(0.028)
2Q2017	26.26	6.85	19.35	0.071^{**}	0.070^{**}
	(35.89)	(8.18)	(27.75)	(0.034)	(0.025)
3Q2017	24.41	8.20	16.35	-0.077^{**}	-0.056^{*}
	(32.60)	(9.03)	(23.69)	(0.038)	(0.032)
N	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01. Z_m: GDP per capita, number of bank branches, Infant Mortality Rate. Each column represents one regression from Eq. 1.1 according to outcomes and sample. Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular.

Table 6 – Demand for housing estimates

1.5.2 Second period results

Table 7 shows differences in housing prices during and after the second change of the law (November 2016). The results are different from those found in the first period of changes. From four to seven months after the last change in the limits (first and second quarters of 2017), we find some difference in housing prices across regions but in the opposite direction. As we saw in the previous section, the number of SFH loans drops dramatically in both regions after the beginning of the economic crisis (2014). However, this difference is less significant than the difference noted in the first period. In addition, it has an opposite signal (smaller collateral in the higher-limit region) and appears in FGTS loans (last column), but it does not appear at the bottom of the distribution (all sample or SFH/SFI loans).

There may be two main reasons for these results. Between 2014 and 2016, the Brazilian GDP per capita has dropped approximately 10%, which may affect housing prices. Although both regions are similar, agricultural places from the Center-West region (belonging to the lower-limit region with the exception of the Federal District) have suffered less from this crisis. Another reason is related to the loan rates. As shown in Figure 3, regular interest rates (SELIC) are historically higher than subsidized rates (SFH and FGTS) for housing loans. Since the 4th quarter of 2016, however, it has dropped from 14.25% to 6.5% (yearly) in 2018. Indeed, since the 3rd quarter of 2017, it began to be lower than the rates for subsidized housing loans. In this manner, housing loans have become less attractive, and the changes may have a reduced effect on the value of housing collaterals.

In contrast, Table 8 considers Loan-to-Value ratio and Maturity as outcomes of interest after the second period of change. The difference in LTV ratios beyond regions is not clear after November 2016 despite the lower LTV for the higher-limit region in some periods of 2016 for all types of loans. The period of maturity of SFH loans seems smaller but not significant in the higher-limit region between the 3rd quarter of 2016 and 2017. Hence, the effect of the CMN's resolution here is less clear than in the first period, suggesting that in a countercyclical economic period, housing loan restrictions are less binding for all outcomes.

	Dependent variable: municipalities' housing prices							
	All sample				SFH and SFI			FGTS
Period	Average	2nd quartile	3rd quartile	90th quartile	1st quartile	Average	3rd quartile	Average
2Q2016	-5062.2	-0.2	-1824.8	-23169.3	-23775.3	-29559.7	-32856.0	-103.3
	(12564.4)	(11498.0)	(12701.7)	(20133.3)	(26159.2)	(32097.0)	(37985.2)	(3887.5)
3Q2016	-1779.6	2442.4	-1425.5	-3161.2	-26937.1**	-20240.8	-14997.1	7547.5
	(7012.5)	(5959.1)	(8902.1)	(13453.8)	(13617.0)	(20920.2)	(22013.0)	(3477.5)
4Q2016	-12480.0	-8198.7	-15497.7*	-22786.7	-24906.3	-3817.0	8321.4	3730.0
	(7687.4)	(6139.5)	(9003.1)	(15776.3)	(41379.4)	(42491.8)	(45498.9)	(3699.6)
1Q2017	-12702.3*	-11420.3	-16734.1*	-26185.9	-15014.3	13378.4	19852.4	-424.4
	(7447.6)	(7034.1)	(9901.7)	(16910.8)	(18795.7)	(22868.1)	(32599.9)	(4996.6)
2Q2017	-18917.9**	-15041.4**	-24822.0	-26005.7	11294.1	36018.4	54844.4	-8253.0**
	(7561.5)	(6375.2)	(9037.8)	(14317.3)	(37566.4)	(39409.3)	(42292.1)	(4047.7)
3Q2017	4236.4	1331.8	5481.2	15718.7	-38265.4**	-21086.6	-7480.4	49.1
	(6253.0)	(5174.4)	(8187.1)	(15168.8)	(12991.1)	(20699.2)	(26673.8)	(3684.5)
N	925	925	925	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01. Z_m: GDP per capita, number of bank branches, Infant Mortality Rate. Each column represents one regression from Equation 1.1 according to the sample and the measure of housing prices. Standard errors are in parenthesis. Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular.

Table 7 – Second period estimates - Housing Prices

	Dependent variable					
	Loan-to-Value (0 to 1)			Maturity (months)		
Period	All sample	SFH	FGTS	All sample	SFH	FGTS
2Q2016	-0.032*	-0.041	-0.046**	-9.980	10.222	-6.957
	(0.019)	(0.026)	(0.023)	(8.083)	(13.005)	(8.422)
3Q2016	0.007	-0.061**	0.023	10.954	-26.537*	19.731***
	(0.015)	(0.025)	(0.018)	(6.494)	(14.644)	(7.018)
4Q2016	0.000	-0.019	0.000	3.185	0.854	0.193
	(0.016)	(0.017)	(0.015)	(6.137)	(13.312)	(5.855)
1Q2017	-0.008	-0.034	-0.002	-2.732	-14.311	-3.022
	(0.015)	(0.029)	(0.013)	(4.277)	(14.327)	(3.501)
2Q2017	0.020*	-0.002	0.015	-1.656	-14.496	0.224
	(0.012)	(0.073)	(0.011)	(13.88)	(7.155)	(2.762)
3Q2017	-0.007	0.007	-0.010	-1.348	-22.43*	2.97
	(0.014)	(0.017)	(0.013)	(2.797)	(13.56)	(2.007)
N	925	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01. Z_m: GDP per capita, number of bank branches, Infant Mortality Rate. Each column represents one regression according to outcomes (LTV or maturity) and sample. Standard erros are in parenthesis. Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular.

Table 8 – Second period estimates - LTV and Maturity

1.6 Robustness Checks

1.6.1 Analyzing counterfactuals

In this section, we perform several tests to check robustness to the RDD procedure. First, there is no evidence of manipulation of the running variable (McCrary test: 0.41, available in Appendix 1.A.5), as expected for a geographic discontinuity design. Following standard practice in nonspatial RDD, we have created falsification tests from municipality variables in addition to covariates used in the estimation. The point is to check whether another outcome changes beyond those regions that could also explain the variations in housing prices, LTV and maturity for SFH loans after the first period of change.

For this robustness, we use municipal bank statistics (ESTBAN) from the Central Bank of Brazil, which provides information about the balance sheet accounts for each regular bank branch. We aggregate this bank branch-level data for each municipality and then construct the ratio between sheet accounts and local Gross Product, such as credit, loans (credit without a specific purpose), saving deposits and all banking deposits. Discontinuity plots of those outcomes are shown in Figure 11, where distance from a boundary is again the running variable for each quarterly plot, LHS represents bins of municipalities from the lower-limit region and RHS represents bins of municipalities from the higher-limit region.

We do not find any differences in those graphs across regions between 3Q2013 and 2Q2014 that could explain any changes in housing prices besides changes in the SFH limit. Migration to cities could explain some changes in housing prices (Gonzalez e Ortega (2013) and Mussa, Nwaogu e Pozo (2017)). However, there are no significant changes in the population around this region over those periods.

Although both compared regions have similar outcomes, here there is the challenge of compound treatments since the boundary of those regions is the same boundary of States, which can transmit some bias to this estimation. In this sense, changes could be related to State outcomes and not only to these municipalities. The comparison between a group of Brazilian States (five states in the lower-limit region and four states in the higher-limit one) may decrease this issue. However, to better investigate this hypothesis, we construct a counterfactual comparison in Figure 12 considering the boundary of the three main Brazilian States that have changed the SFH limit from 500,000 BRL to 750,000 BRL: São Paulo, Rio de Janeiro (both at darker color, under the boundary) and Minas Gerais (clearer color, above the boundary). Both regions compound 706 municipalities together (308 from Minas Gerais and 398 from the other States). This region was chosen because of the similar effects of the law and the larger number of housing loan contracts per municipality.

Table 9 shows results considering the difference in housing prices at this counterfactual region with the same limit. Housing prices in those areas are higher than in the previous regions evaluated because the expanded boundary between São Paulo/Rio de Janeiro and Minas Gerais contain larger cities in Metropolitan Areas. However, there is no evidence of significant, distinct housing prices related to SFH loans throughout the period. This provides more evidence that a change in the limit may impact housing prices distinctly in those Brazilian States.

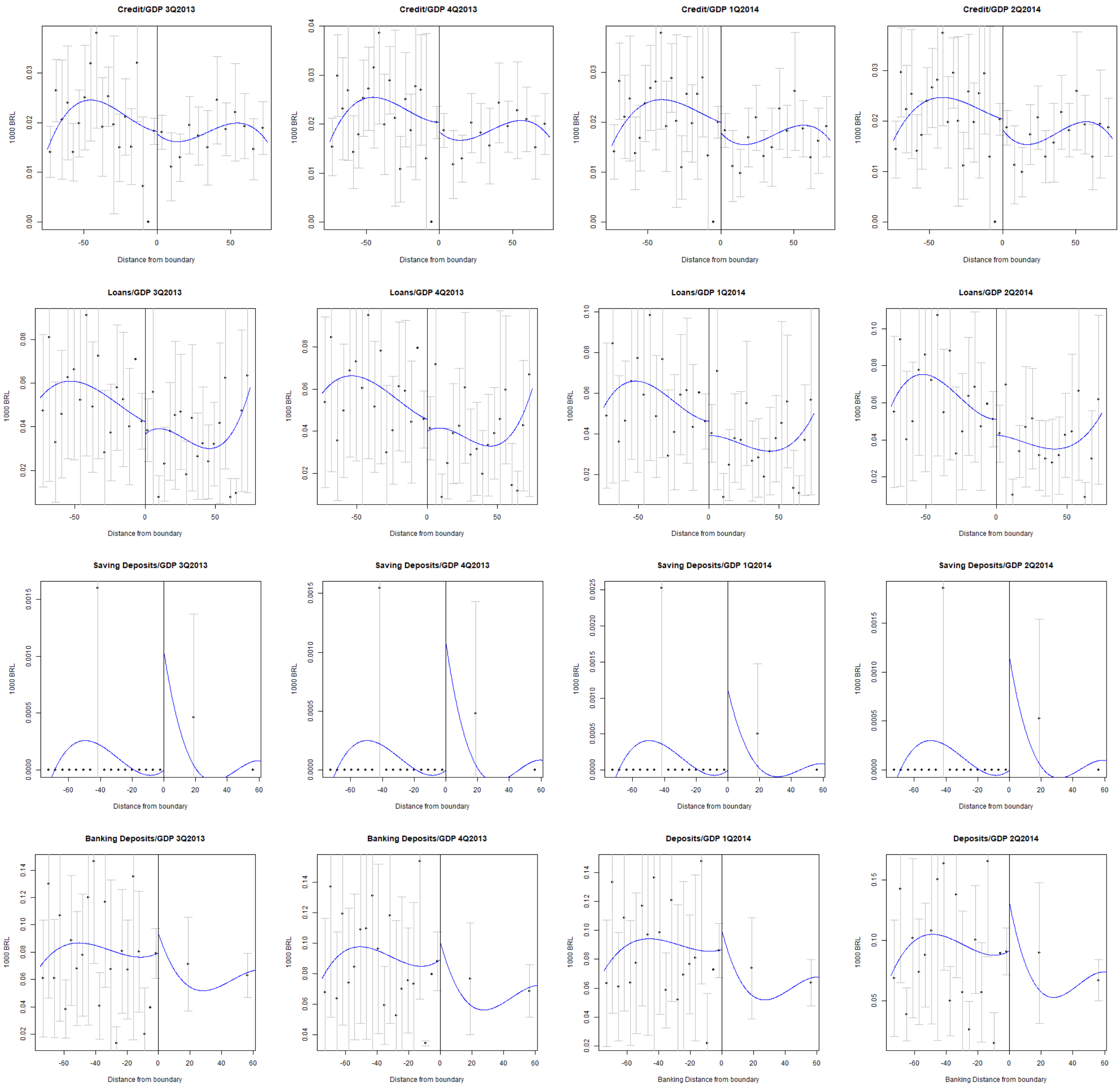
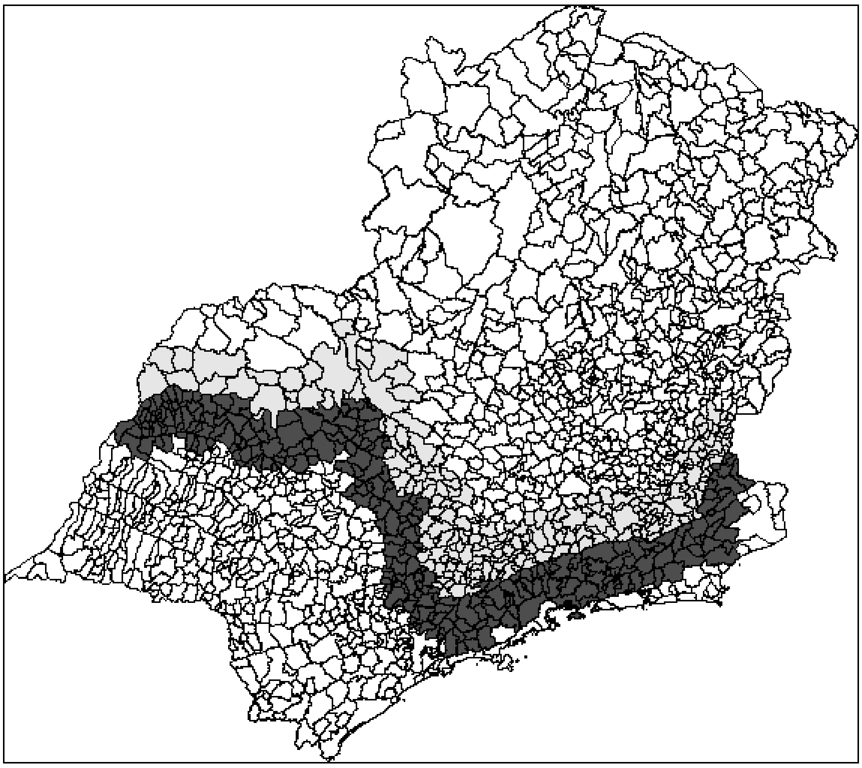


Figure 11 – Counterfactuals outcomes over groups and time

Obs: Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.



First region		Second region	
State	Municipalities	State	Municipalities
Minas Gerais	308	Rio de Janeiro	82
		São Paulo	316
Total	308	Total	398

Figure 12 – Regions of counterfactuals

1.6.2 Whole country

Due to results obtained in the counterfactual regions above, this section consists of evaluating changes in housing prices not only around the boundary of Brazilian States with distinct limits of SFH but for the entire country, where 23 States compound the lower-limit region after 2003 and 4 States (including the Federal District) compound the higher-limit region (Table 2). Most of the housing loans occur in cities with the largest populations, which are those more affected with the SFH limit. In this respect, we consider two types of sample: one that considers only housing loan contracts from the 27 capitals of States, and another that considers only loans from municipalities that belong to metropolitan areas (total of 404 municipalities - 138 that belong to the higher limit area, and 266 that belong to the lower-limit area). As in the previous section, we also restrict the sample to housing loans that use funding resources only from SFH/SFI or from FGTS. Since Brazil is a continental country with larger distances and entire regions with distinct limits are

	Dependent variable: municipalities' housing prices			
	SFH and SFI		FGTS	
Period	Average	2nd quartile	Average	2nd quartile
3Q2013	-353,771.9	-973,069.3	27,902.9	75,298.6
	(341,862.7)	(785,859.6)	(106,121.9)	(170,243.8)
4Q2013	-42,023.2	-1,253,628.5	322,929.2*	357,186.0
	(1,016,364.5)	(1,945,070.5)	(183,102.8)	(247,172.8)
1Q2014	-894,293.9	-888,948.5	119,250.5	691,057.6
	(1,101,949.5)	(1,427,480.6)	(485,100.6)	(792,408.2)
2Q2014	-872,040.2	-609,155.0	-165,846.7	-992,823.0
	(1,137,562.7)	(1,091,564.2)	(493,212.7)	(841,880.6)
3Q2014	495,571.6	604,916.6	1,093,252.1	4,009,114.1
	(434,133.6)	(388,374.9)	(963,552.4)	(4,836,653.9)
4Q2014	-688,873.5	-127,459.6	86,411.1	411,549.9
	(727,693.4)	(647,338.2)	(132,412.1)	(258,721.3)
1Q2015	577,549.2	41,456.2	13,192.5	-40,692.5
	(353,428.6)	(865,813.9)	(123,558.6)	(164,480.9)
2Q2015	152,581.6	69,403.5	-165,846.7	-516,412.2
	(480,797.3)	(832,753.5)	(493,212.7)	(616,828.7)
3Q2015	856,475.7	1,007,467.6	121,412.7	427,235.8
	(602,626.0)	(747,197.2)	(180,495.0)	(371,042.5)
4Q2015	182,014.0	155,222.1	-175,172.3	-568,595.0
	(497,482.5)	(948,537.8)	(230,553.8)	(484,905.5)
N	706	706	706	706

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis. Columns represent regressions from Eq. 1.1 according to the sample and the measure of housing prices. Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular. Polynomial of third order was used.

Table 9 – Counterfactual region - Housing Prices

very different from one another, the procedure of geographical discontinuity design is not appropriate here. In this sense, we consider herein a loan-level estimation.

To verify if the policy affects housing prices on those regions, we introduce a Differences-in-differences estimation:

$$P_{h \in m} = \phi t + \gamma r + \beta t * r + \eta z_m + \psi z_h + \theta c_m \tag{1.2}$$

where P is the price of a real estate h in a municipality (considering 3Q2013 constant prices), t represents whether the period of the contract is before (0) or after (1) the first change in the SFH limit (3Q2013; each quarter after that is tested); D_t is the dummy variable that indicates whether m belongs to a region with a lower or higher SFH limit (0 or 1, respectively), $D_t * r$ is the interaction between both dummies (our variable of interest) and z represents the covariates of house h, such as maturity of the loan, and c and represents covariates of the municipality m, such as area, gross product per capita, distance to the state's capital, human development index (IDH), quality of education index (IDEB) and number of bank branches and similar structures.

Table 10 represents estimations considering contracts only from capitals (columns 1-3) or metropolitan areas (columns 4-6). The impact of the interaction between the period and treated region is clearly more relevant to the main cities. Even with a higher housing prices in those areas (average of 476,957 BRL of SFH/SFI contracts in capitals and 408,346 BRL in metropolitan areas when changing the limit), the impact in both areas is truly greater than the 13% identified at the boundary of the States. The impact on SFH housing prices in capitals can achieve 218,640 BRL or 40% of the average housing price in 1Q2014 (column 2, Panel B) six months after the change. However, unlike the boundary of States, the impact of a higher limit on the main cities seems to be permanent: even at one year after the changes (3rd quarter 2014), the interaction is significant, achieving almost 180,000 BRL in capitals (column 2, Panel D) and 110,000 BRL in metropolitan areas (column 5, Panel D). There is also evidence of small, significant and positive impacts of the changing limit on housing collaterals with funding resources from FGTS in capitals in the short run (column 3), but the results for metropolitan areas are unclear (column 6), demonstrating a negative impact for first six months.

One factor that may explain the distinct magnitude of the impact on prices from the previous chapter is the estimation level. In a municipality-level estimation such as the Geographic RDD, all the cities have the same power. Naturally, larger cities with more housing loan contracts can influence the results in a loan-level estimation. In the latter case, the largest municipalities - São Paulo and Rio de Janeiro - have highly increased housing prices and influence the results for Capitals. In contrast, Brasilia - the largest city at the boundary of the previous section - has suffered a decrease in real housing prices since 2012 due to local factors that could reduce the impact found in Section 1.5.1 in a loan-level estimation.

	Dependent variable: housing price					
	Capitals (27 municipalities)			Metropolitan Areas (404 municipalities)		
	All loans	SFH	FGTS	All loans	SFH	FGTS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 6 months after policy						
Higher-limit	1,484.8	-16,563.8	1,551.4**	-4,105.3	-49,013.6***	17,127.7***
region	(15,831.3)	(22,159.8)	(742.3)	(6,444.5)	(10,448.8)	(272.7)
1Q2014	-71,503.4***	-167,971.4***	2,901.5***	-52,125.4***	-129,729.0***	416.1*
	(10,580.9)	(15,667.0)	(441.6)	(6,162.2)	(10,209.4)	(251.1)
1Q14*High Limit	150,349.8***	218,639.5***	3,324.8***	71,035.6***	127,151.6***	-2,051.1***
	(15,081.6)	(21,030.7)	(755.0)	(8,369.0)	(13,040.7)	(393.1)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,326	101,711	40,615	264,609	171,725	92,884
R^2	0.005	0.005	0.176	0.007	0.006	0.204
Adjusted R^2	0.005	0.005	0.175	0.007	0.005	0.204
F Statistic	72.981***	58.537***	960.823***	186.882***	95.477***	2,376.145***
Panel B: 3 months after policy						
Higher-limit	261.0	-20,712.7	2,839.3***	-5,626.0	-51,690.7***	17,369.6***
region	(15,502.6)	(21,977.2)	(593.2)	(6,352.5)	(10,456.8)	(241.5)
4Q2013	-96,555.7***	-184,689.3***	1,408.5***	-58,603.6***	-131,277.2***	986.5***
	(10,134.7)	(15,304.1)	(337.2)	(5,979.6)	(10,187.1)	(214.0)
4Q13*High Limit	126,848.5***	198,955.6***	-436.0	70,789.9***	130,528.8***	-2,798.0***
	(14,344.0)	(20,407.9)	(571.5)	(8,083.4)	(12,965.6)	(328.3)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146,008	102,638	43,370	273,454	173,100	100,354
R^2	0.005	0.005	0.238	0.007	0.006	0.240
Adjusted R^2	0.005	0.005	0.238	0.007	0.006	0.240
F Statistic	75.424***	56.642***	1,505.371***	203.135***	96.753***	3,163.320***
Panel C: 9 months after policy						
Higher-limit	-6,942.5	-29,732.7	-813.2	-2,765.1	-50,189.6***	15,996.4***
region	(15,123.8)	(21,594.4)	(739.0)	(6,210.1)	(10,240.9)	(287.9)
2Q2014	-95,713.2***	-189,915.8***	4,106.1***	-68,265.1***	-149,815.4***	1,009.6***
	(9,986.1)	(15,196.1)	(427.7)	(5,758.9)	(9,819.9)	(251.9)
2Q14*High Limit	123,680.2***	200,422.8***	6,755.1***	57,135.4***	119,460.4***	854.0**
	(14,281.4)	(20,447.5)	(720.4)	(7,882.5)	(12,639.9)	(390.4)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147,731	102,828	44,903	277,953	175,412	102,541
R^2	0.005	0.006	0.197	0.007	0.006	0.202
Adjusted R^2	0.005	0.006	0.197	0.007	0.006	0.202
F Statistic	82.706***	68.438***	1,225.733***	193.968***	104.237***	2,591.656***
Panel D: 12 months after policy						
Higher-limit	3,616.7	-10,206.1	556.5	-15.7	-41,127.0***	16,051.5***
region	(14,932.3)	(21,963.7)	(1,027.6)	(6,153.2)	(10,458.5)	(378.5)
3Q2014	-78,262.9***	-151,680.5***	5,516.4***	-54,954.9***	-106,992.9***	3,160.9***
	(9,759.8)	(15,578.7)	(571.4)	(5,648.0)	(10,220.9)	(316.4)
3Q14*High Limit	111,505.8***	179,615.9***	6,449.6***	54,789.8***	109,331.4***	462.9
	(13,828.9)	(20,752.1)	(947.3)	(7,702.0)	(13,066.9)	(483.7)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	151,843	101,281	50,562	285,163	170,842	114,321
R^2	0.005	0.005	0.112	0.007	0.005	0.128
Adjusted R^2	0.005	0.005	0.112	0.007	0.005	0.128
F Statistic	80.655***	51.939***	708.333***	200.428***	85.253***	1,673.794***

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parenthesis. Each column represents estimations from Equation 1.2 according to the sample at contract level. Baseline period is 3Q2013. Each panel evaluates the impact one period after baseline.

Table 10 – Differences-in-differences estimation over main cities

To test the hypothesis of a permanent impact of the law, we transform (1.2) to apply an event-study specification to provide some evidence for the period effect of changing the SFH limit. Here, each period represents one quarter before or after changing the limit (3rd quarter of 2013). Equation (1.3) also verifies whether the changes are temporal or permanent.

$$P_{h\in m} = \sum_{t=-1}^{t} \phi D_t + \gamma r + \sum_{t=-1}^{t} \beta(D_t * r) + \eta z_m + \psi z_h + \theta c_m \tag{1.3}$$

Figure 13 presents βs from event-study equation (1.3) over time. Panel A considers only capitals, and Panel B considers all municipalities from Metropolitan Areas. Each plotted line reports those coefficients considering all contracts or restricted samples considering only resources from SFH or FGTS. Shadow areas represent interval confidences for each coefficient.

Results are consistent with those found in the previous section. The impact of policy on SFH contracts (above 100,000 BRL in Metropolitan Areas and above 170,000 BRL in capitals, which represents 25% and 35% of the real estate value, respectively) is truly higher than the impact on FGTS contracts (which has a positive impact only in capitals and is less than 10% of the real estate value). However, the effect on real estate prices in main cities seems to be permanent and begins immediately after changing the limit, leading to expected evidence that limit restriction is more binding in main cities because the value of the housing collaterals is higher on the capitals and metropolitan areas and then can affect not only the upper tail of the housing price distribution.

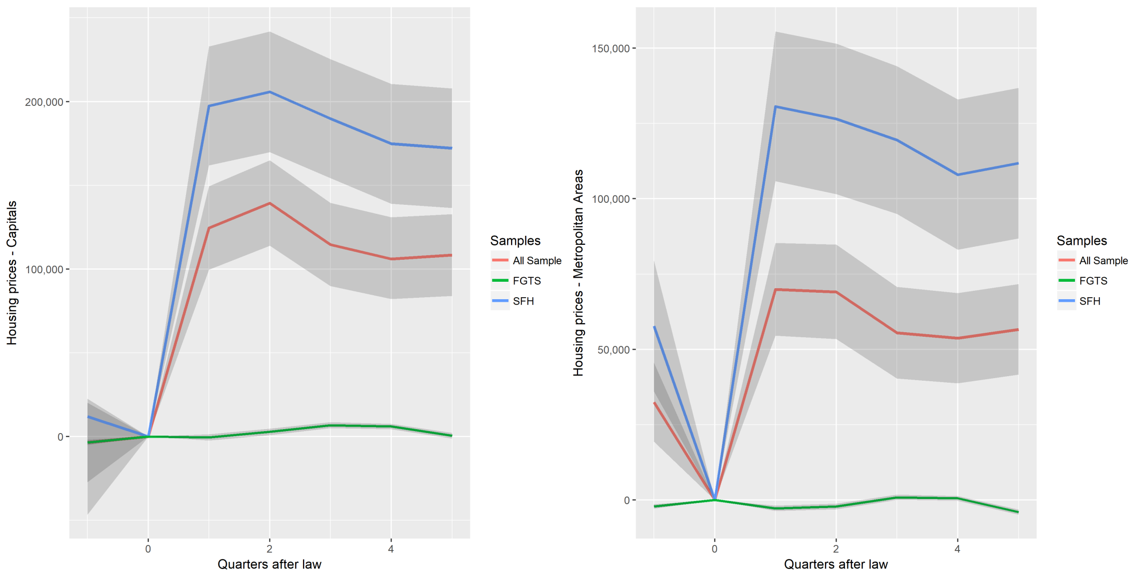


Figure 13 – Effects of changing limit over time
Obs: Those images contain the value of the interaction's coefficient of Equation 1.3 over time according to the sample. Each line represents coefficients for each sample. LHS charts results for Capitals and RHS charts results for Metropolitan Areas. Shadow areas indicate the confidence interval of coefficients.

1.6.3 Tax Effects

In this section, we investigate the effects of the main change in the SFH limit (2013) on municipality revenues considering two outcomes: the urban real estate property tax (*IPTU*, or *Imposto Predial Territorial e Urbano*) and a transfer tax over the real estate property (*ITBI*, or *Imposto de Transmissão de Bens Imóveis*). They represent 28% and 8% of all taxes collected by Brazilian municipalities, respectively, being more relevant for larger cities with a sufficient scale to collect revenues from properties. Both variables are provided by Finances of Brazil (*FINBRA*) at the General Office of National Treasury. Fixed-effect panel data are considered to evaluate the effect of this change over the municipality m and the year t in (1.4):

$$Tax_{mt} = \alpha + \beta Contr_{mt} + \gamma SFH_{mt} + \phi Cov_{mt} + \delta_t + \epsilon_{mt} \tag{1.4}$$

where SFH_{mt} is a dummy variable indicating 0 until 2012 and 1 for municipalities with a higher limit (750,000 BRL) from 2013, $Contr_{mt}$ is the proportion between the number of contracts and 100,000 inhabitants for each municipality and year, and δ_t represents fixed effects. An education index (*Ideb*) - available only in odd years - is included in the estimations as one of the covariates (columns 3-6). Population and GDP per capita are included in all estimations. The dependent variable Tax_{mt} relates to the total amount of that type of tax collected by municipality m in year t.

This panel data are unbalanced. 4,567 (82,4%) of 5,543 municipalities with available data providing complete information between 2012 and 2015, but there is no evidence of bias.

The results are shown in Table 11. Columns 1 and 2 include Housing contracts and the Higher-limit dummy. Columns 3 and 4 does not include the latter variable, and Columns 5 and 6 do not include Housing Contracts in the estimation. Coefficients differ according to the dependent variable. The change of the law seems to impact both taxes (columns 5 and 6). However, the transfer tax is more affected by housing contracts (columns 1 and 3) since it is collected for a fraction of a real estate purchase (usually 2% of the total value of each purchase). Housing contracts have an unexpected signal for property tax revenues, but most real estate may not be purchased regularly. In this case, changing the SFH limit seems to be more important (column 2).

1.6.4 Bunching

The policy design of this housing financing allows us to evaluate the discontinuity also at the threshold point since it creates notches: a marginal variation in housing prices can cause a large change in behavior due to the end of the subsidized loan rates if it crosses the discontinuity.

We estimate how much would change the subsidy at the notches comparing the total amount paid with an SFH loan with the amount paid by a market housing financial. We consider most of the housing loans for middle-income households in Brazil to use a straight-line Amortization (*SAC- Sistema de Amortização Constante*), where the portion that applies to the principal debt remains constant over the payment time. The maturity applied is 330 months, and the Loan-to-Value rate is the maximum rate allowed for regular

Table 11 – Local taxes

	Dependent variable:					
	Transfer Tax	Property Tax	Transfer Tax	Property Tax	Transfer Tax	Property Tax
	(1)	(2)	(3)	(4)	(5)	(6)
Housing contracts	6,392.36***	-9,832.9***	5,826.6***	-5,058.8***		
	(429.88)	(787.83)	(984.98)	(976.99)		
Higher limit	91,955.3	619,704.4***			336,162.4***	803,197.6***
	(97,900.0)	(179,418.6)			(117,904.6)	(193,999.5)
Educational Index	No	No	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Years	2012-2016		2013, 2015		2011, 2013, 2015	
Observations	26,173	26,173	10,272	10,272	15,381	15,381
R^2	0.011	0.012	0.008	0.009	0.003	0.009
R^2 Overall	0.057	0.036	0.062	0.036	0.054	0.039
F Statistic	46.123***	48.384***	8.049***	8.832***	6.306***	17.076***

Note: *p<0.1; **p<0.05; ***p<0.01. Estimations are at municipality-level. Observations are the municipalities plus the years of estimation for each regression. Covariates: *Ideb*, GDP per capita, population.

loans in each period - 80% in 2013 and 70% in 2016. For the main States in Brazil, this indicates a 400,000 BRL financing in 2013 and a 525,000 BRL[4] financing in 2016.

Those notches are represented in Figure 14. Given the housing financing interest rates for both changes[5], we note that the subsidy could reach 22.1% of the whole financing or 19.7% of the present value of the house in September 2013. In contrast, the subsidy in November 2016 is smaller: 12.7% of the financing or 10.7% of the present value of the house. In nominal terms, this indicates an 88,430 BRL subsidy at the 500,000 BRL housing price threshold in 2013 and a 66,689 BRL subsidy at the 750,000 BRL threshold in 2016. As it influences only the loan rates, this subsidy is proportional across all housing prices between 200,000 BRL and 500,000 BRL.

This notch naturally causes a distortion in housing prices before and after those changes. Figure 15 compares the distribution of housing prices between the period with 500,000 BRL-notches (September 2013) with this distortion and one year (September 2014) and one and a half years (March 2015) after the changes, where we assume that there are no distortions, considering contracts from Capitals and Metropolitan Areas, respectively. We note that the last periods have a similar distribution suggesting there is no deviation in housing prices under 650,000 BRL. As expected, the densities of loans are higher in September 2013 for contracts with collateral values below 500,000 BRL and smaller for contracts with more expensive collaterals.

With those distributions, we follow Kleven e Waseem (2013) to estimate the deviation of the pre-

4 80% of 500,000 BRL and 70% of 750,000 BRL, respectively. For this exercise we assume the new limit for the main States.

5 Annual interest rates of 7.9% for SFH loans and 11.48% for regular housing loans in September 2013. In November 2016, rates of 9.4% for SFH loans and 11.78% for regular housing loans. Source: Central Bank of Brazil.

5 For smaller real estate values households can apply for a more subsidized loans.

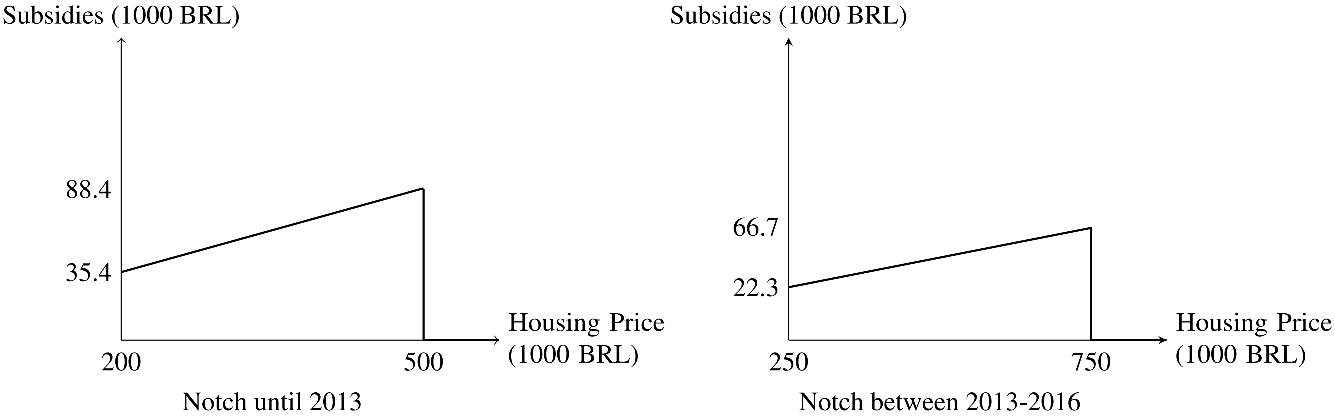
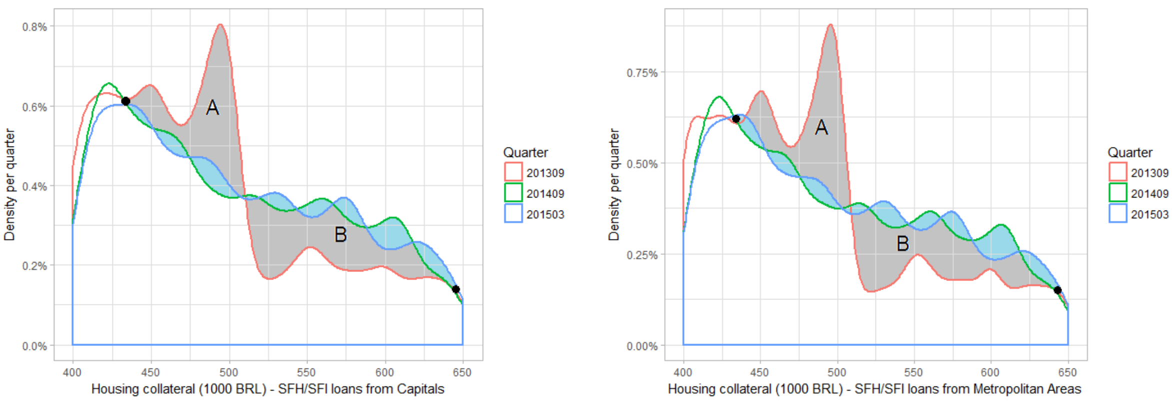


Figure 14 – Incentives to take a SFH Loan

Figure 15 – Distortion of the distribution



notch density from the empirical distribution function $F(k)$ (assumed here as the aggregation of both the post-notch densities of September-2014 and March-2015) by calculating areas A and B of the Figure 15. Graphically, we set the distribution meeting points before (440,000 BRL) and (640,000) BRL after the notch, which give us the Equation 1.5.

$$\hat{F}(k) - F(k) = |\sum_{i=440}^{500} (\hat{m}_i - m_i)(k_i - k_{i-1})| + |\sum_{i=500}^{640} (\hat{m}_i - m_i)(k_i - k_{i-1})|, \tag{1.5}$$

where k_i and k_{i-1} are, respectively, the upper and the lower bounds of each bin i, $\hat{m}$ and m are the frequency of contracts in that bin for the pre-notch and empirical distribution. We set the bin $k_i - k_{i-1} = 2$. Graphically, Equation 1.5 represents the gray color area and half of the turquoise color area in Figure 15. This indicates that mass gross A is 1.77 BRL million for Capitals and 2.75 BRL millions for Metropolitan Areas. In contrast, mass gross B is 1.25 million for Capitals and 1.91 BRL million for Metropolitan Areas. Given the range of both groups, the average price of those houses could be 449 BRL lower in Capitals or 476 BRL lower in Metropolitan Areas without the notch. It is lower than the effect of the notch for real estate transaction tax reduction in England (BEST; KLEVEN, 2017), where Loan-to-Value ratios are higher and most real estate at the lower end of the price distribution is bought by highly leveraged first-time buyers.

As a welfare analysis, we note that total subsidies of SFH housing loans for group A was 364,0 million BRL for Capitals and 541,3 million BRL for Metropolitan Areas. These values are calculated based on the area of LHS in Figure 14 weighted by the density of each value. If we compare this result with the RHS area in the same Figure, the substitution of this notch to distinct limits beyond Brazilian States shows an increased total subsidy for groups A and B in 47.7% and 43.8%, respectively. However, even with more expensive homes, the average subsidy per real estate shows a decrease of 5% in both areas because of the smaller spread between subsidized and regular interest rates from housing loans.

Indeed, we can calculate the notch elasticities. By visual inspection it can be seen that the rise of the collateral of 5% near the notch (from 488,000 BRL to 512,000 BRL) implied a reduction of 50% of the density (0.8% to 0.4%) and 100% of the subsidy before the change in 3Q2013. In this range considering the empirical distribution of 3Q2014 and 1Q2015, there was a reduction of 11% of the density (0.43% to 0.38%), and a 5% increase in the value of the subsidy. Best e Kleven (2017) found higher values for elasticity in the England housing market, which may be related to the lower thresholds and to a more dynamic housing financing market where households are more sensitive to prices.

The smaller gross over B in comparison to A and the distinct shapes of both areas suggest heterogeneity in elasticities and the presence of friction. One possible friction is related to the changes in demand: a household that wants to finance a real estate below the limit can change the house or give up financing. The heterogeneity of the period to process a housing loan or even the transaction can alter the curves. However, the large range of B may imply that behavioral responses to notches are large and can raise efficiency costs (KLEVEN; WASEEM, 2013).

1.7 Conclusions

The results provide four main conclusions. First, in a heterogeneous and continental country such as Brazil, policies have distinct impacts across regions. In particular, distinct restrictions (such as the limit of a conforming loan) should imply distinct decisions if the restriction is binding. In this case, we provide evidence that the initiation of distinct limits for the SFH loan in September 2013 had a temporal impact on housing price differences (approximately 13%) between similar regions after six months. All counterfactuals indicate that the only thing that changed beyond those regions before this difference in housing prices was this limit. However, in a period of economic crisis (as in November 2016 when a new limit was established), a change in the conforming loan limit can alter housing prices in an opposite manner. When we consider housing loans from State Capitals or Metropolitan Areas, the impact of law can be permanent.

The second main conclusion is related to loans only for middle-income households (SFH). There is no evidence that those laws changed any outcome from the housing market for lower-income families. This policy can be related only to the top bottom of the population in the main cities. Demand for housing seems to affect both regions equally.

In addition, policy implications may differ over time and regions. Distribution of housing prices in 2013 provides evidence that eligible-SFH limit of 500,000 BRL was really biding. In 2016, however, SFH limit was less biding due to drop of demand. Hence, changes in this limit have distinct results in both periods. Indeed, the impact of differences in this limit is proportionally higher in capitals (40% of house value) than Metropolitan areas (20%) or around the boundary of States (15%).

The last discussion concerns the efficiency of policies. Notches can create distortions and may alter the welfare of households. The existence of another threshold for housing financing can make most households unresponsive to subsidy incentives and generate asymmetric information in a general equilibrium analysis.

This study has some limitations. Evaluating demand based on the number of contracts can be biased since households can purchase real estate without purchasing a loan. In addition, households can face a tradeoff not only between an SFH or an FGTS loan but also between the housing and rental market. In addition, most housing loans occur in larger cities, and the boundary of the evaluated regions concentrate small municipalities. Another limitation is that a concentrated housing loan market can alter housing prices due to changes in financial institution policies. Finally, in smaller municipalities, there are usually only one or two types of banks. Our concern about the average causal effect of the treatment at the boundary and the inclusion of bank branches as covariates represents an attempt to eliminate this issue.

1.A Appendix

1.A.1 Housing prices distribution - all sample

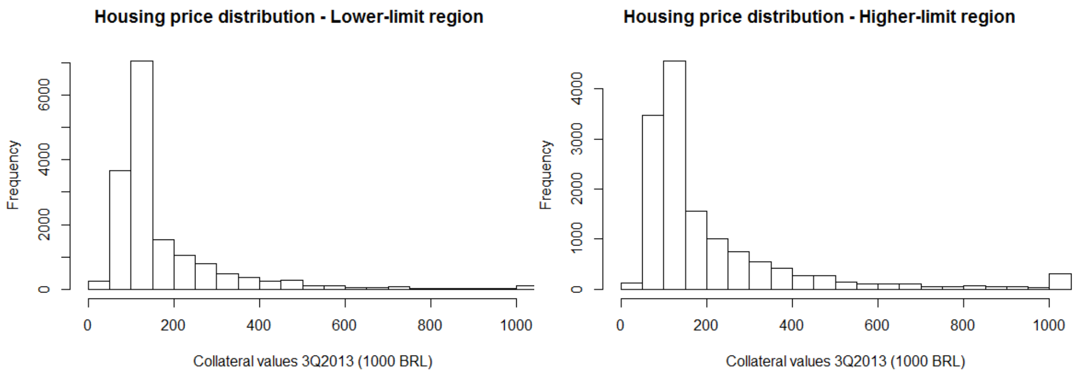


Figure 16 – Distribution - First Period
Note: Each graph charts the distribution around regions with distinct SFH limits on the period of the first change (September-2013). Bin selection was 50,000 BRL. LHS and RHS represent the distribution for the region with lower and higher limit of SFH, respectively.

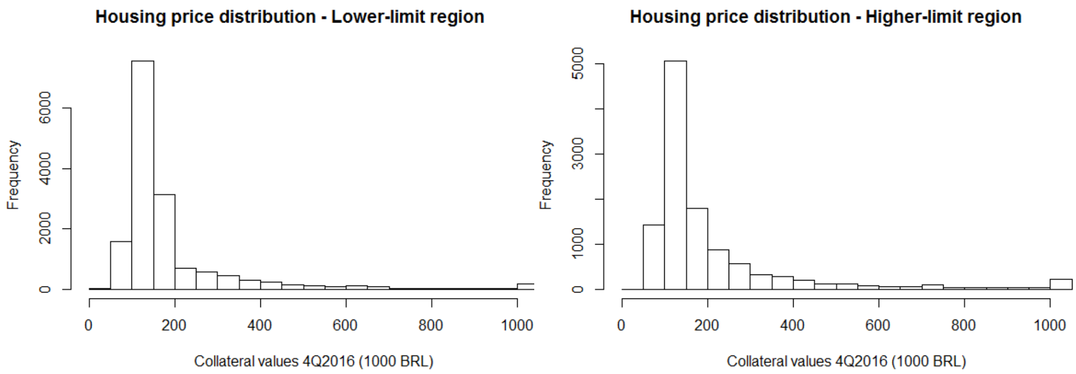
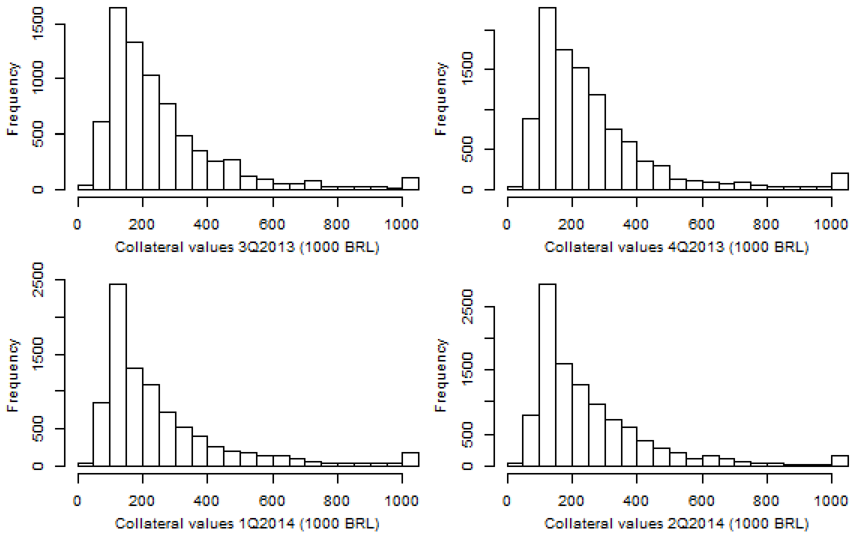


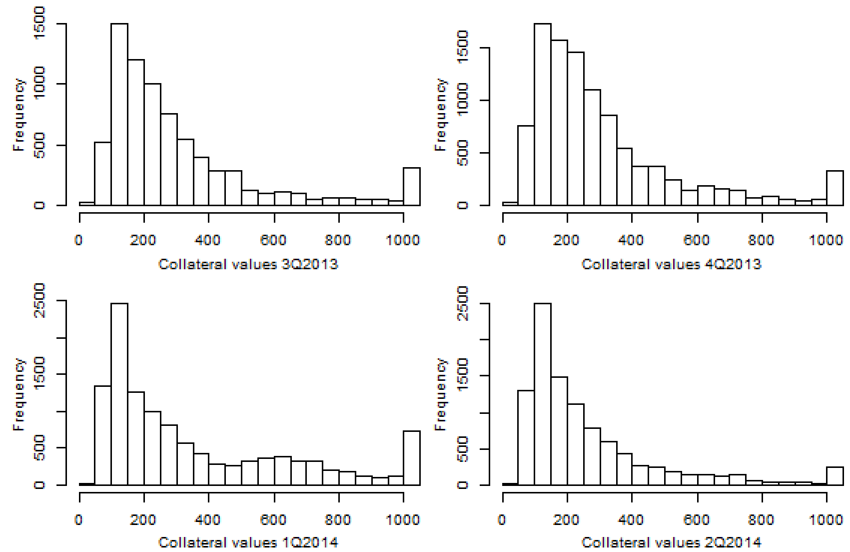
Figure 17 – Distribution - Second Period
Note: Each graph charts the distribution around regions with distinct SFH limits on the period of the second change (end of 2016). Bin selection was 50,000 BRL. LHS and RHS represent the distribution for the region with lower and higher limit of SFH, respectively.

1.A.2 Housing prices distribution per region- SFH and SFI

Figure 18 – Housing price distribution by credit type (1000 BRL)



(a) Lower limit region



(b) Higher limit region

Note: Each graph remains to the distribution of one specific quarter. Bin selection chosen was 50,000 BRL.

1.A.3 RDD estimates using first degree local polynomial

	Dependent variable: municipalities' housing prices							
	All sample				SFH and SFI			FGTS
Period	Average	2nd quartile	3rd quartile	90th quantile	1st quartile	Average	3rd quartile	Average
2Q2013	3,241.9	5,420.5	4,956.8	-1,633.9	19,983.3**	21,077.3*	24,242.7*	-1,238.2
	(8,033.6)	(7,567.5)	(9,279.2)	(12,023.3)	(9,860.5)	(12,054.8)	(12,810.9)	(2,617.6)
3Q2013	5,244.8	5,846.2	6,984.4	5,940.4	5,497.7	10,283.3	9,903.0	5,952.5
	(5,481.7)	(4,876.6)	(6,901.5)	(10,373.5)	(8,174.7)	(10,952.8)	(13,287.3)	(2,811.4)
4Q2013	4,621.6	8,171.5	1,285.4	-4,194.0	6,472.5	4,145.9	6,759.2	282.5
	(6,076.2)	(6,120.5)	(7,092.0)	(9,754.4)	(8,059.3)	(9546.0)	(11,714.0)	(2,474.0)
1Q2014	19,764.8***	12,812.2**	23,957.0***	33,954.6**	13,302.8	23,699.4*	29,735.3*	807.0
	(6,863.9)	(5,813.9)	(8,572.6)	(14,366.5)	(10,022.6)	(12,282.0)	(15,550.8)	(2,641.6)
2Q2014	6,826.6	5,203.0	4,524.6	12,790.9	10,451.3	22,795.5**	19,827.4	1,493.5
	(6,515.0)	(5,339.9)	(7,806.4)	(12,888.0)	(7,643.1)	(10,383.5)	(13,186.9)	(2,538.2)
3Q2014	-184.6	-435.1	-648.8	3,333.1	-4,492.5	4,639.7	13,461.5	-1,151.2
	(6,599.5)	(6,233.3)	(7,320.1)	(10,353.0)	(10,058.9)	(11,500.5)	(13,335.1)	(2,531.3)
4Q2014	-7,112.3	-3,730.7	-4,802.6	-15,099.6	-16,216.7	-8,852.1	-622.8	-37.8
	(6,361.3)	(5,587.3)	(7,078.3)	(11,922.2)	(15,221.7)	(16,675.0)	(18,016.6)	(2,395.9)
N	925	925	925	925	925	925	925	925

Note: *p<0.1; **p<0.05; ***p<0.01

Z_m: GDP per capita, number of bank branches, Infant Mortality Rate.

Bandwidth selection was the optimal Mean Squared Error. Kernel function used was triangular.

Table 12 – First period estimates - Housing Prices

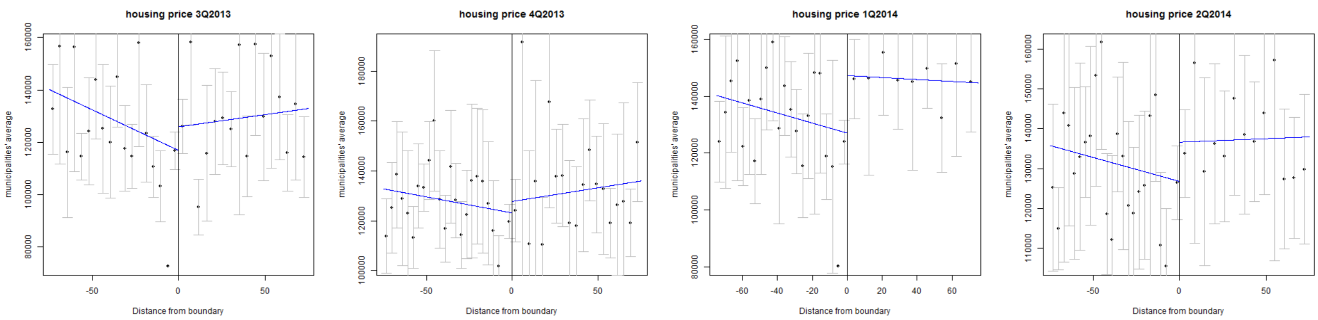


Figure 19a – Municipalities' average housing price over groups and time

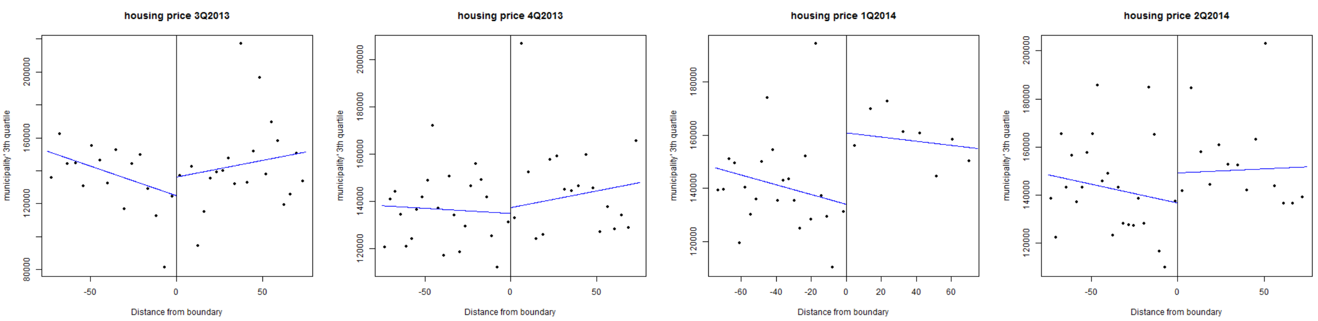


Figure 19b – Municipalities' 3rd quantile housing price over groups and time

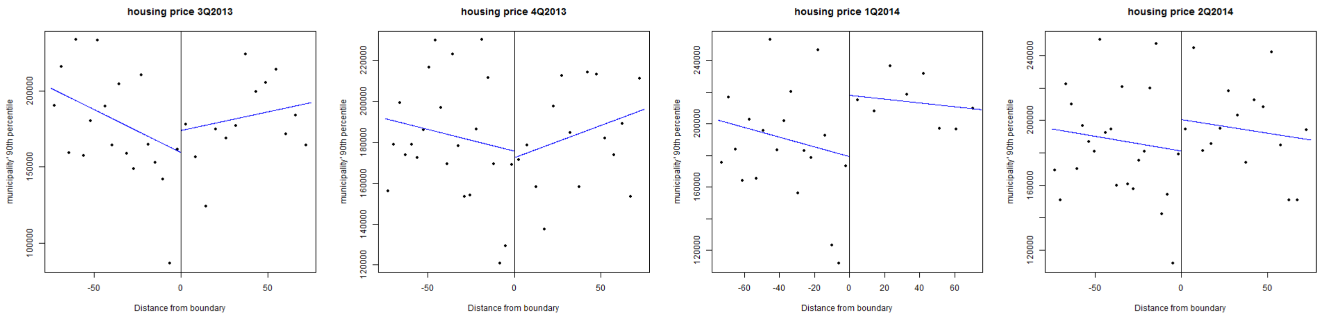


Figure 19c – Municipalities’ 90th percentile housing price over groups and time

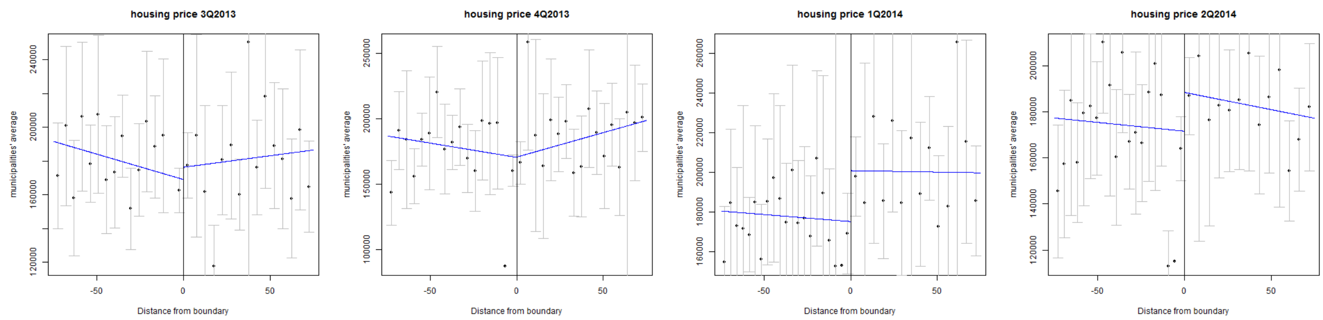


Figure 20a – Municipalities’ average housing price over groups and time - SFH

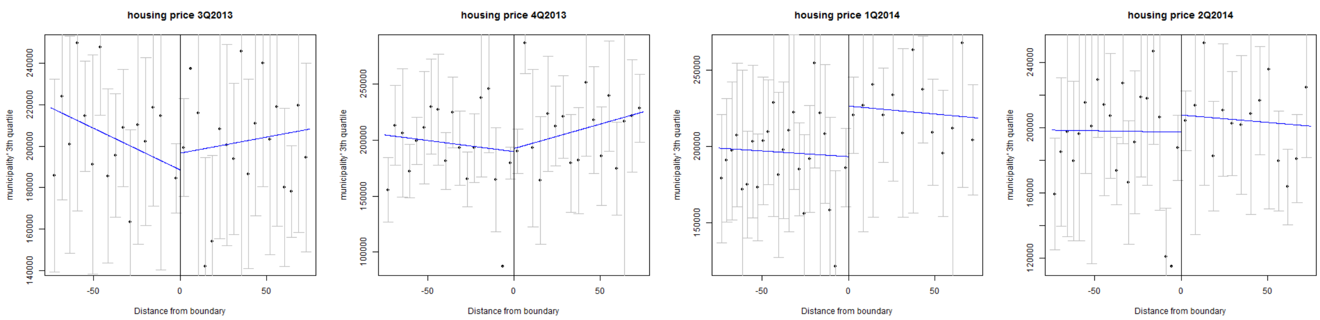


Figure 20b – Municipalities’ 3rd quantile housing price over groups and time - SFH
Obs: Distance from a boundary is the running variable for each graph, LHS and RHS represents municipalities from lower-limit region and higher-limit region, respectively. Each bin point represents a similar group of municipalities.

1.A.4 RDD Specification - average housing prices - 3 degrees polymonial

Table 13 – 3 degrees polynomial - 1Q2014

Number of Obs.	607	
BW type	mserd	
Kernel	Triangular	
VCE method	NN	
Number of Obs.	319	319
Eff. Number of Obs.	288	288
Order est. (p)	3	3
Order bias (p)	4	4
BW est. (h)	90.138	90.138
BW bias (b)	57.453	57.453
rho (h/b)	1.569	1.569

Estimation by rddensity package in R.

1.A.5 McCrary test

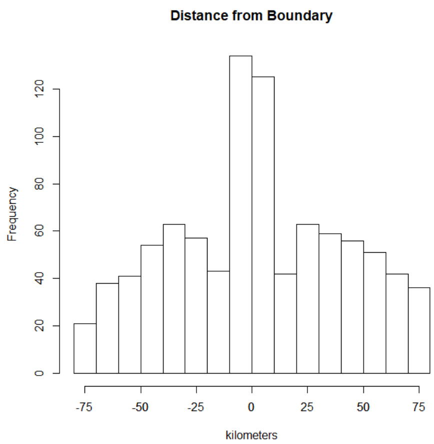


Figure 21 – Municipalities' distance from boundary

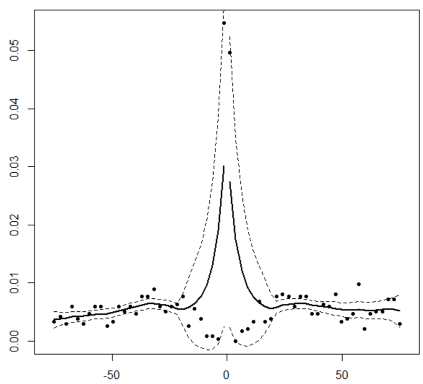


Figure 22 – MCCrary test: 0.41

1.A.6 Missing data

Region	All		Higher limit region		Lower limit region	
Date	n	%	n	%	n	%
4Q2012	201	21.7%	124	26.2%	77	17.1%
1Q2013	205	22.2%	143	30.2%	62	13.7%
2Q2013	149	16.1%	99	20.9%	50	11.1%
3Q2013	164	17.7%	109	23.0%	55	12.2%
4Q2013	96	10.4%	71	15.0%	25	5.5%
1Q2014	150	16.2%	100	21.1%	50	11.1%
2Q2014	117	12.6%	86	18.1%	31	6.9%
3Q2014	105	11.4%	81	17.1%	24	5.3%
4Q2014	107	11.6%	79	16.7%	28	6.2%
1Q2015	118	12.8%	94	19.8%	24	5.3%
2Q2015	115	12.4%	84	17.7%	31	6.9%
3Q2015	122	13.2%	96	20.3%	26	5.8%
4Q2015	135	14.6%	88	18.6%	47	10.4%
1Q2016	155	16.8%	104	21.9%	51	11.3%
2Q2016	157	17.0%	108	22.8%	49	10.9%
3Q2016	154	16.6%	101	21.3%	53	11.8%
4Q2016	142	15.4%	97	20.5%	45	10.0%
1Q2017	170	18.4%	103	21.7%	67	14.9%
2Q2017	148	16.0%	90	19.0%	58	12.9%
3Q2017	131	14.2%	87	18.4%	44	9.8%

Table 14 – Municipalities without any housing loan in that period

There are 925 municipalities in the sample: 474 municipalities on the Higher-Limit region and 451 municipalities on the Lower-Limit region. Each missing % is calculated with those values as the numerators.

2 Local credit and local consumption in Brazil[1]

[1] The views expressed in this work are those of the author and do not necessarily reflect those of the Central Bank of Brazil or its members.

2.1 Introduction

The relationship between the lending channel of credit and consumption promotes various extensions in the literature. Changing the disposal of money for an individual can improve the purchase of durable goods, and in a particular view, of consumer durable goods, such as the computer, television, or phone.

According to this channel view, a monetary policy that changes bank reserves and bank deposits can also modify the supply of bank loans available in an economy. As borrowers (credit firms and/or households) are dependent on bank loans to finance their objectives, such as spending on consumption, this change in bank loans will modify the amount of their investment and also their spending.

Although there is clear evidence of the impact of the monetary policy, that is, the impact of the interest rate reducing the cost of the capital on durable goods spending, the relationship between the lending channel and consumption is not as clear (BERNANKE; GERTLER, 1995) in the literature. However, there is evidence of an impact of the lending channel in housing in some European countries (IACOVIELLO; MINETTI, 2008) or in mortgage lending in the United States (BLACK; HANCOCK; PASSMORE, 2010).

In contrast, in countries with a greater dependence on mortgage credit instruments using housing as collateral for loans, there is strong evidence of an impact of housing prices on consumption. The main point is that impact on a marginal propensity to consume is unequal across regions, even with rising (MIAN; SUFI, 2014) or declining (MIAN; RAO; SUFI, 2013) housing prices at a zip code level in the United States. Thus, there might be an indirect relationship between lending channel credit and consumption by housing, which can also occur at a regional level (CAMPBELL; COCCO, 2007). However, there may be other channels for consumption, such as credit card spending (AGARWAL; QIAN, 2017).

In this paper, we investigate the relationship between local lending channel credit, using the Credit Registry System (SCR) from the Central Bank of Brazil and local consumption in Brazil by weighting area, which is the smallest unit of observation present in the Brazilian census sample[2]. We also evaluate credit by zip code level. Therefore, we explore credit access and its impact on consumption. For local consumption, we use the variation of a durable good's stock.

In Brazil, there are particularities that have mixed relationships with this investigation. Favorably, we currently have a strong correlation between the increase in credit and increase in consumption in the 2000 decade, after several institutional changes in the credit environment. New Payroll consigned credit (2003) has allowed banks to deduct payment of loans directly from costumers' paychecks. The fiduciary property law (2004) has increased the quality of collateral for real estate loans, allowing the retention of title as a guarantee for financing real estate property acquisitions, making it easier to recover the property. Additionally, Bankruptcy Reform (2005) increased the likelihood of recovery of an unpaid loan by a closed company. In addition, several types of physical channels for banks have been created across the country (KUMAR et al., 2005). In contrast, the mortgage credit (when housing as a collateral of the loan) in Brazil is very low (less than 1% of GDP) in comparison to other countries, reducing the impact of a lending channel by housing.

The contribution to the literature of this paper is to analyze the regional difference in the impact of

[2] The census tract is a smaller unit of observation but not available in the Census sample.

the lending channel though financial access on local consumption. There is evidence of an asymmetrical impact of monetary policy for US cities (FRANCIS; OWYANG; SEKHPOSYAN, 2011) and Brazilian States (SERRANO, 2014), but it is not clear for the lending channel. Focus at the local level is important by two factors: low mobility of consumption and large differences across Brazilian regions. This investigation can also improve the limited literature about the development of consumption in Brazil through a focus on durable goods.

Another advantage from this work is the evaluation at a spatial scale level smaller than a municipality. Usually, the literature of local credit considers a municipality level in Brazil. For example, Kroth, Dias et al. (2006) and Mello (2014) use this level to analyze the relation between local credit and local growth. In contrast, Ferro et al. (2016) also merges credit registry data and Brazilian Census, having founded that housing credit can reduce housing deficit in Brazilian municipalities. Evaluation of credit policies were also made in municipality level, such as Da Mata e Resende (2015) and Ponticelli e Alencar (2016). The focus at a level smaller than a municipality can be justified as follows. First, large cities are quite heterogeneous, with distinctions between urban and rural areas and poor and rich neighborhoods; focusing at a smaller spatial scale can address the heterogeneity more effectively. The second reason is granularity: it became possible to study local credit policies with a larger number of observations. The third reason is the possibility to merge the Brazilian Census data with a georeferencing data of financial institutions. In that sense, our contribution to literature is to evaluate the local impact of credit on development using local information for durable consumption.

For estimation, we construct a panel regression considering the variation over time between credit and consumption. One question that emerges from the lending channel is what can influence it without the direct transmission of monetary policy. We investigate the impact of a distance from the nearest place where a person of a family can pursue credit (some physical bank branch or a bank correspondent like a supermarket or a big store), in the supply of credit. Brazil has continental proportions and a large inequality in financial services, so the existence of a physical bank can promote access to credit especially for households and small companies. Concerned about the endogeneity of credit-consumption, we propose an instrumental variable (IV) strategy based on measures of that distance between households and bank channels. For Brazilian Census we use a weighting area level, and for the distance from a bank channel we use a Brazilian zip code (CEP - *Código de Endereçamento Postal*] level, a smaller unit of observation.

Impact of a distance from a bank seems to be relevant (ALESSANDRINI; PRESBITERO; ZAZZARO, 2009) for small and medium companies, and it is still important in banking (BREVOORT; WOLKEN, 2009) currently. For Brazilian households wage payment and distance from home are the most important reasons to choose a bank (BCB 2016). Nevertheless, there is evidence that nearer banks may promote development for a region in long run (PASCALI, 2016).

We found evidence of the impact of local credit on local consumption. An increase of one percent of credit may increase the average of a certain durable good in a local region by 1.4 % . This result is similar for all consumer goods evaluated - except for Vehicles. In sample estimations, we found a larger impact of credit on more developed regions (Southeast and South regions).

Finally, we tested models with spatial dependence. The motivation of this robustness is that the heterogeneity presented in Brazil also exists in credit. As we can see in data (see Appendix), the distribution of types of credit across regions is not uniform. As expected, we also found evidence of spatial dependence that can be reduced by Spatial Auto-regressive Models. The lending channel impact seems smaller but still plays an important role in spatial models. Educational factors are also relevant for consumption.

The paper is organized as follows. Section 2 analyses the credit channel in Brazil and data for credit, especially its institutional framework. Section 3 presents the empirical methodology while Section 4 presents the endogeneity problem and the estimation using the exposure instruments. In Section 5, we perform robustness checks estimating models with spatial dependence. Finally, Section 6 concludes.

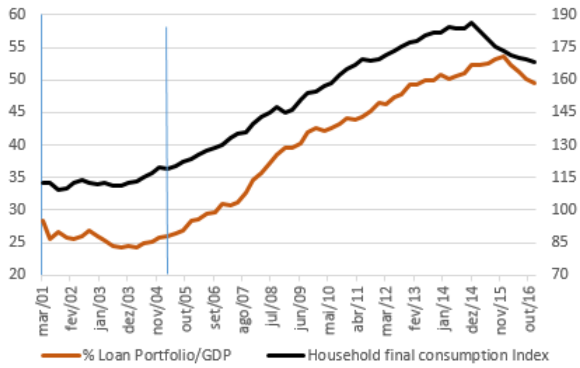
2.2 Credit and Consumption in Brazil

Since the beginning of the century the institutional environment of Brazilian credit has suffered several changes, especially for households. In addition to the consolidation of Real Plan (1994), that reduced inflation in Brazilian economy, Law 10.820 (2003) had allowed the Payroll consigned credit for formal workers, in which bank lenders have the guarantee of worker's paycheck, where a fixed amount is withdrawn for a period as a single debit from the employer's bank, with lower rates than a personal credit. In the same direction, Fiduciary property law (2004) allowed a provisional transfer of ownership of a housing by a debtor to its creditor during the payment of a housing financing loan as a guarantee, increasing the probability of recovery if borrower defaults. After the payment of the guaranteed obligations, the debtor recovers the ownership of the real estate property. Also the Bankruptcy Reform (2005) had an objective to increase secured creditor's chances of recovering a debt when a firm gets liquidated, replacing the concordat rights by the recuperation period when the company has problems in paying debts, in which shareholders must prove business viability and firms must follow a recuperation plan where secured loans have a priority. Although being in an environment with lack of bank competition, Andrade (2015) have found an impact of this law on the interest rate of collateralized loans to firms.

After the enactment of these laws, a large grow of the proportion between loan portfolio and gross domestic product from 26% in 2005 to 53% in 2015 was observed, correlated with the expansion of the Household final consumption index (collected from Brazilian GDP) in the country by almost 50 % on these years. As Figure 23 shows, we saw a strong correlation between those variables during the period 2005-2015 and after the vertical straight line, where the Brazilian economy had a large expansion due to the boom of commodities' prices.

Nevertheless, the household final consumption index includes both durable and non-durable goods. The difficulty to separate both types may explain the rare empirical literature about Brazilian consumption. Gomes (2013) found evidence that consumption of both durable and non-durable goods had exhibited slow but not identical adjustment. However, it is possible to focus on durable good using the sample from the Brazilian Census.

Figure 23 – Correlation between credit and consumption in Brazil, 2001-2015



Obs: vertical line separates the period after institutional changes

2.2.1 Data

We measure weighting area-level consumption using data from 2000 and 2010 Brazilian Census merged with Credit Registry System (*Sistema de Informações de Crédito*, or SCR) from Central Bank of Brazil. SCR collects data on all loans of citizens or companies whose total obligations issued by financial institutions operating in the country are above 5,000 Brazilian Reals (BRL) up to 2012 and above 1,000 BRL after that period.

Credit Registry System has details about the type of borrower (household, firms), the credit type (housing, automotive, personal credit, working capital), Credit Rating [3] and collateral, besides the local information: a zip code or a municipality where the borrower lives, collected from Brazilian Revenue Service (*Receita Federal do Brasil*).

This loan-level database was first aggregated by borrower's last zip code and then aggregated by weighting area level. Weighting area (*área de ponderação*) is a geographic unit formed by a grouping of contiguous census sector (enumerating areas) and has a minimum of 400 occupied households interviewed in Census sample, except for the municipalities that do not reach this total, where the weighting area is the proper municipality itself[4]. Approximately 10% of Brazilian households have been interviewed in this census sample. In that sense, Brazilian weighting areas are similar to a census tract in American census, which is a statistical subdivision of a county and has an optimum size of 4,000 people. The ten biggest cities in Brazil have a total of 929 weighting areas, showing the relevance of dismembering big and heterogeneous cities. In addition to the gain of more local information, weighting area is more homogeneous than a municipality: 75% of them has less than 25,000 inhabitants, and the largest weighting area has less than 350,000 inhabitants.

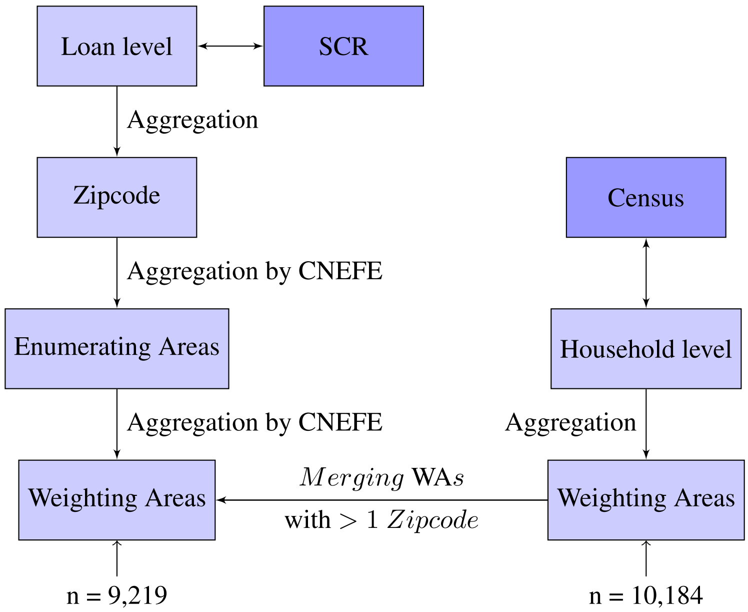
This combined data is possible due to the National Address File for Statistical Purposes (CNEFE) from Brazilian Institute of Geography and Statistics (IBGE), that has the relation between 78 millions of

[3] Resolution 2.682/1999 by National Monetary Council determine that financial institutions should classify the credit operations in a risk increasing order (from AA to H) and should be reviewed depending on the delay verified in the payment of installments of the principal or of charges.

[4] Approximately 80% of Brazilian municipalities has only one weighting area.

addresses, 927,125 Zip Codes and 10,184 weighting areas available for 2010's Brazilian Census. For zip codes that exist in the credit database but are not available in CNEFE (approximately 200,000) we used the closest Zip Code included to identify the weighting area. The comparison of weighting areas between 2000's and 2010's Census is available due to the merged data from IBGE. Then for each weighting area we merged data of aggregated credit types (from Credit Registry System) and data of households and citizens (from Census), which includes information about consumption. The whole process of compilation of data is described in Figure 24. Monetary variables such as credit were constructed considering 2010 constant prices.

Figure 24 – Process of data compilation



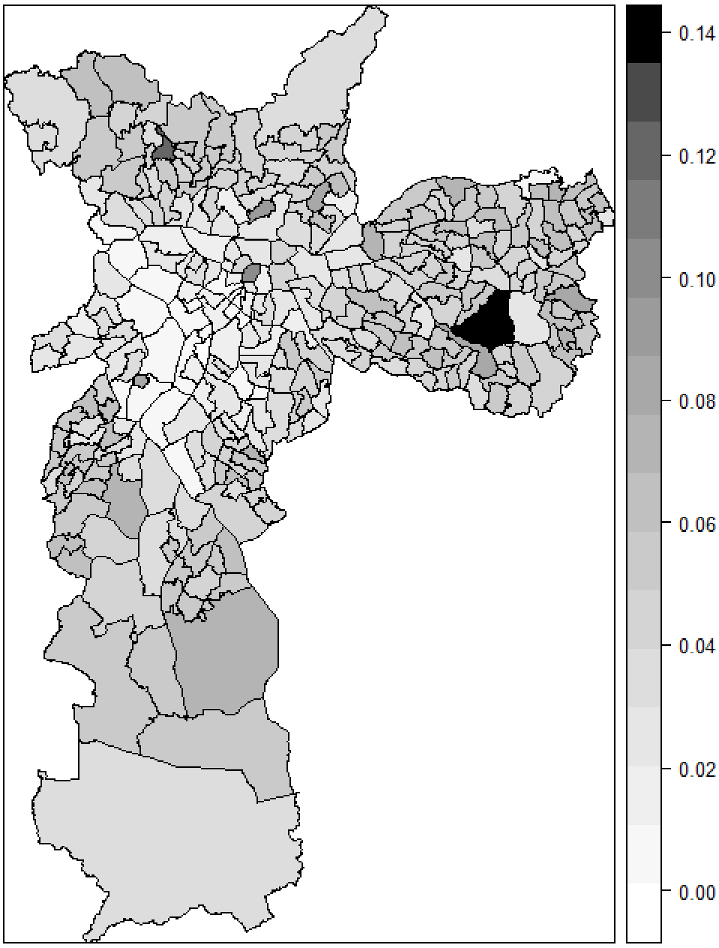
One motivation for using a weighting area level is an example of a shape map from São Paulo, an 11-million municipality with 311 weighting areas in Brazilian 2010 Census. Figure 25 shows that a particular variable (percentage of total credit in arrears) can be distinct inside a bigger municipality. The average size of a weighting area in this municipality is similar to the average size of a municipality in Brazil (40,000).

2.3 Empirical Strategy

We are interested in analyzing the impact of improvement of local credit after institutional changes that happened in Brazil on development in local consumption. To accomplish this task, a panel with fixed effects will be employed. We use the periods of observation: 2005, right after the institutional changes, and 2010, adopting the first-differences estimation. We also include 2015 data for robustness.

The available data has the evolution of credit (2005-2010) and consumption (2000-2010) per weighting

Figure 25 – Credit in arrears at São Paulo by weighting areas, 2010



area i. As Ferro et al. (2016) we don't use credit data before 2005 due to lack of regional information. Nevertheless, the main development of credit and consumption happened after 2003 (GOMES, 2013), which can be seen in figure 23. We then consider a uniform variation over the years to evaluate the period 2005-2010 for consumption.

The use of a durable good that contributes to consumption (or welfare) can be proportional to the stock of the good held by the household (DEATON, 1992). Assuming this perspective, we use consumption information from census sample, that includes approximately 10% of population and households in Brazil, In particular, we consider indicators for having a certain durable good in an individual's home: computer, television, car, washing machine and refrigerator. Those variables have been weighted to the local unit of observation, from 0 (nobody in that weighting area has that good) to 100 (everyone has that good). We construct also indexes of those products whose weights are based on the value of the goods: one with all goods cited and another with all goods except a car or a vehicle[5]. The last index is the main dependent

[5] We considered the following costs for goods: 40,000 BRL for a car, 2,500 BRL for a microcomputer, 2,000 BRL for a refrigerator,

variable and it is detailed in (2.8) on the Appendix.

We utilize as covariates outcomes from the weighting area's sample in the Brazilian Census. There are two types of covariates: the ones that contains information about people interviewed in that weighting area, such as average of literacy rate, high school attendance rate, employment rate, sex (0 if everyone in that weighting area is female and 100 if everyone is male), age and mentally impaired rate, and the one that contains information about households (electric light rate, water supply rate, if lives in an owned house, if house is located in an urban area). Except for age, all covariates also have a value between 0 and 100.

Those variables are present on Brazilian Census of 2000 and 2010. We also include dummies for region and number of weighting areas in the municipality that weighting area belongs. For municipalities that have only one zip code but more than one weighting area we considered as only one unit area. It provided a total of 9,219 available weighting areas.

We utilize the logarithm of the following lines of credit or financing (where the credit works for a specific purpose): total credit; total firm credit (*Crédito Pessoa Jurídica*); total household credit (*Crédito Pessoa Física*); and the main credit types for households: automotive financing, payroll credit, personal credit, housing financing [6] and other goods financing, rural credit and credit card debt. Their description are available in Table 15.

Table 15 – Description of credit types used

	Credit type	Lines
(1)	Housing Financing	Financing real estate for households
(2)	Payroll credit	Consigned credit
(3)	Rural Credit	For investment and trade
(4)	Personal credit	Non-payroll Credit
(5)	Credit Card	from Financial Institution or store
(6)	Automotive Financing	Financing vehicles for households
(7)	Other goods financing	Durable goods
(8)	Household Credit	(1)-(7) + other household credits
(9)	Firm Credit	Credit to firms
(10)	Total Credit	(8) + (9)

Note: those credit types are classified in Credit Registry Data and have been selected by their relevance.

We assume that those credit types can affect consumption in different ways: directly, like payroll credit or vehicle Financing, or indirectly, like firm credit affecting consumption of firm's owners or the role of housing and consumption founded in literature. Table 2 reports the main statistics for variables of the model at the weighting area level. Durable goods are not uniform across type of good or weighting areas: most of the households have purchased a television or a refrigerator but most of them don't have a car, a microcomputer or a washing machine.

2,000 BRL for television and 1,500 BRL for a washing machine. Those costs represent the average current prices for those goods.

[6] We considered the credit from the System of Financing Housing - SFH.

Table 16 – Descriptive Statistics - Weighting area level

Variable	mean	St Dev	N	min	max
TV	93.49	7.39	18438	21.1	100.0
Microcomputer	31.97	20.629	18438	0.2	95.9
Car	33.82	19.569	18438	0.0	94.7
Refrigerator	92.06	10.275	18438	16.1	100.0
Washing Machine	39.63	27.447	18438	0.2	98.1
Consumer Index	40.97	19.359	18438	2.5	94.0
Consumer Index without Vehicles	63.81	14.611	18438	11.8	97.3
Electric Light	98.15	4.789	18438	30.1	100.0
Literacy rate	87.84	9.148	18438	50.8	99.8
Water supply	44.79	37.459	18438	0.0	100.0
age	31.96	3.538	18438	19.6	48.8
log (All Credit)	14.25	1.943	18437	1.3	20.7
log (Firm Credit)	15.97	2.332	18244	2.9	25.0
log (Household Credit)	16.85	1.694	18437	9.3	21.8
log (Credit Card)	11.82	2.352	18055	-4.0	17.6
log (Housing Credit)	14.40	2.205	18135	3.7	20.7
log (Rural Credit)	14.55	1.973	18437	1.5	20.7
log (Personal Credit)	14.14	1.833	18437	5.5	20.2
log (Payroll Credit)	14.72	1.944	18437	6.6	23.8
log (Automotive Financing)	15.33	1.710	18437	8.7	19.8
log (Other Goods Financing)	11.90	1.904	17683	2.9	16.9
log (All Credit in arrears)	17.32	1.866	18437	9.3	25.1
log (Firm Credit in arrears)	13.04	2.227	15856	-4.0	20.7
log (Household Credit in arrears)	13.90	1.855	18413	1.2	19.5

Note: Observations refer to the both periods of 9,219 weighting areas. Logarithm of the credit types have less than 18,438 observations since there are weighting areas without certain credit types. In these cases we consider $log(Credit) = 1$.

A naive panel regression would consider the estimation of equation (2.1). Since we use only two periods - 2000 and 2010 - this becomes a first difference estimation.

$$\Delta Consumption_{it} = \alpha + \beta \Delta ln(Credit_{it}) + \gamma \Delta Covariates_{it} + \Delta e_{it} \tag{2.1}$$

2.4 Identification Strategy

In this section we are concerned about possible endogeneity between credit and consumption: there may be financial shocks that affect both variables, making the correlation not causal between them. Ferro et al. (2016) use as instruments local firm credit and number of bank branches per municipality. Since our focus is on various credit types and we use a smaller unit of observation we then propose a geo-referenced instrument to evaluate the propensity to demand a loan. For most of the credit types in Brazil the customer needs to go to a physical bank channel to ask for a loan, especially for households and small companies, assuring the monotonicity condition for an instrumental variable. Then the distance from a bank seems to be relevant for this service according to the literature.

In that way, we measured (at zip-code level) the Euclidian distance between each zipcode's centroid coordinate and the geographic coordinate of the nearest bank channel. Data containing addresses for each bank channel was collected from Central Bank of Brazil and RAIS (annual social information report). Geographic coordinates about zip codes and bank channels were collected from Google Maps. We consider here three denominations of a bank channel to construct the euclidian distance from the centroid of each zip code:

(i) Only bank branches

At first, we will consider the distance from a regular bank branch (*agências*) at Table 17. It is clear the rise of this physical channel in all Brazilian regions (15% between 2005-2010 and 17% between 2010-2015). In those bank branches you can apply for all credit types. There were bank branches in approximately 65% of municipalities.

Table 17 – Bank branches per region and year

Bank branches	**2005**	**2010**	**2015**
North	676	812	1,149
Northeast	2,456	2,765	3,625
Center-West	1325	1,480	1,831
Southeast	8,972	10,697	11,953
South	3,452	3,734	4,308
Brazil	16,881	19,488	22,866

Source: Central Bank of Brazil

(ii) Bank branches + bank branch-like (PAA, PAB and PAT) Besides the regular bank branches, there are smaller physical bank channels that offer some bank services called bank branch-like (KUMAR et al., 2005). There is also less restriction to define branch hours, services offered and physical location in comparison to a regular branch. We will include three types of bank branch-like that offer credit services: PAA, PAB and PAT.

PAA (*Posto de Atendimento Avançado*) is a tiny bank branch that can be created only in municipalities that do not have a branch of that bank, with a smaller number of employees. Unlike a regular bank branch it does not have a requirement of capital. We see a large increase of PAAs in smaller municipalities that do not have a scale to promote a regular bank operation, in particular at Northeast region.

Table 18 – PAA per region and year

PAA	2005	2010	2015
N	46	134	251
NE	219	834	1,086
CO	27	162	247
SE	37	426	833
S	137	339	423
Brazil	466	1,970	2,840

Source: Central Bank of Brazil

PAB (*Posto de Atendimento Bancário*) provides services only to employees of the company (public or private) where this PAB is physically established and is linked to a regular bank branch in the same municipality, offering the same types of services. In opposite to other physical channels, there is a little reduction of PAB over time, especially in Southeast region.

Table 19 – PAB per region and year

PAB	2005	2010	2015
N	366	347	378
NE	782	759	780
CO	468	481	454
SE	3,809	3,634	3,445
S	1,215	1,407	1,324
Brasil	6,640	6,660	6,381

Source: Central Bank of Brazil

We also include the PAT (*Posto de Atendimento Transitório*), a channel that operates only temporally (less than 90 days) but also provides credit services in places with seasonal demand. However, there are less than 20 PATs in Brazil in any period.

Considering all types [7] of the bank branches, we see a large expansion in all regions during this century. 99% of municipalities have at least one bank branch-like.

Table 20 – All branches that provides credit per region and year

All branches	2005	2010	2015
N	2,183	2,383	3,283
NE	5,966	8,066	8,734
CO	3,187	3,726	4,168
SE	20,096	21,850	20,949
S	6,596	7,886	8,323
Brazil	38,030	44,347	45,457
Abroad	2	2	2

Source: Central Bank of Brazil

(iii) Correspondents

Bank correspondents have been created in 1999 (National Monetary Council, 1999) allowing financial institutions to offer basic services (opening account, payments, deposits, and limited credit services) by companies which provide other types of services stores, , such as markets, post offices, lottery stores and car sellers. We see also a large development of this provision of financial services over time. For correspondents, the local channel is each physical point where services are provided on behalf of the contracting institution[8]. On bank correspondents it is possible to take a loan for a specific purpose, such as automotive financing or other goods financing or even a payroll credit. We have bank correspondents in all Brazilian municipalities.

[7] That also includes PAE (*Posto de Atendimento Eletrônico*), which are the ATMs. We didn't include PAE to measure this distance because it does not provide credit itself.

[8] In the case where, at the same point, services are provided on behalf of more than one contracting institution, this point is considered only once for calculation purposes.

Table 21 – Correspondents per region and year

Correspondents	2000	2005	2010	2015
N	600	2,985	5,931	11,608
NE	3,849	20,379	31,426	42,355
CO	1,842	8,119	12,771	19,882
SE	12,982	51,537	77,201	115,548
S	4,876	21,125	37,552	49,429
Brazil	24,149	104,145	164,881	238,822

Source: Central Bank of Brazil and RAIS.

Table (22) provides descriptive statistics for zip code level. More than half of zip codes are present in Southeast region. Almost 99% of zip codes - named codified - belongs to municipalities that have more than one zip code. The distance from a bank dropped over time - from 1.6 kilometers in 2005 to 1.35 kilometers in 2015. This also happened for other types of bank channel: distance from a bank correspondent dropped more than 50% in ten years.

However, the drop of the distance from a bank over time can also be endogenous: for example, a prosperous region with its economy in development may demand financial services (such as credit) and for this reason, banks install branches there. In that manner, the drop of distance from a bank after 2005 can be related to the economic variables in that period.

Therefore, we construct an instrument with the interaction between the measure of a distance from a bank channel in a specific year - 2005 - and the dummy indicator to the period of observation (2010 as a year basis), considering only the prior distance variable to estimate the first stage. We follow Dix-Carneiro, Soares e Ulyssea (2017) used prior, pre-existing trends to evaluate the effect of regional tariff changes on crime rates. Chioda, Mello e Soares (2016) also considers as an instrument the interaction between a year-dummy variable and another variable at one prior period. This procedure respects the exclusion restriction: the prior distance to a bank channel can affect the variation of durable-goods consumption only through the access to credit.

As in (2.1) we also utilize a panel regression to capture the variation around time and local level, with the following specification:

$$log(Credit_{zt}) = \alpha + \beta_1(d2005_z * Distance_{z2005}) + \beta_2(d2015_z * Distance_{z2005}) + e_{zt}, \qquad (2.2)$$

where $d2005$ is a dummy variable for period of that year, $t = 2005, 2010, 2015$, $z = ZipCode$ and $Distance$ is in kilometers. We also estimate for the two first periods (excluding 2015) to coincide with the second stage data.

Indeed, we transform (2.1) replacing the credit for a weighting area i in the second stage by the predicted credit in (2.2), considering the aggregation of credit estimated in the region of zip codes z that belongs to that weighting area for a given period t, that is:

$$Cr\hat{e}dit_{it} = \sum_{z \in i} Cr\hat{e}dit_{zt} \qquad (2.3)$$

Table 22 – Descriptive Statistics at Zip Code level, pooled data

Variables	Mean	St Dev	N	Min	Max
North	0.0604	0.2382	2,767,341	0	1
Northeast	0.1762	0.3810	2,767,341	0	1
Southeast	0.5023	0.5000	2,767,341	0	1
South	0.1446	0.3517	2,767,341	0	1
Center-West	0.1165	0.3208	2,767,341	0	1
Distance bank branch	1.478	2.8947	2,130,282	0	259.145
2005	1.608	3.0260	598,767	0	259.145
2010	1.504	2.9310	731,009	0	259.145
2015	1.356	2.7520	800,506	0	259.145
Distance bank branch-like	1.166	2.2544	2130282	0	259.145
2005	1.265	2.6866	598,767	0	259.145
2010	1.168	2.1082	731,009	0	178.23
2015	1.089	2.0133	800,506	0	178.23
Codified ZipCode	0.986	0.1195	2,767,341	0	1
Distance Correspondents	0.741	4.2105	2,767,341	0	309.49
2005	1.221	5.4686	720,360	0	309.49
2010	0.699	4.0983	944,254	0	178.35
2015	0.535	3.2307	1,102,727	0	178.35
Total Credit (1000 BRL)	2,240.86	80,612,925	2,767,341	0	73,255,043
log (All Credit)	12.17	2.120	2,355,553	-4.6	25.0
log (Firm Credit)	10.38	3.078	1,214,384	-4.6	25.0
log (Household Credit)	11.99	2.011	2,323,627	-4.6	23.8
log (Credit Card)	9.41	2.310	1,707,743	-4.6	19.4
log (Housing Credit)	11.79	1.588	1214076	-4.2	20.6
log (Rural Credit)	8.95	2.422	981,970	-4.3	21.6
log (Personal Credit)	10.09	1.697	1,638,443	-4.6	20.1
log (Payroll Credit)	10.99	1.612	1,768,470	-1.8	23.8
log (Automotive Financing)	11.18	1.406	1,779,471	1.7	19.4
log (Other Goods Financing)	8.42	1.588	721,134	-4.3	17.1

Source: Own elaboration.

Table 23 provides the results of the first stage for the whole sample. Columns 1-3 represent the estimation for each instrument cited above (distance from only bank branches, distance from a bank branch or a bank branch-like and distance from correspondents) including observations from 2005-2015. The coefficients are similar to the estimates (4-6) that consider only observations from 2005 and 2010, in comparison to the period of the second stage. The coefficients have the expected sign: with greater distance in that period, the interaction with the dummy for 2005 has a negative effect, when the distance from a bank facility was larger. In contrast, with smaller distance, the interaction with the dummy for 2015 has a positive effect, when the distance from a bank facility was smaller. We note that the inclusion of 2015 data does not change largely the coefficients. Nevertheless, the power of a bank branch or a bank branch-like as instruments (t test>10) validates the inclusion restriction of the instrumental variables but it does not apply totally for bank correspondents. As expected, distance from a bank seems more important on credit types involving consumers such as household and payroll credit. Similarly, coefficients for firm credit and rural credit are smaller.

We also estimate Equation 2.3 considering various samples according to two variables: the region of Brazil (North, Northeast, Southeast, South and Center-West) and the codification of Zip Code (dummy if it is codified or not). The zip code is codified if it belongs to a municipality that has a codification of zip codes for streets, blocks or small neighborhoods (it is usually related to cities that have a larger population). Brazilian zip code is compound of eight digits (XXXXX-XXX): the first five digits identify the municipality and the last 3 digits identify the least location (a street, a building or a square) if zip code's municipality is codified [9]. There are 395 municipalities (less than 10%) with a codified zip code in Brazil currently. However, those municipalities aggregate 98% of total zip codes.

The results from the restricted sample are in the Appendix[10]. There is evidence of a strong impact of the distance from a bank on credit in non-codified Zip Codes that represents smaller municipalities. In contrast, the impact of a bank branch in codified (larger) cities are less clear. For that reason, we used the estimation for each restricted sample for the second stage of equation 1. For each regression we made the same estimation considering specific lines of credit mentioned in Table 15.

9 If zip code's municipality is not codified usually the last 3 digits are 000 - for urban areas - or 970 - for rural areas.

10 For 699,105 zip codes we have information for all 3 periods. Other Zip Codes have missing data (no credit). Although the missing data are concentrated in 2005, we didn't see any evidence of bias for the unbalanced panel.

Table 23 – Regression: first stage, considering the whole sample

Instruments	Bank branches	Bank branches-like	Correspondents	Bank branches	Bank branches-like	Correspondents
Data up to	2015	2015	2015	2010	2010	2010
	Dependent variable: log(total credit)					
d2005∗distance	-0.1888***	-0.1976***	-0.0446***	-0.1934***	-0.2025***	-0.0458***
	(0.0006)	(0.0007)	(0.0004)	(0.0006)	(0.0007)	(0.004)
d2015∗distance	0.0687***	0.0729***	0.0186***			
	(0.0005)	(0.0006)	(0.0003)			
	Dependent variable: log(Household credit)					
d2005∗distance	-0.1892***	-0.1981***	-0.0442***	-0.1935***	-0.2026***	-0.0455***
	(0.0006)	(0.0007)	(0.0004)	(0.0006)	(0.0007)	(0.004)
d2015∗distance	0.0684***	0.0724***	0.0176***			
	(0.0005)	(0.0006)	(0.0003)			
	Dependent variable: log(firm credit)					
d2005∗distance	-0.0715***	-0.0732***	-0.0312***	-0.0752***	-0.0770***	-0.0340***
	(0.0011)	(0.0013)	(0.0011)	(0.0012)	(0.0013)	(0.0011)
d2015∗distance	0.0146***	0.0158***	0.0052***			
	(0.001)	(0.0012)	(0.0009)			
	Dependent variable: log(housing financing)					
d2005∗distance	-0.1372***	-0.1503***	-0.0528***	-0.1356***	-0.1473***	-0.0482***
	(0.001)	(0.0012)	(0.0008)	(0.001)	(0.0012)	(0.0009)
d2015∗distance	0.1279***	0.1345***	0.0321***			
	(0.0008)	(0.0010)	(0.0009)			
	Dependent variable: log(credit card)					
d2005∗distance	-0.0690***	-0.0705***	-0.0232***	-0.1182***	-0.1250***	-0.0330***
	(0.0017)	(0.002)	(0.0014)	(0.0013)	(0.0016)	(0.0011)
d2015∗distance	0.4290***	0.4534***	0.1216***			
	(0.0014)	(0.0017)	(0.0010)			
	Dependent variable: log(rural credit)					
d2005∗distance	-0.0325***	-0.0349***	-0.0084***	-0.0416***	-0.0444***	-0.011***
	(0.0011)	(0.0013)	(0.0008)	(0.0012)	(0.0014)	(0.0009)
d2015∗distance	0.0338***	0.0350***	0.0192***			
	(0.0011)	(0.0013)	(0.0008)			
	Dependent variable: log(payroll credit)					
d2005∗distance	-0.1859***	-0.1935***	-0.0454***	-0.1961***	-0.2045***	0.0474***
	(0.0006)	(0.0007)	(0.0004)	(0.0007)	(0.0009)	(0.0005)
d2015∗distance	0.07595***	0.0795***	0.0175***			
	(0.0005)	(0.0006)	(0.0003)			
	Dependent variable: log(personal credit)					
d2005∗distance	-0.1030***	-0.1085***	-0.0299***	-0.1091***	-0.1148***	-0.0314***
	(0.0007)	(0.0008)	(0.0005)	(0.0007)	(0.0008)	(0.0005)
d2015∗distance	0.0561***	0.0588***	0.0140***			
	(0.0006)	(0.0007)	(0.0005)			
	Dependent variable: log(Automotive Financing)					
d2005∗distance	-0.1381***	-0.1450***	-0.0347***	-0.1388***	-0.1457***	-0.0362***
	(0.0005)	(0.0005)	(0.0003)	(0.0006)	(0.0007)	(0.0004)
d2015∗distance	-0.0219***	-0.0228***	-0.0061***			
	(0.0004)	(0.0005)	(0.0003)			
	Dependent variable: log(other household credit)					
d2005∗distance	-0.0073***	-0.0074***	0.0044***	-0.0134***	-0.0136***	0.0010
	(0.0013)	(0.0015)	(0.0011)	(0.0015)	(0.0017)	(0.0014)
d2015∗distance	0.0527***	0.0552***	0.0157***			
	(0.0011)	(0.0012)	(0.0008)			

Note: *p<0.1; **p<0.05; ***p<0.01. Distance was measured in 2005. Standard errors are in parenthesis. Each column represents first stage estimations (Equation 2.3) for distance of each type of bank channel. Columns 1-3 use data from 2005 to 2015. Columns 4-6 use data from 2005 and 2010. Each panel uses one credit type as a dependent variable.

2.4.1 Second stage

We consider then the following estimation, with a first difference regression since we use only two periods.

$$\Delta Consumption_{it} = \alpha + \beta ln(\hat{Credit_{it}}) + \gamma \Delta Covariates_{it} + e_{it} \quad (2.4)$$

, where $ln(\hat{Credit_{it}})$ was estimated on first stage.

We used the restricted estimations (by region and type of zip code) of the predicted first stage on this step. We present here the main results (other results are on the Appendix). For each table, column 1 shows the estimation without any instrument. Column 2 uses the distance from a bank branch or a bank branch-like as an instrument. On the other hand, column 3 uses the distance only from a bank branch as an instrument. Finally, column 4 shows the estimation using the distance from a correspondent as an instrument.

In the second stage, the impact of credit is smaller than in the naive regression, but it is still relevant. The interpretation on table 24 here is that one percent increase of household credit in that weighting area can induce up to a 3.1% (column 1) more of a consumer index with TV, Refrigerator, Washing Machine and Computer. When we use an instrument it can be reduced to 1.4% (columns 2 and 3) or 1.55% (column 4). We also see expected signals and significant effects of most of the covariates: positive effect for literacy, electric light, employment, high school attendance, and urban rates, and negative effects for mentally impaired rates. We have an unexpected effect of sex (% of male in that weighting area) and water supply. Results for each type of good present in that index (television, computer, washing machine or refrigerator) are similar.

Table 25 considers the total amount of credit in that weighting area as financial information. One percent increase of total credit can provide from 1.2% to 1.6% increase in local consumption. Educational variables (literacy rate and high school attendance rate) can together increase more than one percent of local consumption when we consider instrumental variables to explain total credit of each weighting area (columns 2 to 4). Except for sex and water supply rate all other variables have an expected signal.

Table 26 relates results for each type of credit. For all credit types we can find significant impacts on consumption. Except for total credit, household credit and automotive financing, the impact of credit is smaller when we don't use an instrument (column 1). When we use the distance from a bank branch or a bank branch like as an instrument, the impact of credit goes from 0.9% (automotive financing) to 1,7% (rural credit). Coefficients increase when we consider bank correspondents as an instrument (column 4). In the Appendix, we show the complete results for those estimations.

We note a positive, significant impact of credit on consumption of having most of the goods evaluated - except for vehicles. Tables 27 and 28 show results considering if that weighting area contains people with vehicles as a dependent variable and using household credit and total credit as credit types, respectively. We observe an unexpected negative impact of credit on consumption of vehicles considering an estimation without any instrument (column 1) or using bank correspondents as an instrument (column 4). A high number of correspondents and a really smaller distance to a bank may explain that effect. When we use the distance from a bank (or a bank branch) as an instrument, the impact of credit significant becomes smaller

Table 24 – Consumer Index (except Vehicles) as dependent variable and using Household Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.521***	0.647***	0.647***	0.709***
	(0.013)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.253***	0.231***	0.226***	0.263***
	(0.005)	(0.006)	(0.006)	(0.006)
Δ sex	0.174***	0.199***	0.194***	0.350***
	(0.029)	(0.031)	(0.031)	(0.033)
Δ working	0.233***	0.237***	0.236***	0.283***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ high school	0.346***	0.387***	0.387***	0.309***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ water supply	−0.005	−0.011***	−0.012***	0.007*
	(0.003)	(0.004)	(0.004)	(0.004)
Δ own home	−0.012*	−0.020***	−0.021***	−0.008
	(0.007)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.652***	−0.537***	−0.547***	−0.881***
	(0.066)	(0.070)	(0.070)	(0.075)
Δ urban	0.055***	0.034***	0.036***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.012***	0.012***	0.012***	0.018***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Household Credit	3.172***			
	(0.058)			
Δ Household Credit (Bank branch-like)		1.448***		
		(0.035)		
Δ Household Credit (Bank branch)			1.429***	
			(0.035)	
Δ Household Credit (Correspondents)				1.554***
				(0.096)
Observations	9,219	9,219	9,219	9,219
R^2	0.941	0.934	0.935	0.925
Adjusted R^2	0.941	0.934	0.934	0.924
F Statistic (df = 11; 9208)	13,445.630***	11,940.100***	11,945.550***	10,253.950***

Note: *p<0.1; **p<0.05; ***p<0.01
Column 1 refers to the estimation without an instrument. Columns 2, 3 and 4 refer to the Bank branch-likes, Bank Branches and correspondents as instruments, respectively. Standard errors are in parenthesis.

than the impact for other goods (around 0.35% for both total credit and household credit). Table Table 42 of the Appendix shows results for Vehicles considering the other credit types.

Concerning about regional differences we also made those estimations for each one of the five regions in Brazil. Results can be seen in Table 29. We see a big heterogeneity of impact of credit across regions. Without instruments, it is clear that the most development regions (Southeast and South) have more impact of credit on consumption and the least development ones (North and Northeast) have a smaller effect. When we include instruments, North region clearly contains a smaller effect. It contains 45% of Brazilian territory but less than 10% of the population and has the longest average distance from a bank. In the Northeast region, we have bigger effects using bank branch-likes as an instrument for almost all types of credit types. This is a region with a larger number of small municipalities where it may not have a regular bank branch but only a bank branch-like. Rising one percent of personal credit in a weighting area at Southeast region can increase the probability of having a certain good in up to 3.1% (using correspondents as an instrument). In contrast, a one-percent impact of rural credit on consumption can achieve 3.2% in the

Table 25 – Consumer Index (except Vehicles) as dependent variable and using Total Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.570***	0.671***	0.650***	0.710***
	(0.013)	(0.014)	(0.013)	(0.014)
Δ Electric light rate	0.253***	0.267***	0.228***	0.265***
	(0.005)	(0.006)	(0.006)	(0.006)
Δ sex	0.204***	0.207***	0.197***	0.344***
	(0.030)	(0.032)	(0.031)	(0.033)
Δ working	0.237***	0.248***	0.235***	0.283***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ high school	0.346***	0.383***	0.387***	0.309***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ water supply	−0.004	−0.008**	−0.012***	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.013*	−0.023***	−0.021***	−0.010
	(0.007)	(0.008)	(0.007)	(0.008)
Δ mentally impaired	−0.660***	−0.624***	−0.548***	−0.881***
	(0.068)	(0.071)	(0.070)	(0.075)
Δ urban	0.048***	0.028***	0.035***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.013***	0.013***	0.012***	0.018***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Total Credit	2.815***			
	(0.060)			
Δ Total Credit (Bank branch-like)		1.223***		
		(0.033)		
Δ Total Credit (Bank branch)			1.437***	
			(0.035)	
Δ Total Credit (Correspondents)				1.625***
				(0.103)
Observations	9,219	9,219	9,219	9,219
R^2	0.937	0.932	0.934	0.924
Adjusted R^2	0.937	0.932	0.934	0.924
F Statistic (df = 11; 9208)	12,532.500***	11,531.500***	11,941.890***	10,243.430***

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are in parenthesis. Column 1 refers to the estimation without instrument. Columns 2, 3 and 4 refer to the Bank branch-likes, Bank Branches and correspondents as instruments, respectively.

South region. The complete local estimations for regions are also in the Appendix 2.A.4. In addition, table 43 of the Appendix shows results considering the population of the weighting area.

Table 26 – Estimations per type of Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Instrument	Without Instrument	Bank branches	Bank branches-like	Bank Correspondents
Δ Firm Credit	0.493^{***}	1.612^{***}	1.593^{***}	2.255^{***}
	(0.027)	(0.033)	(0.032)	(0.084)
Δ Payroll Credit	1.432^{***}	1.214^{***}	1.174^{***}	1.540^{***}
	(0.034)	(0.029)	(0.029)	(0.067)
Δ Automotive Financing	2.002^{***}	0.936^{***}	0.955^{***}	1.752^{***}
	(0.054)	(0.052)	(0.051)	(0.093)
Δ Personal Credit	1.258^{***}	1.490^{***}	1.463^{***}	1.974^{***}
	(0.045)	(0.034)	(0.034)	(0.093)
Δ Other goods Financing	0.144^{***}	1.205^{***}	1.194^{***}	1.525^{***}
	(0.019)	(0.032)	(0.032)	(0.094)
Δ Rural Credit	1.052^{***}	1.790^{***}	1.793^{***}	2.671^{***}
	(0.050)	(0.034)	(0.034)	(0.086)
Δ Credit Card	0.510^{***}	1.196^{***}	1.147^{***}	1.631^{***}
	(0.025)	(0.029)	(0.029)	(0.066)
Δ Housing Financing	0.495^{***}	1.322^{***}	1.300^{***}	1.993^{***}
	(0.024)	(0.031)	(0.031)	(0.081)
Observations	9,219	9,219	9,219	9,219
Controls	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Each coefficient belongs to a separate regression. Standard errors are in parenthesis. Estimations were provided by Eq. 2.4. Covariates were the same of Tables 24 and 25.

Table 27 – Model - Vehicles as dependent variable and using Household Credit

	Dependent variable: Δ Vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.458^{***}	0.330^{***}	0.328^{***}	0.381^{***}
	(0.019)	(0.019)	(0.019)	(0.018)
Δ Electric light rate	-0.016^{**}	-0.027^{***}	-0.029^{***}	-0.021^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
Δ sex	0.217^{***}	0.076^{*}	0.072^{*}	0.144^{***}
	(0.042)	(0.043)	(0.043)	(0.042)
Δ working	0.311^{***}	0.271^{***}	0.270^{***}	0.290^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Δ high school	0.408^{***}	0.435^{***}	0.437^{***}	0.430^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Δ water supply	-0.007	-0.015^{***}	-0.016^{***}	-0.013^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
Δ own home	0.037^{***}	0.031^{***}	0.031^{***}	0.034^{***}
	(0.010)	(0.010)	(0.010)	(0.010)
Δ mentally impaired	-0.376^{***}	-0.187^{*}	-0.183^{*}	-0.272^{***}
	(0.094)	(0.098)	(0.097)	(0.095)
Δ urban	-0.001	0.012^{**}	0.013^{**}	0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Δ age	0.011^{***}	0.007^{***}	0.007^{***}	0.009^{***}
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Δ Household Credit	-1.522^{***}			
	(0.083)			
Δ Household Credit (Bank branch-like)		0.327^{***}		
		(0.050)		
Δ Household Credit (Bank branch)			0.349^{***}	
			(0.049)	
Δ Household Credit (Correspondents)				-1.439^{***}
				(0.123)
Observations	9,219	9,031	9,031	9,186
R^2	0.696	0.686	0.686	0.689
Adjusted R^2	0.696	0.686	0.686	0.689
F Statistic	$1{,}917.606^{***}$	$1{,}790.621^{***}$	$1{,}792.765^{***}$	$1{,}850.403^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01

Column 1 refers to the estimation without an instrument. Columns 2, 3 and 4 refer to the Bank branch-likes, Bank Branches and correspondents as instruments, respectively. Standard errors are in parenthesis below coefficients.

Table 28 – Model - Vehicles as dependent variable and using Total Credit

	Dependent variable: Δ Vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.424***	0.328***	0.328***	0.386***
	(0.019)	(0.020)	(0.019)	(0.020)
Δ Electric light rate	−0.016**	−0.034***	−0.029***	−0.030***
	(0.008)	(0.009)	(0.008)	(0.009)
Δ sex	0.191***	0.119***	0.070	0.203***
	(0.042)	(0.046)	(0.043)	(0.045)
Δ working	0.305***	0.279***	0.269***	0.300***
	(0.011)	(0.012)	(0.011)	(0.012)
Δ high school	0.410***	0.430***	0.438***	0.422***
	(0.011)	(0.012)	(0.011)	(0.012)
Δ water supply	−0.008*	−0.012**	−0.016***	−0.010*
	(0.005)	(0.006)	(0.005)	(0.005)
Δ own home	0.037***	0.042***	0.031***	0.045***
	(0.010)	(0.011)	(0.010)	(0.011)
Δ mentally impaired	−0.357***	−0.188*	−0.176*	−0.286***
	(0.095)	(0.103)	(0.097)	(0.101)
Δ urban	0.004	0.010	0.013**	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Δ age	0.010***	0.007***	0.007***	0.008***
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Δ Total Credit	−1.173***			
	(0.084)			
Δ Total Credit (Bank branch-like)		0.385***		
		(0.053)		
Δ Total Credit (Bank branch)			0.376***	
			(0.050)	
Δ Total Credit (Correspondents)				−1.488***
				(0.133)
Observations	9,219	8,394	9,036	8,539
R^2	0.692	0.684	0.686	0.687
Adjusted R^2	0.691	0.684	0.686	0.687
F Statistic	1,877.586***	1,651.027***	1,795.139***	1,701.566***

Note: *p<0.1; **p<0.05; ***p<0.01

Column 1 refers to the estimation without an instrument. Columns 2, 3 and 4 refer to the Bank branch-likes, Bank Branches and correspondents as instruments, respectively. Standard errors are in parenthesis below coefficients.

Table 29 – Second stage – Estimates per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
Δ Total credit	1.794***	1.992***	3.711***	2.324***	2.050***
	(0.186)	(0.094)	(0.102)	(0.132)	(0.220)
Δ Total Credit (Bank branch-like)	0.554	1.542***	1.160***	1.542***	1.182***
	(0.883)	(0.069)	(0.058)	(0.084)	(0.111)
Δ Total Credit (Bank branch)	0.850***	1.449***	1.201***	1.519***	1.184***
	(0.109)	(0.068)	(0.058)	(0.081)	(0.111)
Δ Total Credit (Correspondents)	−0.999	1.072***	2.501***	1.412***	0.858***
	(0.815)	(0.149)	(0.159)	(0.246)	(0.281)
Δ Household Credit	1.349***	2.147***	5.043***	3.079***	2.290***
	(0.159)	(0.093)	(0.097)	(0.133)	(0.224)
Δ Household Credit (Bank branch-like)	0.848***	1.499***	1.166***	1.553***	1.188***
	(0.113)	(0.067)	(0.058)	(0.084)	(0.111)
Δ Household Credit (Bank branch)	0.838***	1.401***	1.208***	1.532***	1.193***
	(0.108)	(0.066)	(0.058)	(0.082)	(0.111)
Δ Household Credit (Correspondents)	1.687***	1.045***	2.524***	1.369***	0.834***
	(0.261)	(0.144)	(0.158)	(0.242)	(0.281)
Δ Firm Credit	0.121*	0.284***	0.642***	0.938***	0.467***
	(0.063)	(0.031)	(0.055)	(0.089)	(0.103)
Δ Firm Credit (Bank branch-like)	1.141***	1.786***	1.666***	1.931***	1.374***
	(0.110)	(0.067)	(0.056)	(0.078)	(0.107)
Δ Firm Credit (Bank branch-like)	1.105***	1.715***	1.691***	1.933***	1.356***
	(0.106)	(0.066)	(0.055)	(0.076)	(0.108)
Δ Firm Credit (Correspondents)	1.480***	1.315***	2.998***	2.787***	0.958***
	(0.216)	(0.153)	(0.124)	(0.223)	(0.227)
Δ Payroll Credit	0.648***	0.718***	1.891***	2.046***	1.700***
	(0.105)	(0.042)	(0.066)	(0.094)	(0.124)
Δ Payroll Credit (Bank branch-like)	0.758***	1.039***	1.238***	1.464***	1.113***
	(0.098)	(0.051)	(0.052)	(0.073)	(0.094)
Δ Payroll Credit (Bank branch)	0.713***	0.942***	1.259***	1.503***	1.063***
	(0.091)	(0.051)	(0.051)	(0.070)	(0.094)
Δ Payroll Credit (Correspondents)	1.185***	0.767***	2.338***	2.134***	1.037***
	(0.170)	(0.096)	(0.112)	(0.176)	(0.205)
Δ Automotive Financing	0.477***	0.731***	3.735***	2.535***	1.627***
	(0.117)	(0.077)	(0.099)	(0.141)	(0.182)
Δ Automotive Financing (Bank branch-like)	0.248**	0.370***	2.052***	0.846***	0.975***
	(0.116)	(0.067)	(0.105)	(0.128)	(0.188)
Δ Automotive Financing (Bank branch)	0.293**	0.341***	2.115***	0.933***	0.945***
	(0.115)	(0.067)	(0.104)	(0.123)	(0.189)
Δ Automotive Financing (Correspondents)	1.789***	1.128***	2.606***	1.781***	1.064***
	(0.226)	(0.144)	(0.147)	(0.247)	(0.267)
Δ Personal Credit	0.958***	0.523***	2.181***	1.897***	2.659***
	(0.133)	(0.052)	(0.091)	(0.125)	(0.243)
Δ Personal Credit (Bank branch-like)	0.954***	1.523***	1.401***	1.674***	1.210***
	(0.113)	(0.066)	(0.059)	(0.081)	(0.111)
Δ Personal Credit (Bank branch)	0.942***	1.432***	1.419***	1.685***	1.182***
	(0.109)	(0.065)	(0.059)	(0.079)	(0.111)
Δ Personal Credit (Correspondents)	1.912***	1.105***	3.157***	2.418***	0.905***
	(0.274)	(0.137)	(0.153)	(0.225)	(0.264)
Δ Other goods Financing	0.167***	0.109***	0.078**	0.284***	0.346***
	(0.046)	(0.023)	(0.036)	(0.061)	(0.096)
Δ Other goods Financing (Bank branch-like)	1.071***	1.573***	1.189***	1.663***	1.444***
	(0.122)	(0.078)	(0.058)	(0.081)	(0.109)
Δ Other goods Financing (Bank branch)	1.063***	1.577***	1.194***	1.641***	1.425***
	(0.121)	(0.078)	(0.058)	(0.080)	(0.110)
Δ Other goods Financing (Correspondents)	1.188***	1.129***	1.585***	2.093***	1.233***
	(0.277)	(0.175)	(0.132)	(0.230)	(0.235)
Δ Rural Credit	0.348***	0.439***	1.949***	1.156***	1.002***
	(0.105)	(0.064)	(0.094)	(0.148)	(0.231)
Δ Rural Credit (Bank branch-like)	1.035***	1.662***	1.793***	1.977***	1.254***
	(0.117)	(0.073)	(0.055)	(0.084)	(0.110)
Δ Rural Credit (Bank branch)	1.029***	1.651***	1.820***	1.979***	1.247***
	(0.114)	(0.073)	(0.055)	(0.083)	(0.110)
Δ Rural Credit (Correspondents)	2.638***	1.657***	2.998***	3.240***	0.737***
	(0.355)	(0.181)	(0.110)	(0.239)	(0.223)
Δ Credit Card	0.108	0.366***	0.848***	0.375***	0.654***
	(0.070)	(0.031)	(0.050)	(0.060)	(0.086)
Δ Credit Card (Bank branch-like)	0.975***	1.350***	1.353***	1.593***	1.285***
	(0.112)	(0.060)	(0.055)	(0.074)	(0.102)
Δ Credit Card (Bank branch)	0.935***	1.261***	1.359***	1.594***	1.221***
	(0.106)	(0.060)	(0.054)	(0.073)	(0.102)
Δ Credit Card (Correspondents)	1.194***	0.739***	2.385***	1.477***	1.144***
	(0.193)	(0.114)	(0.109)	(0.132)	(0.198)
Δ Housing Financing	0.052	0.236***	0.939***	1.370***	0.457***
	(0.042)	(0.029)	(0.052)	(0.085)	(0.083)
Δ Housing Financing (Bank branch-like)	1.216***	1.672***	1.398***	1.582***	1.308***
	(0.121)	(0.069)	(0.054)	(0.077)	(0.103)
Δ Housing Financing (Bank branch)	1.182***	1.568***	1.446***	1.598***	1.323***
	(0.116)	(0.067)	(0.054)	(0.074)	(0.105)
Δ Housing Financing (Correspondents)	1.273***	1.351***	2.301***	2.266***	1.228***
	(0.201)	(0.152)	(0.115)	(0.200)	(0.235)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691

Note: *p<0.1; **p<0.05; ***p<0.01. Each column represents estimations from a unique Brazilian region. Each coefficient belongs to a separate regression. Standard errors are in parenthesis. Estimations were provided by Eq. 2.4. Covariates were the same of Tables 24 and 25. The complete estimations are on the Appendix 2.A.4.

2.5 Robustness tests - Spatial Dependence

To address robustness for the results, in this section we will consider models with spatial dependence. The main motivation of these models is the distinct impact that we found after restricting the sample by region and local covariates: lending channel can be distinct across regions. In addition, there is a possibility of double spatial dependence: the amount of credit of a region i can impact the amount of a neighbor region j by the distance from a bank channel, especially in small cities with scarce bank services, but the credit in region i can also impact the consumption of durable goods in a neighbor region j by the proximity of stores and households.

For this step we construct a Brazilian territory shape for 9,219 available [11] weighting areas by union of enumerating areas (shape available from IBGE - Brazilian Institute of Geography and Statistics) to investigate the relevance of the focus at this type of observation. There is a clear asymmetry between weighting areas inside a municipality, as we saw in figure 25. We hence constructed a spatial contiguity matrix using the inverse of euclidian distances between the centroids of these units of observation. Considering costs of transportation, a spillover between credit and consumption seems to depend more of the distance than the boundary of weighting areas.

We initially estimate a spatial autoregressive model (SAR), where the dependent variable may present some interaction between neighborhoods (ANSELIN, 1988), so the error term may be correlated with a spatial lag and a homoscedastic error ε. Variables are in first differences and the estimation does not have a constant to make a comparison with the panel estimation from the previous section. Therefore we have:

$$\begin{aligned} \Delta Consumption_i &= \beta_1 \Delta \hat{Credit_i} + \beta_2 \Delta Covariates_i + e_i \\ e_i &= \rho_i W e_i + \varepsilon_i, \text{ where } \varepsilon_i \sim \mathcal{N}(0,\, \sigma^2 I) \end{aligned} \tag{2.5}$$

where ρ_s is the lag coefficient situated inside a unit root and W is the connectivity matrix between weighting area's neighbors, and $\sigma^2 I = diag[\sigma_1^2, \sigma_2^2, ..., \sigma_1^2]$. W is constructed through the distance of centroids for each weighting area available and it did not change over time. The covariates are the same of Equation (2.1). As we can see in (2.5) we can split this spatial model into stochastic (spatial) and deterministic components.

Results are in table 30. Panel A considers the total amount of credit in each weighting area and Panel B considers only the household credit type. We see that the impact of credit on consumption is smaller using spatial models but still significant. Effects of total credit (Panel A) are significant only using bank branches or bank branches-like as an instrument. We find evidence that 1% increase of total credit can improve only 0.11% the propensity of having a mix of durable goods.

[11] There are 10,184 weighting areas, but we merged weighting areas that contain only one zip code information for credit data.

Table 30 – SAR Model

Panel A: using Total credit	*Dependent variable: Δ Consumer Index without vehicles*			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.4800***	0.4789***	0.4791***	0.4800***
	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Δ Electric light rate	0.3015***	0.3014***	0.3010***	0.3016***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Δ sex	−0.0669***	−0.0669***	−0.0666***	−0.0664***
	(0.0190)	(0.0191)	(0.0191)	(0.0190)
Δ working	0.0763***	0.0767***	0.0766***	0.0761***
	(0.056)	(0.0056)	(0.0056)	(0.0056)
Δ high school	0.3543***	0.3536***	0.3538***	0.3542***
	(0.059)	(0.0059)	(0.0059)	(0.0059)
Δ water supply	0.0163***	0.0164***	0.0164***	0.0162***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Δ own home	−0.0023	−0.0018	−0.0021	−0.0022
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Δ mentally impaired	−0.1182***	−0.1213***	−0.1217***	−0.1188***
	(0.0439)	(0.0439)	(0.0439)	(0.0439)
Δ urban	0.0361***	0.0357***	0.0359***	0.0360***
	(0.028)	(0.0028)	(0.0028)	(0.0028)
Δ age	0.0026***	0.0026***	0.0026***	0.0025***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Total Credit	0.0175			
	(0.0438)			
Δ Total Credit (Bank branch-like)		0.1136***		
		(0.0324)		
Δ Total Credit (Bank branch)			0.0849***	
			(0.0317)	
Δ Total Credit (Correspondents)				−0.0816
				(0.2016)
Observations	9,219	9,219	9,219	9,219
ρ	0.942	0.942	0.940	0.942
ρ (Std. Error)	0.00279	0.00279	0.00296	0.00278
AIC	47,581	47,570	47,575	47,580
Panel B: using household credit	*Dependent variable: Consumer Index without vehicles*			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.4809***	0.4789***	0.4789***	0.4800***
	(0.0097)	(0.0097)	(0.0097)	(0.097)
Δ Electric light rate	0.3014***	0.3011***	0.3010***	0.3016***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Δ sex	−0.0664***	−0.0669***	−0.0668***	0.0664***
	(0.0191)	(0.0191)	(0.0190)	(0.042)
Δ working	0.0764***	0.0767***	0.0766***	0.0761***
	(0.0056)	(0.0056)	(0.0056)	(0.0056)
Δ high school	0.3550***	0.3536***	0.3538***	0.3541***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Δ water supply	0.0162***	0.0164***	0.0163***	0.0162* * *
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Δ own home	−0.0025	−0.0019	−0.0020	−0.0022
	(0.0046)	(0.0047)	(0.0407)	(0.0047)
Δ mentally impaired	−0.1191***	−0.1216***	−0.1219***	−0.1192***
	(0.0439)	(0.0439)	(0.0439)	(0.0439)
Δ urban	0.0361***	0.0358***	0.0358***	0.0360***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Δ age	0.0026***	0.0026***	0.0026***	0.0025***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Household Credit	0.1372***			
	(0.0551)			
Δ Household Credit (Bank branch-like)		0.0996***		
		(0.0315)		
Δ Household Credit (Bank branch)			0.0894***	
			(0.0313)	
Δ Household Credit (Correspondents)				−0.0891
				(0.0613)
Observations	9,219	9,219	9,219	9,219
ρ	0.940	0.940	0.940	0.942
ρ (Std. Error)	0.00294	0.00296	0.00296	0.00278
AIC	47,576	47,572	47,574	47,579

Note: *p<0.1; **p<0.05; ***p<0.01. Column 1 refers to the Eq. 2.5 without an instrument. Columns 2-4 use bank branch-likes, bank branches and correspondents as instruments, respectively. Standard errors are in parenthesis. ρ is the spatial component.

Impact of credit in this spatial model is also smaller when we consider household credit (Panel B of table 30). There is no evidence of lending channel using bank correspondents as an instrument. In both estimations, spatial dependence seems important. Except for sex, all other covariates have expected signal of coefficients. Both educational variables (literacy rate and high school rate) play an important role on consumption of durable goods: one percent increase of these rates on a weighting area can provide an increase of 0.83% (0.48+0.35) on consumption of durable goods. Electric light (that attends approximately 95% of the Census sample) still seems relevant in this process.

Table 31 reports estimations per credit type. It suggests that lending channel can work only in general credit types that a household or an small enterprise can only apply in a bank branch, such as personal, rural and firm credit. For credit types with a specific purpose, there is no evidence of lending channel affecting consumption.

Table 31 – Estimations per type of Credit - SAR Model

	Dependent variable:			
	Δ Consumer Index without vehicles			
Instrument	Without Instrument	Bank branches	Bank branches-like	Bank Correspondents
Δ Firm Credit	0.031^{***}	0.090^{***}	0.088^{***}	0.064
	(0.016)	(0.030)	(0.029)	(0.062)
Δ Payroll Credit	0.049^{**}	0.031	0.026	-0.082^{*}
	(0.025)	(0.024)	(0.024)	(0.046)
Δ Automotive Financing	−0.032	−0.019	−0.025	-0.161^{***}
	(0.037)	(0.031)	(0.031)	(0.063)
Δ Personal Credit	0.099^{***}	0.076^{***}	0.069^{**}	−0.084
	(0.029)	(0.031)	(0.030)	(0.064)
Δ Other goods Financing	0.007	0.043	0.040	-0.136^{*}
	(0.011)	(0.026)	(0.026)	(0.052)
Δ Rural Credit	0.082^{***}	0.126^{***}	0.130^{***}	0.084
	(0.032)	(0.032)	(0.032)	(0.069)
Δ Credit Card	−0.014	0.045^{**}	0.040^{*}	−0.001
	(0.015)	(0.023)	(0.023)	(0.046)
Δ Housing Financing	−0.012	0.039	0.041	−0.015
	(0.014)	(0.025)	(0.025)	(0.054)
Observations	9,219	9,219	9,219	9,219
Controls	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Each coefficient belongs to a separate regression. Column 1 refers to the Equation 2.5 without an instrument. Columns 2-4 use bank branch-likes, bank branches and correspondents as instruments, respectively. Standard errors are in parenthesis.

We also estimate a Spatial Simultaneous Autoregressive Lag Model Estimation (LSAR) by maximum likelihood estimation. It considers a linear model with spatial lag on dependent variable to estimate the regional impact of credit, that is:

$$\Delta Consumption_i = \rho W \Delta Consumption_i + \beta_1 \Delta \hat{Credit_i} + \beta_2 \Delta Covariates_i + e_i, \tag{2.6}$$

where ρ and W are similar to the equation (2.5).

Results for this model are present in table 32. Here, the lending channel has a clear effect on consumption, although it is smaller than the effect without spatial effect. A one percent increase on local credit can increase a 0.32% the propensity of having a certain good (Panel A, column 2). Water supply rate has an unexpected negative effect on consumption. Educational coefficients again appear as positive and significant.

To test spatial autocorrelation of credit and the efficiency of spatial models we calculated Moran's I (ANSELIN, 1988) for each type of estimation and credit type.

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2}, \tag{2.7}$$

where w_{ij} are elements of the spatial weight matrix W, which capture the neighborly relationship between weighting area i and weighting area j, and z is the variable of interest normalized and $S_0 = \sum \sum w_{ij}$.

Results are illustrated in table 33. Moran's I are similar for all instruments and credit types but are really different depending on the model. There is strong evidence of spatial autocorrelation of residual errors of first difference estimators identified on the previous section. This evidence can be vanished applying SAR models (low value). However, there is still evidence of spatial autocorrelation using LSAR models.

Table 32 – LSAR Model

Panel A: using total credit	*Dependent variable: Δ Consumer Index without vehicles*			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.4616***	0.4733***	0.4742***	0.4771***
	(0.0100)	(0.0099)	(0.0099)	(0.0099)
Δ Electric light rate	0.1990***	0.1958***	0.1935***	0.1974***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Δ sex	−0.0420*	−0.0579**	−0.0470**	−0.0342
	(0.0225)	(0.0226)	(0.0226)	(0.0226)
Δ working	0.1186***	0.1158***	0.1164***	0.1188***
	(0.060)	(0.0060)	(0.0060)	(0.0060)
Δ high school	0.3274***	0.3391***	0.3347***	0.3215***
	(0.057)	(0.0059)	(0.0059)	(0.0057)
Δ water supply	−0.0090***	−0.0109***	−0.0105***	−0.0078***
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Δ own home	−0.0053	−0.0081	−0.0065	−0.0043
	(0.0053)	(0.0053)	(0.0053)	(0.0047)
Δ mentally impaired	−0.2006***	−0.1666***	−0.1733***	−0.2074***
	(0.0503)	(0.0503)	(0.0505)	(0.0504)
Δ urban	0.0644***	0.0609***	0.0624***	0.0632***
	(0.030)	(0.0030)	(0.0030)	(0.0030)
Δ age	0.0048***	0.0042***	0.0044***	0.0049***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Total Credit	0.5396***			
	(0.0498)			
Δ Total Credit (Bank branch-like)		0.3221***		
		(0.0251)		
Δ Total Credit (Bank branch)			0.2602***	
			(0.0277)	
Δ Total Credit (Correspondents)				0.1679**
				(0.0701)
Observations	9,219	9,219	9,219	9,219
ρ	0.509	0.515	0.517	0.538
ρ (Std. Error)	0.00581	0.00553	0.00571	0.00522
AIC	48,032	47,981	48,058	48,237
Panel B: using household credit	*Dependent variable: Δ Consumer Index without vehicles*			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.4523***	0.4735***	0.4737***	0.4778***
	(0.0101)	(0.0099)	(0.0099)	(0.0099)
Δ Electric light rate	0.2003***	0.1940***	0.1933***	0.1971***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Δ sex	−0.0431*	−0.0470**	−0.0475**	−0.0331
	(0.0225)	(0.0226)	(0.0226)	(0.0226)
Δ working	0.1205***	0.1167***	0.1166***	0.1188***
	(0.060)	(0.0060)	(0.0060)	(0.0060)
Δ high school	0.3283***	0.3349***	0.3347***	0.3219***
	(0.057)	(0.0060)	(0.0059)	(0.0057)
Δ water supply	−0.0092***	−0.0104***	0.0106***	−0.0079***
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Δ own home	−0.0052	−0.0065	−0.0065	−0.0042
	(0.0053)	(0.0053)	(0.0053)	(0.0047)
Δ mentally impaired	−0.2099***	−0.1706***	−0.1734***	−0.2069***
	(0.0502)	(0.0505)	(0.0505)	(0.0505)
Δ urban	0.0658***	0.0622***	0.0625***	0.0630***
	(0.030)	(0.0030)	(0.0030)	(0.0030)
Δ age	0.0048***	0.0044***	0.0044***	0.0049***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Household Credit	0.7058***			
	(0.0520)			
Δ Household Credit (Bank branch-like)		0.2670***		
		(0.0279)		
Δ Household Credit (Bank branch)			0.2578***	
			(0.0275)	
Δ Household Credit (Correspondents)				0.0916
				(0.0662)
Observations	9,219	9,219	9,219	9,219
ρ	0.495	0.516	0.517	0.539
ρ (Std. Error)	0.00608	0.00570	0.00571	0.00525
AIC	47,969	48,054	48,058	48,141

Note: *p<0.1; **p<0.05; ***p<0.01. Column 1 refers to the Equation 2.5 without an instrument. Columns 2-4 use bank branch -likes, bank branches and correspondents as instruments, respectively. Standard errors are in parenthesis. ρ is the spatial component.

Table 33 – Moran's I of residual errors of estimations

Panel A	No Instrument			Instrument: Bank branch		
Model	FD	SAR	LSAR	FD	SAR	LSAR
	(1)	(2)	(3)	(4)	(5)	(6)
Total Credit	0.343	-0.0556	0.088	0.335	-0.0541	0.121
Household Credit	0.336	-0.0555	0.075	0.336	-0.0541	0.121
Firm Credit	0.349	-0.0555	0.119	0.337	-0.0541	0.120
Payroll Credit	0.349	-0.0553	0.111	0.338	-0.0542	0.120
Automotive Fin.	0.349	-0.0558	0.102	0.347	-0.0555	0.110
Personal Credit	0.349	-0.0555	0.112	0.338	-0.0540	0.121
Other goods Fin.	0.348	-0.0555	0.121	0.331	-0.0536	0.122
Rural Credit	0.348	-0.0555	0.117	0.341	-0.0543	0.118
Credit Card	0.349	-0.0556	0.118	0.339	-0.0544	0.120
Housing Fin.	0.347	-0.0555	0.119	0.335	-0.0538	0.121
Panel B	Instrument: Bank branch-likes			Instrument: Correspondents		
Model	FD	SAR	LSAR	FD	SAR	LSAR
	(1)	(2)	(3)	(4)	(5)	(6)
Total Credit	0.340	-0.0539	0.121	0.338	-0.0553	0.104
Household Credit	0.337	-0.0542	0.121	0.338	-0.0553	0.102
Firm Credit	0.338	-0.0542	0.120	0.342	-0.0555	0.100
Payroll Credit	0.338	-0.0542	0.120	0.344	-0.0554	0.104
Automotive Fin.	0.347	-0.0555	0.110	0.339	-0.0551	0.100
Personal Credit	0.335	-0.0541	0.121	0.341	-0.0553	0.100
Other goods Fin.	0.332	-0.0537	0.122	0.344	-0.0553	0.108
Rural Credit	0.341	-0.0544	0.118	0.337	-0.0552	0.092
Credit Card	0.339	-0.0544	0.120	0.344	-0.0554	0.101
Housing Fin.	0.336	-0.0539	0.121	0.344	-0.0551	0.103

Obs: Each number corresponds to a Moran's I for each regression. Columns (1) and (4) from Panels A and B were estimated by Equation 2.4. Columns (2) and (5) were provided by Equation 2.5. And columns (3) and (6) were estimated by Equation 2.6.

2.6 Conclusion

In this paper, we investigate the impact of lending channel evaluating the relation between local credit and local consumption of durable goods. We merged a credit registry database from Central Bank of Brazil and a Census sample using a weighting area level. We also use the distance from various types of a bank channel as a mechanism to analyze clearly that channel.

We shed some light about the relevance of evaluating financial issues at a regional view since Brazil is a continental and heterogeneous country. The significance of the spatial effect suggests that studies with a small unit of observation such as weighting areas can be useful for credit analysis. In addition, the distinct impact of lending channel over size of the weighting areas and Brazilian regions suggest that the local view is important for financial inclusion.

Our results report evidence of the role of the lending channel in the Brazilian case. The strong impact found is that a rise of one percent of credit may increase the average of a mix of durable goods in a local region by 1.4 %. Nevertheless, when we consider spatial effects, the lending facility we found smaller but still significant impact in weighting areas. Using bank branch-like as an instrument, one percent of credit may increase the average of a certain durable good in a local region by 0.1 % even considering spatial models. In opposite, there isn't evidence of impact of credit on consumption when we use bank correspondents as an instrument in a spatial model, addressing that the role of financial inclusion is complex. Those results are in line to the literature and are similar to all credit types.

This work may improve discussions about financial access. Since online banking is heterogeneous across Brazilian regions a physical bank channel still plays an important role in this process. Having a bank correspondent near home seems to have a smaller or no effect in consumption of durable goods, but bank branch-likes located in small municipalities can be useful for citizens that demand services such as a loan. In addition, we also found evidence that educational factors also remain important to increase consumption.

One limitation of this study is our focus on bank lending channel, since the policies related may also affected interest rates (ANDRADE, 2015), a variable that has limitations on credit data considering a local level. Another issue is the lack of data at zip code level that restricted estimations at first stage. In addition, the use of a Census does not allow to follow of a specific household over time. Finally, households' can modify their utility of having certain durable goods over time, witch bias can be reduced by using a consumer index with a mix of goods.

2.A Appendix

2.A.1 Consumer Index without vehicles

Dependent Variable:

$$\Delta \begin{array}{l}\text{Consumer Index}\\ \text{without vehicles}\end{array} = \frac{25^{*}\Delta\text{Computer} + 20^{*}\Delta\text{Refrigerator} + 20^{*}\Delta\text{TV} + 15^{*}\Delta\text{Washing Machine}}{80} \tag{2.8}$$

Table 34 – Firm Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.709***	0.624***	0.625***	0.685***
	(0.014)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.258***	0.241***	0.237***	0.268***
	(0.006)	(0.005)	(0.005)	(0.006)
Δ sex	0.343***	0.164***	0.161***	0.335***
	(0.033)	(0.030)	(0.030)	(0.032)
Δ working	0.279***	0.208***	0.208***	0.265***
	(0.009)	(0.008)	(0.008)	(0.008)
Δ high school	0.330***	0.372***	0.373***	0.289***
	(0.009)	(0.008)	(0.008)	(0.008)
Δ water supply	0.002	−0.007*	−0.008**	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.012	−0.019***	−0.020***	−0.006
	(0.008)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.820***	−0.527***	−0.533***	−0.898***
	(0.075)	(0.068)	(0.068)	(0.073)
Δ urban	0.034***	0.033***	0.035***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.017***	0.011***	0.011***	0.017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Firm Credit	0.493***			
	(0.027)			
Δ Firm Credit (Bank branch-like)		1.612***		
		(0.033)		
Δ Firm Credit (Bank branch)			1.593***	
			(0.032)	
Δ Firm Credit (Correspondents)				2.255***
				(0.084)
Observations	9,219	9,219	9,219	9,219
R^2	0.925	0.939	0.939	0.928
Adjusted R^2	0.925	0.938	0.939	0.928
Residual Std. Error (df = 9208)	4.744	4.296	4.294	4.651
F Statistic (df = 11; 9208)	10,334.400***	12,784.980***	12,801.000***	10,785.430***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel A represents the estimations from the first row of Table 26.

Table 35 – Payroll Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.638***	0.651***	0.650***	0.697***
	(0.013)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.219***	0.232***	0.225***	0.263***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.217***	0.192***	0.191***	0.332***
	(0.031)	(0.031)	(0.031)	(0.033)
Δ working	0.250***	0.236***	0.238***	0.275***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ high school	0.378***	0.382***	0.381***	0.305***
	(0.008)	(0.008)	(0.008)	(0.008)
Δ water supply	−0.012***	−0.012***	−0.013***	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.019***	−0.021***	−0.021***	−0.005
	(0.007)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.525***	−0.551***	−0.566***	−0.858***
	(0.070)	(0.070)	(0.070)	(0.074)
Δ urban	0.048***	0.036***	0.038***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.013***	0.012***	0.012***	0.017***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Payroll Credit	1.432***			
	(0.034)			
Δ Payroll Credit (Bank branch-like)		1.214***		
		(0.029)		
Δ Payroll Credit (Bank branch)			1.174***	
			(0.029)	
Δ Payroll Credit (Correspondents)				1.540***
				(0.067)
Observations	9,219	9,219	9,219	9,219
R^2	0.935	0.935	0.934	0.927
Adjusted R^2	0.935	0.935	0.934	0.926
Residual Std. Error (df = 9208)	4.412	4.428	4.437	4.696
F Statistic (df = 11; 9208)	12,077.170***	11,984.810***	11,933.080***	10,562.920***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel B represents the estimations from the second row of Table 26.

Table 36 – Automotive Financing

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.648***	0.714***	0.712***	0.703***
	(0.014)	(0.014)	(0.014)	(0.014)
Δ Electric light rate	0.241***	0.254***	0.251***	0.264***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.234***	0.335***	0.331***	0.340***
	(0.032)	(0.033)	(0.033)	(0.033)
Δ working	0.252***	0.284***	0.283***	0.280***
	(0.008)	(0.009)	(0.009)	(0.009)
Δ high school	0.357***	0.320***	0.321***	0.306***
	(0.008)	(0.008)	(0.008)	(0.008)
Δ water supply	−0.006*	0.003	0.003	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.016**	−0.012	−0.012	−0.006
	(0.008)	(0.008)	(0.008)	(0.008)
Δ mentally impaired	−0.704***	−0.846***	−0.846***	−0.883***
	(0.071)	(0.074)	(0.074)	(0.074)
Δ urban	0.042***	0.034***	0.035***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.014***	0.017***	0.017***	0.017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Automotive Financing	2.002***			
	(0.054)			
Δ Automotive Financing (Bank branch-like)		0.936***		
		(0.052)		
Δ Automotive Financing (Bank branch)			0.955***	
			(0.051)	
Δ Automotive Financing (Correspondents)				1.752***
				(0.093)
Observations	9,219	9,219	9,219	9,219
R^2	0.933	0.925	0.925	0.925
Adjusted R^2	0.932	0.925	0.925	0.925
Residual Std. Error (df = 9208)	4.502	4.745	4.740	4.737
F Statistic (df = 11; 9208)	11,565.460***	10,328.070***	10,354.730***	10,369.110***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel C represents the estimations from the third row of Table 26.

Table 37 – Personal Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.688***	0.640***	0.641***	0.698***
	(0.014)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.243***	0.233***	0.229***	0.267***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.303***	0.185***	0.183***	0.337***
	(0.032)	(0.031)	(0.031)	(0.033)
Δ working	0.264***	0.227***	0.228***	0.277***
	(0.008)	(0.008)	(0.008)	(0.009)
Δ high school	0.341***	0.386***	0.386***	0.305***
	(0.008)	(0.008)	(0.008)	(0.008)
Δ water supply	−0.006	−0.012***	−0.013***	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.016**	−0.018**	−0.017**	−0.004
	(0.008)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.756***	−0.543***	−0.556***	−0.892***
	(0.073)	(0.069)	(0.069)	(0.074)
Δ urban	0.041***	0.034***	0.035***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.015***	0.012***	0.012***	0.017***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Personal Credit	1.258***			
	(0.045)			
Δ Personal Credit (Bank branch-like)		1.490***		
		(0.034)		
Δ Personal Credit (Bank branch)			1.463***	
			(0.034)	
Δ Personal Credit (Correspondents)				1.974***
				(0.093)
Observations	9,219	9,219	9,219	9,219
R^2	0.928	0.936	0.936	0.926
Adjusted R^2	0.928	0.936	0.935	0.926
Residual Std. Error	4,635	4,395	4,399	4,714
F Statistic (df = 11; 9208)	10,868.120***	12,179.020***	12,154.350***	10,478.360***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel D represents the estimations from the fourth row of Table 26.

Table 38 – Other goods Financing

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.739***	0.679***	0.682***	0.720***
	(0.014)	(0.014)	(0.014)	(0.014)
Δ Electric light rate	0.260***	0.268***	0.268***	0.270***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.362***	0.247***	0.247***	0.350***
	(0.034)	(0.032)	(0.032)	(0.033)
Δ working	0.286***	0.233***	0.233***	0.282***
	(0.009)	(0.008)	(0.008)	(0.009)
Δ high school	0.323***	0.358***	0.358***	0.316***
	(0.009)	(0.008)	(0.008)	(0.009)
Δ water supply	0.002	−0.002	−0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.012	−0.005	−0.005	−0.002
	(0.008)	(0.008)	(0.008)	(0.008)
Δ mentally impaired	−0.887***	−0.645***	−0.648***	−0.891***
	(0.076)	(0.071)	(0.071)	(0.075)
Δ urban	0.030***	0.027***	0.028***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.017***	0.013***	0.013***	0.018***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Other goods Financing	0.144***			
	(0.019)			
Δ Other goods Financing (Bank branch-like)		1.205***		
		(0.032)		
Δ Other goods Financing (Bank branch)			1.194***	
			(0.032)	
Δ Other goods Financing (Correspondents)				1.525***
				(0.094)
Observations	9,219	9,219	9,219	9,219
R^2	0.923	0.933	0.933	0.925
Adjusted R^2	0.923	0.932	0.932	0.924
Residual Std. Error (df = 9208)	4.814	4.501	4.502	4.761
F Statistic (df = 11; 9208)	10,013.980***	11,574.400***	11,565.340***	10,256.250***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel A represents the estimations from the fifth row of Table 26.

Table 39 – Rural Credit

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.719***	0.613***	0.613***	0.676***
	(0.014)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.268***	0.250***	0.249***	0.280***
	(0.006)	(0.005)	(0.005)	(0.006)
Δ sex	0.357***	0.153***	0.152***	0.321***
	(0.033)	(0.030)	(0.030)	(0.032)
Δ working	0.271***	0.205***	0.204***	0.261***
	(0.009)	(0.008)	(0.008)	(0.008)
Δ high school	0.327***	0.378***	0.379***	0.285***
	(0.008)	(0.008)	(0.008)	(0.008)
Δ water supply	0.009**	−0.003	−0.003	0.016***
	(0.004)	(0.003)	(0.003)	(0.004)
Δ own home	−0.014*	−0.019***	−0.019***	−0.006
	(0.008)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.816***	−0.470***	−0.471***	−0.910***
	(0.074)	(0.067)	(0.067)	(0.072)
Δ urban	0.028***	0.032***	0.032***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.017***	0.011***	0.011***	0.017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Rural Credit	1.052***			
	(0.050)			
Δ Rural Credit (Bank branch-like)		1.790***		
		(0.034)		
Δ Rural Credit (Bank branch)			1.793***	
			(0.034)	
Δ Rural Credit (Correspondents)				2.671***
				(0.086)
Observations	9,219	9,219	9,219	9,219
R^2	0.926	0.940	0.940	0.930
Adjusted R^2	0.926	0.940	0.940	0.930
Residual Std. Error (df = 9208)	4.715	4.243	4.237	4.592
F Statistic (df = 11; 9208)	10,473.340***	13,126.400***	13,167.620***	11,087.490***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel B represents the estimations from the sixth row of Table 26.

Table 40 – Credit Card

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.717***	0.651***	0.652***	0.697***
	(0.014)	(0.013)	(0.014)	(0.014)
Δ Electric light rate	0.244***	0.260***	0.255***	0.270***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.336***	0.206***	0.208***	0.337***
	(0.033)	(0.031)	(0.031)	(0.033)
Δ working	0.280***	0.231***	0.234***	0.271***
	(0.009)	(0.008)	(0.008)	(0.009)
Δ high school	0.349***	0.373***	0.371***	0.304***
	(0.009)	(0.008)	(0.008)	(0.008)
Δ water supply	−0.007*	−0.005	−0.006	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.019**	−0.012*	−0.012*	−0.0004
	(0.008)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.747***	−0.649***	−0.662***	−0.906***
	(0.074)	(0.070)	(0.070)	(0.073)
Δ urban	0.039***	0.030***	0.032***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.016***	0.013***	0.013***	0.017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Credit Card	0.510***			
	(0.025)			
Δ Credit Card (Bank branch-like)		1.196***		
		(0.029)		
Δ Credit Card (Bank branch)			1.147***	
			(0.029)	
Δ Credit Card (Correspondents)				1.631***
				(0.066)
Observations	9,219	9,219	9,219	9,219
R^2	0.926	0.934	0.934	0.927
Adjusted R^2	0.926	0.934	0.934	0.927
Residual Std. Error (df = 9208)	4.719	4.443	4.457	4.677
F Statistic (df = 11; 9208)	10,453.300***	11,900.770***	11,817.350***	10,654.790***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel C represents the estimations from the seventh row of Table 26.

Table 41 – Housing Financing

	Dependent variable: Δ Consumer Index without vehicles			
	(1)	(2)	(3)	(4)
Δ Literacy rate	0.716***	0.657***	0.658***	0.694***
	(0.014)	(0.013)	(0.013)	(0.014)
Δ Electric light rate	0.249***	0.258***	0.255***	0.269***
	(0.006)	(0.006)	(0.006)	(0.006)
Δ sex	0.342***	0.198***	0.195***	0.335***
	(0.033)	(0.031)	(0.031)	(0.033)
Δ working	0.274***	0.226***	0.226***	0.272***
	(0.009)	(0.008)	(0.008)	(0.009)
Δ high school	0.329***	0.369***	0.370***	0.297***
	(0.008)	(0.008)	(0.008)	(0.008)
Δ water supply	0.001	−0.007*	−0.008**	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ own home	−0.008	−0.013*	−0.013*	−0.003
	(0.008)	(0.007)	(0.007)	(0.008)
Δ mentally impaired	−0.830***	−0.594***	−0.605***	−0.888***
	(0.074)	(0.070)	(0.070)	(0.073)
Δ urban	0.035***	0.030***	0.032***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ age	0.016***	0.012***	0.012***	0.017***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)
Δ Housing Financing	0.495***			
	(0.024)			
Δ Housing Financing (Bank branch-like)		1.322***		
		(0.031)		
Δ Housing Financing (Bank branch)			1.300***	
			(0.031)	
Δ Housing Financing (Correspondents)				1.993***
				(0.081)
Observations	9,219	9,219	9,219	9,219
R^2	0.926	0.935	0.935	0.927
Adjusted R^2	0.926	0.935	0.935	0.927
Residual Std. Error (df = 9208)	4.719	4.418	4.419	4.675
F Statistic (df = 11; 9208)	10,451.300***	12,042.870***	12,040.280***	10,666.620***

Note: *p<0.1; **p<0.05; ***p<0.01. Panel D represents the estimations from the eighth row of Table 26.

2.A.2 Vehicles

Table 42 – Vehicles as Dependent Variable

	Dependent variable: Δ Vehicles							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm Credit	Payroll Credit	Automotive Financing	Personal Credit	Other goods Financing	Rural Credit	Credit Card	Housing Financing
	Panel A: Without instrument							
Δ Credit type	-0.069^{*}	-0.150^{***}	-0.559^{***}	-0.292^{***}	0.041^{*}	-0.312^{***}	-0.056^{*}	0.010
	(0.035)	(0.047)	(0.073)	(0.059)	(0.025)	(0.064)	(0.032)	(0.031)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,219	9,219	9,219	9,219	9,219	9,219	9,219	9,219
R^2	0.685	0.685	0.688	0.686	0.685	0.686	0.685	0.685
Adjusted R^2	0.685	0.685	0.687	0.686	0.685	0.685	0.685	0.685
F Statistic	$1{,}821.972^{***}$	$1{,}823.846^{***}$	$1{,}773.101^{***}$	$1{,}837.802^{***}$	$1{,}821.670^{***}$	$1{,}827.620^{***}$	$1{,}821.771^{***}$	$1{,}820.896^{***}$
	Panel B: Bank branch-like as instrument							
Δ Credit type	0.297^{***}	-0.292^{***}	-0.489^{***}	0.365^{***}	0.412^{***}	0.202^{***}	0.309^{***}	0.359^{***}
	(0.051)	(0.043)	(0.067)	(0.059)	(0.053)	(0.052)	(0.048)	(0.049)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,865	8,941	9,219	8,952	8,302	8,982	8,530	8,655
R^2	0.688	0.687	0.687	0.688	0.700	0.686	0.693	0.694
Adjusted R^2	0.687	0.687	0.687	0.687	0.699	0.685	0.692	0.694
F Statistic	$1{,}771.930^{***}$	$1{,}781.686^{***}$	$1{,}771.930^{***}$	$1{,}791.232^{***}$	$1{,}757.069^{***}$	$1{,}778.419^{***}$	$1{,}745.593^{***}$	$1{,}781.659^{***}$
	Panel C: Bank branch as instrument							
Δ Credit type	0.310^{***}	0.273^{***}	-0.441^{***}	0.374^{***}	0.443^{***}	0.211^{***}	0.310^{***}	0.376^{***}
	(0.050)	(0.042)	(0.066)	(0.050)	(0.052)	(0.052)	(0.047)	(0.049)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,865	8,865	9,219	8,952	8,302	8,982	8,530	8,655
R^2	0.688	0.687	0.687	0.688	0.700	0.686	0.693	0.694
Adjusted R^2	0.687	0.688	0.686	0.688	0.700	0.685	0.692	0.694
F Statistic	$1{,}773.101^{***}$	$1{,}781.962^{***}$	$1{,}773.101^{***}$	$1{,}792.371^{***}$	$1{,}760.309^{***}$	$1{,}778.857^{***}$	$1{,}746.107^{***}$	$1{,}783.578^{***}$
	Panel D: Correspondents as instrument							
Δ Credit type	-1.210^{***}	-0.844^{***}	-1.475^{***}	-1.360^{***}	-1.346^{***}	-1.683^{***}	-0.972^{***}	-1.107^{***}
	(0.111)	(0.087)	(0.119)	(0.120)	(0.121)	(0.113)	(0.087)	(0.105)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,054	9,125	9,166	9,129	8,508	9,160	8,765	8,897
R^2	0.690	0.689	0.690	0.690	0.700	0.692	0.694	0.695
Adjusted R^2	0.690	0.690	0.690	0.690	0.699	0.692	0.694	0.694
F Statistic	$1{,}831.996^{***}$	$1{,}834.158^{***}$	$1{,}852.139^{***}$	$1{,}845.824^{***}$	$1{,}816.150^{***}$	$1{,}870.820^{***}$	$1{,}804.532^{***}$	$1{,}838.850^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age. Each panel and each column correspond to one separated regression. *Credit* belongs to the coefficient of Δ of that credit type indicated in the column considering the instrument of the first stage indicated in that Panel.

2.A.3 Per population of weighting area

Table 43 – Per size of the weighting area

	Dependent variable: Δ Consumer Index without Vehicles							
	Total Credit				Household Credit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Population	<8850	8850-15750	15750-25000	>25000	<8850	8850-15750	15750-25000	>25000
	Panel A: Without instrument							
Δ Credit type	1.465***	3.593***	2.647***	2.791***	1.557***	3.719***	2.937***	3.673***
	(0.113)	(0.131)	(0.117)	(0.136)	(0.119)	(0.123)	(0.113)	(0.135)
Covariates	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,368	2,261	2,240	1,890	2,368	2,261	2,240	1,890
R^2	0.934	0.945	0.944	0.949	0.934	0.948	0.947	0.955
Adjusted R^2	0.934	0.945	0.944	0.948	0.934	0.948	0.947	0.955
F Statistic	3,023.527***	3,534.232***	3,426.565***	3,156.069***	3,028.331***	3,736.768***	3,639.424***	3,618.910***
	Panel B: Bank branch-like as instrument							
Δ Credit type	1.652***	1.622***	1.532***	1.560***	1.624***	1.560***	1.530***	1.614***
	(0.067)	(0.067)	(0.071)	(0.111)	(0.065)	(0.065)	(0.067)	(0.102)
Covariates	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,200	2,115	1,965	1,655	2,352	2,211	2,151	1,858
R^2	0.943	0.942	0.944	0.944	0.944	0.942	0.944	0.945
Adjusted R^2	0.942	0.941	0.943	0.944	0.944	0.942	0.944	0.944
F Statistic	3,269.641***	3,084.909***	2,983.162***	2,542.439***	3,595.345***	3,263.625***	3,305.968***	2,866.124***
	Panel C: Bank branch as instrument							
Δ Credit type	1.650***	1.570***	1.533***	1.626***	1.634***	1.547***	1.533***	1.629***
	(0.064)	(0.065)	(0.067)	(0.101)	(0.064)	(0.065)	(0.066)	(0.100)
Covariates	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,353	2,213	2,153	1,858	2,352	2,211	2,151	1,858
R^2	0.945	0.942	0.945	0.945	0.945	0.942	0.945	0.945
Adjusted R^2	0.945	0.942	0.944	0.945	0.944	0.942	0.945	0.945
F Statistic	3,656.689***	3,263.906***	3,320.544***	2,881.299***	3,636.019***	3,263.636***	3,330.346***	2,890.700***
	Panel D: Correspondents as instrument							
Δ Credit type	−0.171	1.204***	1.588***	3.104***	−0.161	1.241***	1.678***	3.370***
	(0.165)	(0.200)	(0.211)	(0.324)	(0.158)	(0.187)	(0.190)	(0.308)
Covariates	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,210	2,153	2,036	1,681	2,361	2,252	2,230	1,884
R^2	0.927	0.927	0.932	0.941	0.929	0.928	0.933	0.941
Adjusted R^2	0.926	0.926	0.932	0.941	0.929	0.928	0.933	0.941
F Statistic	2,526.580***	2,458.937***	2,536.316***	2,425.491***	2,797.114***	2,634.666***	2,831.481***	2,716.044***

Note: *p<0.1; **p<0.05; ***p<0.01. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age. Each panel and each column correspond to one separated regression. *Credit* belongs to the coefficient of Δ of Total Credit (Columns 1 to 4) or Δ of Household Credit (Columns 5 to 8). Columns 1 and 5 consider only weighting areas with fewer than 8,850 inhabitants. Columns 2 and 6 consider only weighting areas from 8,850 to 15,750 inhabitants. Columns 3 and 7 consider only weighting areas from 15,750 to 25,000 inhabitants. Columns 4 and 8 restricts the sample to the weighting areas that have more than 25,000 inhabitants.Instruments of the first stage are indicated in each Panel.

2.A.4 Per region

Table 44 – Total Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Total Credit	1.794^{***}	1.992^{***}	3.711^{***}	2.324^{***}	2.050^{***}
	(0.186)	(0.094)	(0.102)	(0.132)	(0.220)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.968	0.960	0.948	0.923	0.951
Adjusted R^2	0.967	0.960	0.948	0.923	0.950
Residual Std. Error	3,518	3,635	3,723	4,711	4,064
F Statistic	$1{,}795.659^{***}$	$5{,}278.926^{***}$	$5{,}992.152^{***}$	$1{,}974.702^{***}$	$1{,}195.724^{***}$
	Panel B: Bank branches-like as instrument				
Δ Total Credit	0.554	1.542^{***}	1.160^{***}	1.542^{***}	1.182^{***}
	(0.883)	(0.069)	(0.058)	(0.084)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	17	2,352	3,563	1,786	676
R^2	0.991	0.961	0.936	0.924	0.952
Adjusted R^2	0.974	0.961	0.935	0.924	0.951
Residual Std. Error	3,025	3,598	4,136	4,674	4,017
F Statistic	57.948^{***}	$5{,}294.659^{***}$	$4{,}697.029^{***}$	$1{,}970.544^{***}$	$1{,}199.635^{***}$
	Panel C: Bank branches as instrument				
Δ Total Credit	0.850^{***}	1.449^{***}	1.201^{***}	1.519^{***}	1.184^{***}
	(0.109)	(0.068)	(0.058)	(0.081)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	659	2,352	3,563	1,786	676
R^2	0.966	0.961	0.936	0.925	0.952
Adjusted R^2	0.965	0.960	0.936	0.924	0.951
Residual Std. Error	3,595	3,629	4,119	4,659	4,017
F Statistic	$1{,}673.250^{***}$	$5{,}199.469^{***}$	$4{,}737.898^{***}$	$1{,}983.929^{***}$	$1{,}199.297^{***}$
	Panel D: Bank correspondents as instrument				
Δ Total Credit	-0.999	1.072^{***}	2.501^{***}	1.412^{***}	0.858^{***}
(Correspondents)	(0.815)	(0.149)	(0.159)	(0.246)	(0.281)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	18	2,409	3,618	1,807	687
R^2	0.994	0.954	0.933	0.912	0.945
Adjusted R^2	0.984	0.954	0.933	0.911	0.944
Residual Std. Error	2.203	3.918	4.215	5.050	4.293
F Statistic	99.785^{***}	$4{,}501.640^{***}$	$4{,}596.440^{***}$	$1{,}682.360^{***}$	$1{,}059.762^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel A in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel A in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 45 – Household Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Household Credit	1.349^{***}	2.147^{***}	5.043^{***}	3.079^{***}	2.290^{***}
	(0.159)	(0.093)	(0.097)	(0.133)	(0.224)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.967	0.961	0.959	0.931	0.952
Adjusted R^2	0.966	0.961	0.959	0.930	0.951
Residual Std. Error	3.567)	3.585	3.296	4.476	4.018
F Statistic	$1{,}744.757^{***}$	$5{,}434.093^{***}$	$7{,}732.454^{***}$	$2{,}205.202^{***}$	$1{,}224.735^{***}$
	Panel B: Bank branches-like as instrument				
Δ Household Credit	0.848^{***}	1.499^{***}	1.166^{***}	1.553^{***}	1.188^{***}
	(0.113)	(0.067)	(0.058)	(0.084)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	658	2,350	3,562	1,785	676
R^2	0.966	0.961	0.936	0.925	0.952
Adjusted R^2	0.965	0.961	0.936	0.924	0.951
Residual Std. Error	3,608	3,603	4,132)	4,663	4,015
F Statistic	$1{,}661.001^{***}$	$5{,}269.082^{***}$	$4{,}705.978^{***}$	$1{,}979.460^{***}$	$1{,}200.324^{***}$
	Panel C: Bank branches as instrument				
Δ Household Credit	0.838^{***}	1.401^{***}	1.208^{***}	1.532^{***}	1.193^{***}
	(0.108)	(0.066)	(0.058)	(0.082)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	658	2,350	3,562	1,785	676
R^2	0.966	0.960	0.936	0.925	0.952
Adjusted R^2	0.965	0.960	0.936	0.925	0.951
Residual Std. Error	3,598	3,637	4,114	4,648	4,015
F Statistic	$1{,}670.701^{***}$	$5{,}166.476^{***}$	$4{,}749.301^{***}$	$1{,}993.360^{***}$	$1{,}200.442^{***}$
	Panel D: Correspondents as instrument				
Δ Household Credit	1.687^{***}	1.045^{***}	2.524^{***}	1.369^{***}	0.834^{***}
	(0.261)	(0.144)	(0.158)	(0.242)	(0.281)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	667	2,408	3,618	1,806	687
R^2	0.965	0.954	0.934	0.911	0.945
Adjusted R^2	0.965	0.954	0.933	0.911	0.944
Residual Std. Error	3,648	3,918)	4,210	5,053	4,295
F Statistic	$1{,}664.146^{***}$	$4{,}495.194^{***}$	$4{,}607.430^{***}$	$1{,}679.434^{***}$	$1{,}058.927^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel B in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel B in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 46 – Firm Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Firm Credit	0.121*	0.284***	0.642***	0.938***	0.467***
	(0.063)	(0.031)	(0.055)	(0.089)	(0.103)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.963	0.954	0.931	0.915	0.946
Adjusted R^2	0.963	0.954	0.931	0.915	0.945
Residual Std. Error	3,747	3,894	4,276	4,947	4,251
F Statistic	1,575.469***	4,570.802***	4,462.597***	1,775.052***	1,087.296***
	Panel B: Bank branches-like as instrument				
Δ Firm Credit	1.141***	1.786***	1.666***	1.931***	1.374***
	(0.110)	(0.067)	(0.056)	(0.078)	(0.107)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	636	2,252	3,542	1,767	668
R^2	0.968	0.965	0.943	0.934	0.954
Adjusted R^2	0.968	0.965	0.943	0.933	0.954
Residual Std. Error	3,446	3,422	3,898	4,375	3,910
F Statistic	1,744.850***	5,603.166***	5,296.771***	2,249.790***	1,251.961***
	Panel C: Bank branches as instrument				
Δ Firm Credit	1.105***	1.715***	1.691***	1.933***	1.356***
	(0.106)	(0.066)	(0.055)	(0.076)	(0.108)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	636	2,252	3,542	1,767	668
R^2	0.969	0.964	0.944	0.935	0.954
Adjusted R^2	0.968	0.964	0.943	0.934	0.953
Residual Std. Error	3,441	3,446	3,876	4,344	3,924
F Statistic	1,750.136***	5,520.792***	5,360.721***	2,283.916***	1,242.932***
	Panel D: Correspondents as instrument				
Δ Firm Credit	1.480***	1.315***	2.998***	2.787***	0.958***
	(0.216)	(0.153)	(0.124)	(0.223)	(0.227)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	648	2,329	3,604	1,791	682
R^2	0.966	0.955	0.939	0.917	0.945
Adjusted R^2	0.965	0.955	0.939	0.917	0.944
Residual Std. Error	3,609	3,865	4,040	4,883	4,281)
F Statistic	1,634.335***	4,456.846***	5,012.260***	1,794.157***	1,056.116***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel C in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel C in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 47 – Payroll Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Payroll Credit	0.648***	0.718***	1.891***	2.046***	1.700***
	(0.105)	(0.042)	(0.066)	(0.094)	(0.124)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.965	0.958	0.942	0.929	0.957
Adjusted R^2	0.965	0.958	0.942	0.928	0.956
Residual Std. Error	3,654	3,735	3,929	4,533	3,818
F Statistic	1,659.541***	4,987.664***	5,344.571***	2,145.966***	1,362.904***
	Panel B: Bank branches-like as instrument				
Δ Payroll Credit	0.758***	1.039***	1.238***	1.464***	1.113***
	(0.098)	(0.051)	(0.052)	(0.073)	(0.094)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	655	2,294	3,551	1,768	673
R^2	0.966	0.960	0.939	0.928	0.953
Adjusted R^2	0.966	0.960	0.938	0.927	0.953
Residual Std. Error	3,590	3,630	4,041	4,558	3,949
F Statistic	1,670.791***	4,999.713***	4,922.651***	2,056.628***	1,233.499***
	Panel C: Bank branches as instrument				
Δ Payroll Credit	0.713***	0.942***	1.259***	1.503***	1.063***
	(0.091)	(0.051)	(0.051)	(0.070)	(0.094)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	655	2,294	3,551	1,768	673
R^2	0.966	0.959	0.939	0.930	0.953
Adjusted R^2	0.966	0.959	0.939	0.929	0.952
Residual Std. Error	3,584	3,674	4,025	4,506	3,978)
F Statistic	1,676.589***	4,876.213***	4,963.928***	2,108.433***	1,214.831***
	Panel D: Correspondents as instrument				
Δ Payroll Credit	1.185***	0.767***	2.338***	2.134***	1.037***
	(0.170)	(0.096)	(0.112)	(0.176)	(0.205)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	666	2,366	3,613	1,794	686
R^2	0.966	0.954	0.937	0.918	0.946
Adjusted R^2	0.965	0.954	0.936	0.917	0.946
Residual Std. Error	3,631	3,898	4,113	4,866	4,238
F Statistic	1,676.778***	4,412.744***	4,839.497***	1,806.109***	1,085.541***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel D in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel D in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 48 – Automotive Financing - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Automotive Financing	0.477***	0.731***	3.735***	2.535***	1.627***
	(0.117)	(0.077)	(0.099)	(0.141)	(0.182)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.964	0.955	0.949	0.924	0.950
Adjusted R^2	0.964	0.954	0.949	0.923	0.950
Residual Std. Error	3,711	3,887	3,692	4,693	4,081
F Statistic	1,607.336***	4,588.730***	6,098.549***	1,990.752***	1,185.381***
	Panel B: Bank branches-like as instrument				
Δ Automotive Financing	0.248**	0.370***	2.052***	0.846***	0.975***
	(0.116)	(0.067)	(0.105)	(0.128)	(0.188)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.963	0.953	0.936	0.912	0.947
Adjusted R^2	0.963	0.953	0.935	0.912	0.946
Residual Std. Error	3,745	3,936	4,145	5,035	4,232
F Statistic	1,577.566***	4,471.061***	4,768.560***	1,707.891***	1,097.913***
	Panel C: Bank-branches as instrument				
Δ Automotive Financing	0.293**	0.341***	2.115***	0.933***	0.945***
	(0.115)	(0.067)	(0.104)	(0.123)	(0.189)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.964	0.953	0.936	0.913	0.947
Adjusted R^2	0.963	0.953	0.936	0.912	0.946
Residual Std. Error	3,739	3,939	4,127	5,017	4,237)
F Statistic	1,582.328***	4,462.543***	4,814.758***	1,721.954***	1,094.885***
	Panel D: Correspondents as instrument				
Δ Automotive Financing	1.789***	1.128***	2.606***	1.781***	1.064***
	(0.226)	(0.144)	(0.147)	(0.247)	(0.267)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	664	2,396	3,618	1,802	686
R^2	0.967	0.954	0.935	0.912	0.946
Adjusted R^2	0.966	0.954	0.934	0.912	0.945
Residual Std. Error	3,587	3,907	4,178	5,023	4,270
F Statistic	1,719.941***	4,493.186***	4,685.634***	1,695.559***	1,071.492***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel E in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel E in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 49 – Personal Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Personal Credit	0.958***	0.523***	2.181***	1.897***	2.659***
	(0.133)	(0.052)	(0.091)	(0.125)	(0.243)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.966	0.955	0.939	0.920	0.953
Adjusted R^2	0.965	0.955	0.938	0.920	0.952
Residual Std. Error	3,619	3,878	4,046	4,799	3,978
F Statistic	1,693.813***	4,611.372***	5,022.894***	1,896.497***	1,250.435***
	Panel B: Bank branches-like as instrument				
Δ Personal Credit	0.954***	1.523***	1.401***	1.674***	1.210***
	(0.113)	(0.066)	(0.059)	(0.081)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	655	2,296	3,554	1,773	674
R^2	0.967	0.962	0.938	0.928	0.952
Adjusted R^2	0.966	0.962	0.938	0.927	0.952
Residual Std. Error	3,549	3,558	4,051	4,563	4,007
F Statistic	1,709.827***	5,283.049***	4,898.917***	2,058.933***	1,204.295***
	Panel C: Bank branches as instrument				
Δ Personal Credit	0.942***	1.432***	1.419***	1.685***	1.182***
	(0.109)	(0.065)	(0.059)	(0.079)	(0.111)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	655	2,296	3,554	1,773	674
R^2	0.967	0.961	0.939	0.929	0.952
Adjusted R^2	0.966	0.961	0.938	0.928	0.951
Residual Std. Error	3,540	3,597	4,039	4,533	4,022
F Statistic	1,718.672***	5,164.724***	4,930.733***	2,088.066***	1,194.935***
	Panel D: Correspondents as instrument				
Δ Personal Credit	1.912***	1.105***	3.157***	2.418***	0.905***
	(0.274)	(0.137)	(0.153)	(0.225)	(0.264)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	665	2,364	3,616	1,797	687
R^2	0.966	0.954	0.936	0.915	0.945
Adjusted R^2	0.965	0.954	0.936	0.915	0.944
Residual Std. Error	3,621	3,891	4,122	4,939	4,286
F Statistic	1,682.993***	4,460.217***	4,819.675***	1,753.749***	1,063.700***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel F in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel F in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 50 – Other goods Financing - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Other goods Financing	0.167^{***}	0.109^{***}	0.078^{**}	0.284^{***}	0.346^{***}
	(0.046)	(0.023)	(0.036)	(0.061)	(0.096)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.964	0.953	0.929	0.911	0.946
Adjusted R^2	0.963	0.953	0.929	0.911	0.945
Residual Std. Error	3,721	3,941	4,354	5,066	4,275
F Statistic	$1{,}598.582^{***}$	$4{,}457.740^{***}$	$4{,}291.122^{***}$	$1{,}685.604^{***}$	$1{,}074.838^{***}$
	Panel B: Bank branches-like as instrument				
Δ Other goods Financing	1.071^{***}	1.573^{***}	1.189^{***}	1.663^{***}	1.444^{***}
(Bank branch-like)	(0.122)	(0.078)	(0.058)	(0.081)	(0.109)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	572	1,911	3,437	1,722	660
R^2	0.969	0.962	0.938	0.929	0.955
Adjusted R^2	0.969	0.962	0.938	0.928	0.955
Residual Std. Error	3,429	3,488	4,061	4,555	3,873
F Statistic	$1{,}609.496^{***}$	$4{,}403.672^{***}$	$4{,}729.954^{***}$	$2{,}026.844^{***}$	$1{,}265.579^{***}$
	Panel C: Bank branches as instrument				
Δ Other goods Financing	1.063^{***}	1.577^{***}	1.194^{***}	1.641^{***}	1.425^{***}
(Bank branch)	(0.121)	(0.078)	(0.058)	(0.080)	(0.110)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	572	1,911	3,437	1,722	660
R^2	0.969	0.962	0.938	0.929	0.955
Adjusted R^2	0.969	0.962	0.938	0.929	0.954
Residual Std. Error	3,428	3,486	4,058	4,547	3,889
F Statistic	$1{,}609.938^{***}$	$4{,}407.596^{***}$	$4{,}738.032^{***}$	$2{,}033.917^{***}$	$1{,}254.554^{***}$
	Panel D: Correspondents as instrument				
Δ Other goods Financing	1.188^{***}	1.129^{***}	1.585^{***}	2.093^{***}	1.233^{***}
	(0.277)	(0.175)	(0.132)	(0.230)	(0.235)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	600	2,017	3,522	1,761	678
R^2	0.966	0.955	0.934	0.915	0.946
Adjusted R^2	0.966	0.954	0.933	0.914	0.945
Residual Std. Error	3,614	3,812	4,213	4,963	4,255
F Statistic	$1{,}542.792^{***}$	$3{,}828.204^{***}$	$4{,}487.649^{***}$	$1{,}710.974^{***}$	$1{,}067.039^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel G in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel G in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 51 – Rural Credit - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Rural Credit	0.348^{***}	0.439^{***}	1.949^{***}	1.156^{***}	1.002^{***}
	(0.105)	(0.064)	(0.094)	(0.148)	(0.231)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.964	0.954	0.936	0.913	0.946
Adjusted R^2	0.963	0.953	0.936	0.912	0.945
Residual Std. Error	3,727	3,922	4,118	5,013	4,257
F Statistic	$1{,}593.572^{***}$	$4{,}504.363^{***}$	$4{,}836.456^{***}$	$1{,}725.009^{***}$	$1{,}084.419^{***}$
	Panel B: Bank branches-like as instrument				
Δ Rural Credit	1.035^{***}	1.662^{***}	1.793^{***}	1.977^{***}	1.254^{***}
	(0.117)	(0.073)	(0.055)	(0.084)	(0.110)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	649	2,327	3,558	1,774	674
R^2	0.968	0.962	0.945	0.932	0.953
Adjusted R^2	0.967	0.962	0.945	0.932	0.952
Residual Std. Error	3,496	3,582	3,834	4,433	3,983
F Statistic	$1{,}748.582^{***}$	$5{,}288.533^{***}$	$5{,}512.601^{***}$	$2{,}195.824^{***}$	$1{,}219.485^{***}$
	Panel C: Bank branches as instrument				
Δ Rural Credit	1.029^{***}	1.651^{***}	1.820^{***}	1.979^{***}	1.247^{***}
(Bank branch)	(0.114)	(0.073)	(0.055)	(0.083)	(0.110)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	649	2,327	3,558	1,774	674
R^2	0.968	0.962	0.945	0.932	0.953
Adjusted R^2	0.967	0.961	0.945	0.932	0.952
Residual Std. Error	3,490	3,585	3,819	4,426	3,987
F Statistic	$1{,}754.564^{***}$	$5{,}278.934^{***}$	$5{,}559.781^{***}$	$2{,}203.065^{***}$	$1{,}217.547^{***}$
	Panel D: Correspondents as instrument				
Δ Rural Credit	2.638^{***}	1.657^{***}	2.998^{***}	3.240^{***}	0.737^{***}
	(0.355)	(0.181)	(0.110)	(0.239)	(0.223)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	660	2,395	3,618	1,800	687
R^2	0.967	0.954	0.941	0.918	0.945
Adjusted R^2	0.967	0.954	0.941	0.918	0.944
Residual Std. Error	3,562	3,888	3,970	4,856	4,288
F Statistic	$1{,}734.665^{***}$	$4{,}543.856^{***}$	$5{,}223.907^{***}$	$1{,}825.340^{***}$	$1{,}062.396^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel H in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel H in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 52 – Credit Card - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Credit Card	0.108	0.366***	0.848***	0.375***	0.654***
	(0.070)	(0.031)	(0.050)	(0.060)	(0.086)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.963	0.955	0.934	0.912	0.949
Adjusted R^2	0.963	0.955	0.934	0.911	0.948
Residual Std. Error	3.751	3,848	4,191	5,043	4,143
F Statistic	1,572.083***	4,687.027***	4,657.599***	1,702.519***	1,148.127***
	Panel B: Bank branches-like as instrument				
Δ Credit Card	0.975***	1.350***	1.353***	1.593***	1.285***
	(0.112)	(0.060)	(0.055)	(0.074)	(0.102)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	612	2,082	3,497	1,688	651
R^2	0.967	0.962	0.940	0.932	0.956
Adjusted R^2	0.966	0.962	0.940	0.931	0.955
Residual Std. Error	3,519	3,478	3,988	4,466	3,842
F Statistic	1,586.678***	4,818.777***	4,981.494***	2,082.553***	1,265.344***
	Panel C: Bank-branches as instrument				
Δ Credit Card	0.935***	1.261***	1.359***	1.594***	1.221***
(Bank branch)	(0.106)	(0.060)	(0.054)	(0.073)	(0.102)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	612	2,082	3,497	1,688	651
R^2	0.967	0.962	0.940	0.933	0.955
Adjusted R^2	0.966	0.961	0.940	0.932	0.954
Residual Std. Error	3,514	3,517	3,980	4,442	3,880
F Statistic	1,592.005***	4,709.368***	5,005.066***	2,106.373***	1,239.473***
	Panel D: Correspondents as instrument				
Δ Credit Card	1.194***	0.739***	2.385***	1.477***	1.144***
(Correspondents)	(0.193)	(0.114)	(0.109)	(0.132)	(0.198)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	625	2,176	3,567	1,727	670
R^2	0.965	0.954	0.938	0.918	0.949
Adjusted R^2	0.965	0.953	0.938	0.917	0.948
Residual Std. Error	3,629	3,847	4,059	4,884	4,148
F Statistic	1,545.709***	4,050.005***	4,909.479***	1,746.690***	1,107.130***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel I in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel I in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

Table 53 – Housing Financing - per region

	Dependent variable: Δ Consumer Index without vehicles				
	North	Northeast	Southeast	South	Center-West
	Panel A: Without instrument				
Δ Housing Financing	0.052	0.236***	0.939***	1.370***	0.457***
	(0.042)	(0.029)	(0.052)	(0.085)	(0.083)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	669	2,417	3,622	1,820	691
R^2	0.963	0.954	0.935	0.921	0.947
Adjusted R^2	0.963	0.954	0.934	0.921	0.946
Residual Std. Error	3,753	3,907	4,174	4,764	4,223
F Statistic	1,569.998***	4,538.685***	4,698.292***	1,927.411***	1,103.044***
	Panel B: Bank branches-like as instrument				
Δ Housing Financing	1.216***	1.672***	1.398***	1.582***	1.308***
(Bank branch-like)	(0.121)	(0.069)	(0.054)	(0.077)	(0.103)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	555	2,175	3,515	1,756	654
R^2	0.969	0.964	0.940	0.928	0.955
Adjusted R^2	0.969	0.964	0.940	0.928	0.954
Residual Std. Error	3,392	3,426	3,988	4,572	3,885
F Statistic	1,570.797***	5,279.129***	5,016.207***	2,043.804***	1,245.139***
	Panel C: Bank-branches as instrument				
Δ Housing Financing	1.182***	1.568***	1.446***	1.598***	1.323***
(Bank branch)	(0.116)	(0.067)	(0.054)	(0.074)	(0.105)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	555	2,175	3,515	1,756	654
R^2	0.970	0.964	0.941	0.929	0.955
Adjusted R^2	0.969	0.963	0.941	0.929	0.954
Residual Std. Error	3,385	3,452	3,965	4,533	3,891
F Statistic	1,577.701***	5,196.568***	5,077.101***	2,080.914***	1,241.314***
	Panel D: Correspondents as instrument				
Δ Housing Financing	1.273***	1.351***	2.301***	2.266***	1.228***
(Correspondents)	(0.201)	(0.152)	(0.115)	(0.200)	(0.235)
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	589	2,258	3,588	1,788	674
R^2	0.966	0.956	0.936	0.916	0.947
Adjusted R^2	0.966	0.955	0.936	0.916	0.946
Residual Std. Error	3,583	3,797	4,119	4,920	4,229
F Statistic	1,514.348***	4,394.119***	4,790.593***	1,764.813***	1,075.447***

Note: *p<0.1; **p<0.05; ***p<0.01. Panels A and B represent the estimations from the first and the second row of Panel J in the Table 29, respectively. Panels C and D represent the estimations from the third and the fourth row of Panel J in the Table 29, respectively. Covariates: Δ Literacy rate, Δ Electric light rate, Δ sex, Δ working, Δ high school, Δ water supply, Δ house, Δ mentally impaired, Δ urban, and Δ age.

3 Housing Lotteries and Consumption: Evidence from credit registry data[1]

Abstract

This paper explores the impact of housing lotteries on outcomes related to credit. We combine data from lower-income applicants of *Minha Casa Minha Vida*, a social, highly subsidized housing program that uses draws to pick up beneficiaries, with the Brazilian Credit Registry Data.

Keywords: Housing Programs, Housing Project Developments, Housing Lotteries, Credit, Consumption, Financial inclusion.

[1] The views expressed in this work are those of the author and do not necessarily reflect those of the Central Bank of Brazil or its members.

3.1 Introduction

Wealth effects and credit are together an important topic in economics. When a household or company becomes wealthier, its decisions regarding savings and consumption may change. In this sense, the proportion of consumer spending can increase when there is a feeling of raising the overall value of assets. This behavior can be common in a credit constraint scenario.

There is an extensive literature on wealth effects based on aggregate data at the country level, with certain studies targeting the regional level ((DONG; HUI; JIA, 2017)). However, studies focusing on wealth effects transmitted by housing and based on individual-level data are less frequent. (BOSTIC; GABRIEL; PAINTER, 2009) analyze housing wealth elasticities derived from the U.S. household expenditure surveys from 1989 to 2001. They find significant, large housing wealth effects on consumption spending. Based on a panel estimation for a sample of the Danish population, (BROWNING; GØRTZ; LETH-PETERSEN, 2013) find little evidence of impacts of variations in housing prices on consumption. In contrast, (CHO, 2011) investigate household level data for South Korea and find evidence of heterogeneous effects: a positive and significant housing wealth effect for high-income households but a negative effect for the low-income group. Varying elasticities for different income levels are also found in (KHALIFA; SECK; TOBING, 2013), using Panel Study of Income Dynamics for 2000's decade.

In the short run, the wealth effect can be stronger among credit constrained households ((ALADANGADY, 2017)), since the value of real estate can serve as their only means to finance consumption when their access to credit is denied. Therefore, when a non-homeowner household acquires its first source of real estate, this may lead to consumption through the ownership of collateral that changes in value by weakening borrowing constraints that may lead to indirect consumption and by promoting financial inclusion to poor households over the long run. In addition, moving to a better neighborhood can improve access to and enhance the use of credit. Miller e Soo (2018) find that young children who participate in the Moving to Opportunity experiment had changed their credit decisions into adulthood.

Our contribution to the literature is an analysis of wealth effects of a Brazilian housing program at an individual level across multiple periods. Brazil's My House My Life Program (*Programa Minha Casa Minha Vida", henceforth PMCMV*) is a social housing program launched in 2009 due to a historical housing deficit in urban areas. It targets lower income families who have difficulty accessing housing loans. In particular, Group 1 of this program covers households up to three minimum wages and is the focus of this study. Phase 1 (2009-2011) and Phase 2 (2011-2015) of PMCMV resulted in the construction of 4,3 millions of households in 96% of all Brazilian municipalities, providing access to a real estate for 10 millions of citizens. The PMCMV delivered 1,1 million habitation units for Group 1 households between 2009 and 2016. Some evidence shows that housing financing helped reduce the housing deficit in Brazil over this century (FERRO et al., 2016). Furthermore, PMCMV beneficiaries could obtain a particular, subsidized credit facility for durable goods for housing between 2013 and 2015 through the Housing Better Program (*Programa Minha Casa Melhor*).

To evaluate corresponding effects on credit and consumption, we use the results of six PMCMV lotteries from housing projects that occurred between 2011 and 2013 in the city of Rio de Janeiro due to strong demand for real estate in major cities. This information is combined with Credit Registry Data from the Central Bank of Brazil, which includes data on all loans taken from PMCMV applicants before and after the lotteries. When an individual wins a lottery, he can receive a strong subside (Group 1) or a subsidized mortgage (Groups 2 and 3) for a housing project in his municipality. We then compare outcomes of credit types for the winners and non-winners of this lottery through an Analysis of Covariance. Some of the examined credit types are strictly associated with consumption. We also evaluate differences between beneficiaries and non-beneficiaries of the program through the use of an instrumental variables procedure.

In this sense, borrowing can be a proxy for household consumption: durable goods have specific credit facilities, and the use of credit cards and related products can be related to overall consumption. Upon owning one's first house, one may be more likely to consume as a result of feeling much richer. There is evidence of the impact of winning high price lotteries on the propensity to consume ((IMBENS; RUBIN; SACERDOTE, 2001)). In contrast, purchasing a house as the most important portfolio asset can create a binding, nonnegativity constraint on riskless assets ((FLAVIN; YAMASHITA, 2002)) for households. Therefore, real estate can constitute an important asset whereby an individual concentrates on paying mortgage debt despite the availability of other types of loans. A lower price in experimental draws can also reduce the impact of lottery winners ((MILLS et al., 2008)).

We confirm the hypothesis given in the literature showing that owning real estate can change a lower income household's portfolio. However, effects can be distinct across lotteries. First lotteries had a neutral or negative effect of treated individuals on the amount of credit borrowed. In contrast, we note evidence of wealth effect on previous lotteries, increasing borrowing related to consumption for treated households across most of credit types. Indeed, we note general, strong effects of treatment on borrowing through the Goods Financing as a consequence of My Better House Program. Such treatment increased the propensity to access loans across all lotteries, suggesting the role of financial inclusion in poor-income households.

This paper is organized as follows. Section 2 explains the housing policy in Brazil with focus on My House My Life program. Section 3 presents the data and credit statistics from lotteries applicants. Section 4 presents the empirical strategy. Section 5 lays out the results from My House My Life Programs for each lottery. Section 6 adds supplementary analysis of the previous results. Section 7 concludes.

3.2 My House My Life Program

In Brazil, there have historically been some housing programs related to a significant housing deficit in urban cities and to the difficulties associated with long-term lending ((HADDAD; MEYER, 2011)). Brazilian Housing Finance System (SFH) was established in 1964 (Law 4,380) together with the National Housing Bank (BNH), providing directly the provision of housing finance at subsidized loan rates ((UN-HABITAT, 2013)). This bank closed in 1986 due to a context of high inflation and significant loan defaults and was replaced to *Caixa Economica Federal* (a public, savings bank that focuses on real estate loans- the fourth largest bank in Brazil in assets) in developing housing policies. After 1988's Constitution, those policies were decentralized to States and municipalities.

The Real Estate Financing System (Law 9,514 of 1997) and the Fiduciary property law (Law 10,931 of 2004) smoothed the recovery of unpaid property, allowing for the retention of collateral (the proper real estate) by the lender to finance real estate property acquisitions. Housing loans then grew from 1.5% to 9.0% of the Gross Domestic Product over ten years.

According to the 2010 Census, there are 57.3 million households in Brazil, where 49.2 million belong to the urban areas and 8,1 billion belong to the rural areas. Almost 36 millions of households in urban cities are house homeowners (2.6 million have been still financing their homes) while 10.3 millions are tenants.

The 2008 Crisis has affected Brazil's construction industry. Indeed, in April 2009, the My House My Life Program was created by the Brazilian Government (Law 11,977) with the objective to reduce housing deficits for low-income families. Under this policy, the Federal government provided resources to funds managed by *Caixa Economica Federal*.

This program targeted three groups: **Group (*Faixa*) 1**, which focus households that are not already homeowners of a real estate with less than three minimum wages; **Group 2**, for households with earnings ranging from three to six minimum wages; and **Group 3**, that includes households from six to 10 minimum wages. In Group 1 Housing of Social Interest subsidizes up to 90% of the real estate value. The maximum level of beneficiaries' financing installments cannot exceed 10% of the monthly gross family income, which has an eligible limit of 1,395 BRL ($\approx$ 600 USD in April 2009) in Phase 1 and 1,500 BRL ($\approx$ 720 USD in June 2012) in Phase 2, and lower-bound payment is 50 BRL. Interest rates are also subsidized and tied to inflation. The maximum duration of this financing is 120 months. After this point, the beneficiary is allowed to sell or rent his property if he did not default on this mortgage.

Group 1 uses one specific fund (*Residential Leasing Fund, or FAR*) for urban projects dedicated to municipalities with more than 50,000 inhabitants ((HIROMOTO, 2018)). It is financed directly from the federal budget and is managed by *Caixa*. Hence, this financing is considered an economic subsidy and not an official housing loan, which is the case for Groups 2 and 3. Municipalities must apply for this fund by signing a compliance contract with the Ministry of Cities, after which local projects are selected and approved by local administrations with Caixa's cooperation. Beneficiaries of this fund must not already be homeowners.

Ministry of Cities' Order 140 from 2010 defined the selection criteria for Group 1 of the PMCMV. For each local project whose demand exceeds supply, there must be a lottery for selecting beneficiaries. Six months before the conclusion of a housing project, *Caixa* must inform by public notice the specifications of the given project (the number of units, the location, the expected date for unit construction and delivery) while requesting a list of selected candidates.

Applicants are sorted based on national and local criteria (municipalities can establish up to three criteria). Families living in risk-prone areas or that are affected by natural disasters can be selected without joining the lottery. For each local project a certain amount of housing is allotted for the elderly and for persons with special needs through their respective lotteries. Households are not charged for applying to the lottery. The number of applicant winners must exceed the number of housing units for a given project to form a reserve list. Demand is separated into different groups according to the fulfillment of these criteria. Meanwhile, for lotteries that apply only three criteria, there is a single demand group with each applicant facing the same odds.

Furthermore, Law 12,793 of 2013 allowed the Brazilian government to provide resources to *Caixa* to finance durable goods for MCMV's mortgage takers. Law 12,868 of 2013 authorized maximum of BRL 8 billion (circa 3.4 USD billion) for that purpose dedicated to My Better House Program (*Programa Minha Casa Melhor*). Resolution 4,223 of June 2013 from the National Monetary Council (CMN) established that PMCMV beneficiaries of all income groups who are not defaulting on their mortgages would be eligible for this program. The My Better House Program allowed for a subsidized credit facility (5% yearly interest rates) up to 5,000 BRL for each individual until four years of maturity were reached. The beneficiary needed to apply to this credit type by phone. He then received a magnetic card with the funds and was given one year to spend it on suppliers of durable consumer goods authorized by *Caixa*. The resolution also established maximum values for each durable good purchased[2]. The program was suspended at the start of 2015 after reaching 600 thousand households and suffering from high default rates.

Although there is no direct penalty outlined under the PMCMV for not paying a loan from the My Better House Program by law, being in default to a financial institution worsens consumer's credit rate in all financial system[3] and can disqualify a consumer from specific credit types with better interest rates. For PMCMV housing subsidies, when the beneficiary's debt is in arrears over more than 90 days, *Caixa* is allowed to seize the property. However, the treatment of Group 1's beneficiaries is less rigid. For example, the 60th article of Law 13,043 of 2014 release the bank from auctioning the non-paid real estate for a given group.

3.3 Data

Our data consider six lotteries affecting Group 1 of the My House My Life Program for Rio de Janeiro, the second largest city in Brazil with 6,3 million inhabitants and 2,1 million households and with almost 25% being tenants or living in ceded houses. One lottery belongs to Phase 1 and the other five lotteries belong to Phase 2 of PMCMV. The upper-bound value of a real estate provided in this municipality through this policy was 51,000 BRL (house) or 47,000 BRL (apartment) in Phase 1 and 75,000 BRL (house or apartment) in Phase 2. Only national criteria (Families living in risk-prone and unhealthy areas, Female-headed households and Families of people with disability) are used for the selection of applicants in Rio. Applicants thus face the same odds of winning each lottery.

Given the maximum value of 75,000 BRL of a housing unit of PMCMV's Group 1 for this city, the minimum payment of 50 BRL required from the beneficiaries over 10 years (total of 50x120 = 6,000 BRL in nominal terms or 8% of the total amount) implies a maximum 92%-subsidy for the acquisition of the property, creating incentives for a household to take part in this program even from a distant PMCMV housing project ((Da Mata; MATION, 2018)).

Those lotteries cover more than 2 million applicants from 517,062 unique CPFs[4] because most of the households applied for several draws. When an applicant was not selected for one lottery, he was

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2 Furniture allowed: wardrobe, double bed, bunk bed, single bed, crib, sofa, shelf, rack, kitchen furniture. Household appliances allowed: refrigerator, stove, microwave, washing machine, TV, computer, notebook, tablet.

3 Resolution 2,682/1999 from the National Monetary Council automatically worse individual's credit rates according to the period that the loan operation is in arrears. This credit rate is transmitted to all new non-collateral loans taken by the individual.

4 Brazilian individual taxpayer registry identification.

Table 54 – Data lotteries

Lottery	Phase PMCMV	Applicants (a)	Winners (b)	% (b/a)	Mortgage Takers (c)	% (c/b)	Signature of Contract
June 2011	1	267,172	2,685	1.00%	647	0.24%	March 2012
August 2011	2	325,247	6,505	2.00%	926	0.28%	June 2012
November 2011	2	351,222	14,053	4.00%	1,508	0.43%	September 2012
September 2012	2	348,643	338	0.10%	93	0.03%	June 2015
October 2013	2	404,646	473	0.12%	224	0.06%	October 2014
December 2013	2	418,440	2,090	0.50%	805	0.19%	April 2015
Total Applicants		2,115,370	26,144	1.24%	4,273	0.20%	
Unique Applicants		517,062	25,986				

Note: Each applicant in (a) that does not win the lottery is automatically registered to the next one. A lottery winner that gave up sign a contract can apply for other lotteries.

automatically included in the next lottery for his municipality. Table 54 describes the studied lotteries. The proportion of the lottery winners varies from 0.1% (September 2012) to 4.0% (November 2011), However, less than 20% of lottery winners really adopt a subsidy line of PMCMV (0.2 % of all applicants). The period between a lottery and mortgage contract signing lasts less than one year for lotteries in 2011, lasts 2.5 years for lotteries in 2012 and lasts 1-1.5 years for lotteries in 2013.

Lottery data were transformed into panel data for each individual and quarter of a year, including dummy indicators for participation in each lottery, whether an individual had already won a lottery or whether a lottery winner had already signed a PMCMV mortgage contract.

This information was merged with credit registry data (SCR) from the Central Bank of Brazil. For each applicant of this housing program, we collect quarterly information on the number of credit operations, on credit types, on the amount of credit and the defaults between December-2010 and December-2017 (29 quarters) considering credit types for households. We identify the most common credit types and the ones that are related to consumption and demanded by at least ten lottery winners in each quarter. For each line, we calculate the value of credit and credit in arrears and the number of loan contracts given per individual and period. We also construct an indicator for when an individual is exposed to each credit type in a given period. All nominal variables are converted into 2015 constant prices using the Brazilian IPCA (official inflation index). We also collected indicators for when an individual is written-off, i.e., when his debt is declared non-collectible by the financial institution that provided him credit after being in arrears for a long period.

Appendix's table 68 shows the nine credit types evaluated here (besides total credit lending for households), and their construction in the Credit Registry Data. Those lines are already considered in the literature ((BRAZIL, 2018), (GARBER et al., 2018) and (SILVA; BRITO; MARTINS, 2018)). Payroll Credit (when the wage is a collateral), Personal Credit (no collateral) and Overdraft (where current accounts are negative) are not necessarily related to consumption. Housing financing, automotive financing and (durable) goods financing have specific purposes. In contrast, credit card (purchasing, without interest rates), credit card revolving (when a household pays only a portion of a credit card bill, incurring high-interest rates) and credit card debt (when its financed from a financial institution, incurring in lower interest rates) may be related to consumption. Household credit aggregates all those lines plus small credit types related to individuals.

The data show an increase in the number of individuals exposed to credit due to reductions in the lower-bound reporting threshold occurring in June of 2012 (from at least 5,000 BRL of **total** debt obligations per individual or firm to 1,000 BRL) and March of 2016 (from 1,000 BRL to 200 BRL). This is also noted in Garber et al. (2018).

Figure 26 illustrates the path of evolution observed for those 517,062 individuals over time. In the start of 2012, only 20% have at least one loan reported in the Credit Registry Data. Between 2012 and 2015 approximately 45% of those households demanded a loan above this limit. After the last decline in the threshold (March 2016), more than half of the lottery applicants were reported as loan takers for any type of Household Credit. In average, 41.9% of these individuals were exposed to some loan. These changes are more closely related to Credit Card lines with low amounts involved. For PMCMV Group 1 (up to three minimum wages) households, we find that being exposed to non-collateral loans (25.78% of individuals exposed for Credit Card, 19% for Revolving Credit Card, 10.9% for Overdraft and 9.38% for Debt Credit Card) seems more important than collateral loans as Payroll Credit (14.3%) or financing for a specific purpose (4.3% for Automotive Financing, 3.2% for Housing Financing and 0.7% for Goods Financing).

Changes in the 2012 and 2016 thresholds are also representative when we consider loan exposure. An individual is exposed to a credit facility when he has at least one loan contract for that line. This is a better measure of access to credit because one can have several short loan contracts of lesser value than that of an average loan contract. In December of 2011, only 5.6% of the applicants were exposed to at least three (of nine) credit types (and consequently to the aggregated Household Credit). This proportion had risen to 17.6% in December of 2014 and to 23.0% in December of 2017. The number of exposed credit types per applicant was 0.39 at the end of 2011, 1.07 at the end of 2014 and 1.32 at the end of 2017.

These jumps also occur when we observe lottery winners alone (Figure 33 on Appendix). The relevance of non-collateral loans is also greater for this population. For the applicant takers, i.e., those who are effectively beneficiaries of the housing program, Goods Financing was the most important credit facility between 2013 and 2015 due to the program My Better House. Even in the following years, there are remaining contracts from this policy. Since the signature of PMCMV contracts occurs at least six months after the lottery, the credit exposure of this population starts in 2012.

Figure 27 relates the amount of each credit facility of those individuals over time. The effect of reducing the threshold for June of 2012 and March of 2016 is less significant than that observed in Figure 26 due to the high value of some operations, but it is still relevant. In 2017, all 517,062 lottery applicants borrowed six billion BRL. Housing Financing, Payroll Credit and Automotive Financing are the most important credit types identified for these individuals since their contracts demand more credit. The situation is similar when we restrict our analysis to lottery winners: for those receiving real estate from the PMCMV, Housing Financing became irrelevant as a substitute good (Figure 33 on Appendix). All 25,986 lottery winners lent BRL 300 million in 2017. For the beneficiaries, goods financing is still a relevant credit facility, even with the 5,000 BRL maximum limit applied per contract. Levels of household credit are similar across

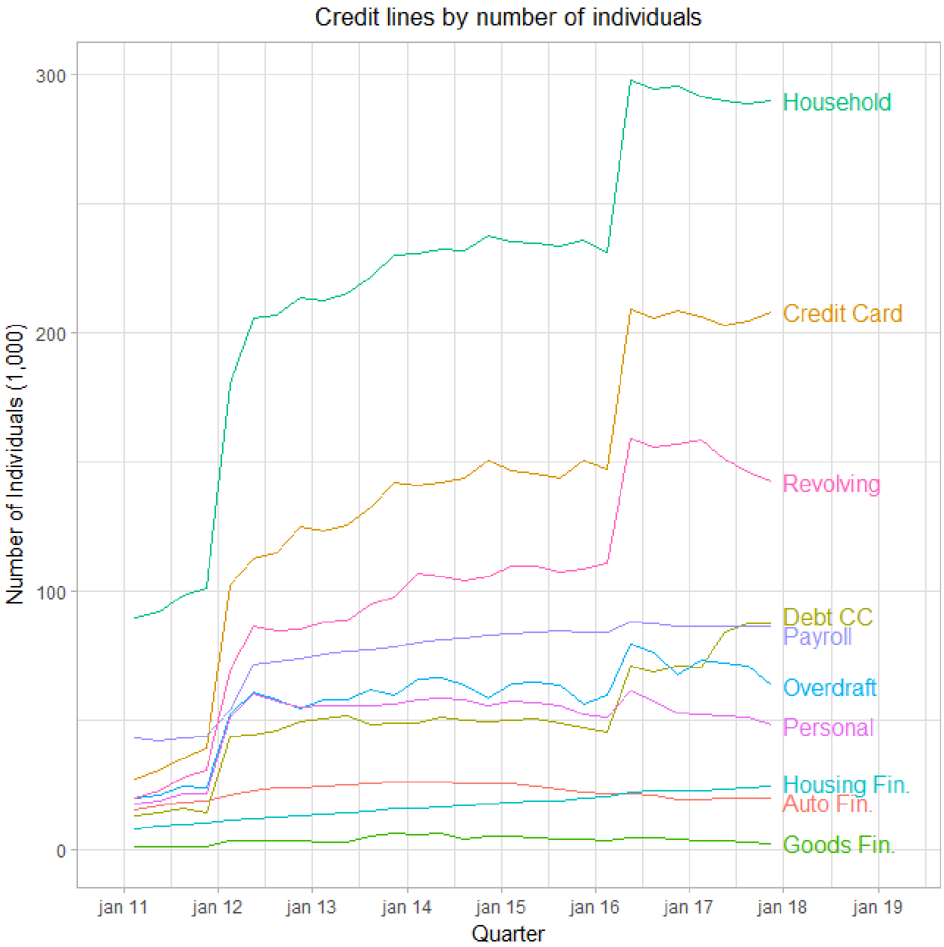

Figure 26 – Individuals on the Credit Registry Data over time

Note: each line corresponds to the number of the 517,062 lottery applicants that are exposed to that credit type. Graph was constructed quarterly. Jumps in 2012 and 2016 occurred due to the changes on the minimum value of loan obligation reported to the Credit Registry Data.

those lotteries (Figure 36 on Appendix) because non-winners continue to apply to subsequent lotteries.

Lower income households do not borrow large sums of money. Since most operations are related to non-collateral loans, obligations usually remain at below 10,000 BRL (3,000 USD in 2017 values). Figure 28 presents the distribution of all household operations. Figure 37 on the Appendix shows that the distribution for Household Credit changes over the years due to variations on thresholds. Loan contracts of less than 5,000 BRL that were not registered in 2011 because of the threshold were registered in 2014 or especially in 2017, increasing the density of cheaper contracts across the distribution of past periods. We fix this bias by inputting a zero value of credit for missing information. In particular, Figure 38 of the Appendix exhibits the distribution of loans across the other nine credit types, signaling a difference in values between collateral loans (Housing Financing, Automotive Financing and Payroll Credit) and non-collateral loans.

Table 55 details statistics on outcomes of the credit types evaluated here. The average amount of household credit borrowed by a lottery applicant is 7,841 BRL. In spite of the few contracts it represents, Housing Financing has the most relevant value since the loan contracts are of higher value. Naturally, the order of importance for credit types echoes what is shown in Figure 28. Even though 58% of the data do not show any exposure to a loan, the average number of loan contracts provided for a lottery applicant is 3.27. The average amount of credit given in arrears is 258 BRL, leaving an average overdue credit rate of 258/7841 = 3.3%. Revolving Credit Card and Overdraft show the largest overdue rates of 115/298.3 = 38.5% and 21.8/122.3 = 17.9%, respectively. In contrast, the migration to the Revolving and the Debt Credit Card renders the Credit Card overdue rates insignificant. The other lower overdue rates belong to credit types that require collateral: Housing Financing (0.31%), Automotive Financing (1.48%) and Payroll Credit (1.77%).

Table 55 – Descriptive Statistics

Credit Type	Observations	Credit Amount (BRL)		Loan Contracts (numbers)		Exposure (0 to 1)		In arrears (BRL)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household Credit	14,994,798	7,841.5	(28,102.3)	3.27	(5.21)	0.420	(0.494)	258.4	(2,213.8)
Revolving Credit Card	14,994,798	298.3	(1,603.9)	0.65	(1.35)	0.190	(0.393)	115.0	(1,175.3)
Debt Credit Card	14,994,798	109.6	(716.0)	0.25	(1.13)	0.095	(0.293)	2.3	(105.0)
Overdraft	14,994,798	122.3	(846.7)	0.24	(0.63)	0.109	(0.312)	21.8	(439.3)
Auto Financing	14,994,798	967.1	(6,406.1)	0.06	(0.26)	0.043	(0.202)	14.3	(470.0)
Goods Financing	14,994,798	24.5	(537.7)	0.04	(0.28)	0.007	(0.083)	2.0	(125.7)
Payroll Credit	14,994,798	1,960.3	(8,127.3)	0.43	(1.45)	0.143	(0.350)	34.7	(785.0)
Personal Credit	14,994,798	469.3	(3,113.0)	0.34	(1.13)	0.095	(0.293)	33.5	(659.3)
Credit Card	14,994,798	607.9	(1,970.6)	0.97	(2.63)	0.258	(0.437)	0.0	(7.5)
Housing Financing	14,994,798	2,907.7	(22,721.3)	0.04	(0.19)	0.032	(0.176)	9.1	(443.9)

Note: Observations include 517,062 lottery applicants registered in all 29 quarters of data. Household Credit includes all nine credit types listed above plus other credit types related to individuals with short number of contracts. Credit Amount and Credit in Arrears are converted into 2015 constant prices. Exposure is an indicator if the applicant has or do not has a loan of that credit type.

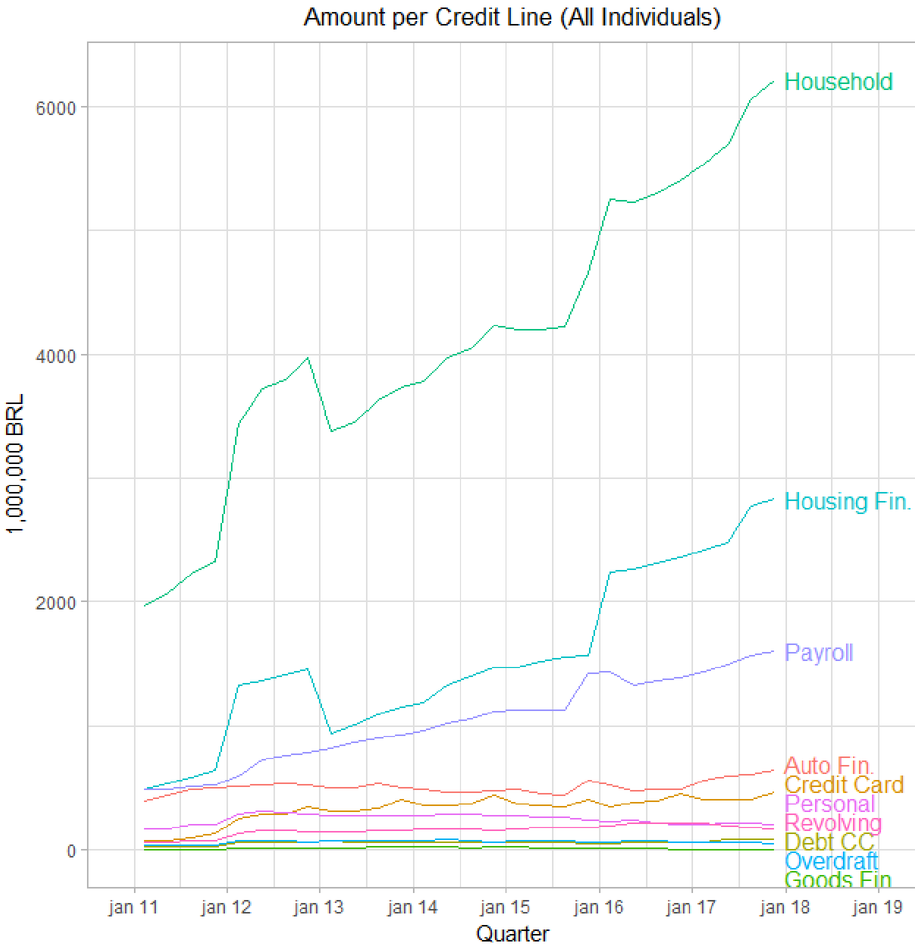

Figure 27 – Amount of the credit per credit type over time

Note: each line corresponds to the total amount of that credit type borrowed by the 517,062. Graph was constructed quarterly. Those amounts are converted into 2015 constant prices. Jumps in 2012 and 2016 occurred due to the changes on the minimum value of total loan obligation reported to the Credit Registry Data.

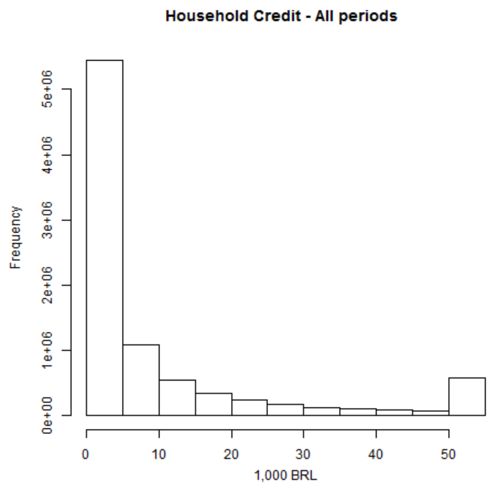

Figure 28 – Distribution of all household credit

Note: This graph shows the distribution of values of exposition to a credit type in all periods from December-2010 to December 2017. Bin selection was 5,000 BRL. Those values are converted into 2015 constant prices.

3.4 Empirical Strategy

We are interested in analyzing the effects of winning this lottery on outcomes related to credit and consumption. Lotteries occur at different times, but all of them have multiple post-treatment outcomes. Changes in threshold limit reporting in 2012 and 2016 can bias a naive panel estimation. As winning a lottery is a necessary but not sufficient condition for signing a PMCMV contract we are addressing an intention-to-treat effect.

Indeed, when outcomes are highly autocorrelated and when multiple post-treatment measures are involved, estimating treatment effects by an Analysis of Covariance (ANCOVA) model can increment power (MCKENZIE, 2012). In this case, we include for baseline value of the variable of interest in our specification.

For each lottery l we have the following estimation:

$$Y_{it}^{POS} = \alpha + \gamma Z_i + \delta Y_{il}^{PRE} + \delta_t + e_{it}, \tag{3.1}$$

where y_{POSit} is the variable of interest on $t - l$ periods after the lottery for an individual i in quarter t, y_{il}^{PRE} is the value of dependent variable one quarter before the lottery l, Z_i is an indicator for when an individual wins that lottery, δ_t represents quarterly fixed effects and e_{it} denotes errors clustered at the individual level.

Furthermore, the PMCMV mortgage taker serves as a proper treatment effect. Being a beneficiary of the program is related a local average treatment effect (LATE) since some households (Families living in risk-prone areas, for example) do not need to join the lottery to enter the PMCMV. Evaluating the effect of joining the PMCMV directly can be biased because this treatment effect may be correlated by unobservables. We then apply an instrumental variables procedure in Equation (3.2) while using the ITT (uncorrelated with the error since the lottery is random) as an instrument of being a beneficiary of the program. Then we also have:

$$Y_{it}^{POS} = \alpha + \gamma D_i + \delta Y_{il}^{PRE} + \delta_t + e_{it}, \tag{3.2}$$

where D_i is the indicator of signing a PMCMV contract, instrumented by Z_i. In this case the baseline for y_{il}^{PRE} is the value of dependent variable one quarter before signing the contract of PMCMV for each lottery l. Da Mata e Mation (2018) provided evidence that those lotteries are balanced to pre-treatment characteristics such as applicant age and sex.

3.5 Results

Each table of results presents estimations for one lottery. Columns report estimations for each credit facility and the first column depicts results for all Household Credit. Four variables of interest were considered: the amount of credit (Panel A, in BRL), number of loan contracts (Panel B), an overdue rate, i.e., the proportion (in percentages of 0 and 100) between total credit in arrears (more than 90 days) and all credit (Panel C) and an indicator (0 or 1) for when an individual is exposed to credit (Panel D). We reported coefficients from the treatment and the baseline variable y_i^{PRE}.

Tables 56 to 61 contain estimations of Equation (3.1). The first lottery (Table 56) held in June 2011 may have a negative impact on Household Credit due to the relevance of Credit Card and Housing Financing, which seems to serve as a substitute good of PMCMV when a household does not win the lottery. A strong, positive impact on Goods Financing is observed due to My Better House Program. Even though the lottery winners finance specific goods 110 BRL more than non-winners, given the limited importance of this credit facility, it does not influence the full value of household credit. However, it influences the credit exposure indicator: winners exhibit 3.8% greater propensity to be exposed to some loan than non-winners, suggesting it was the first loan contract designed for the individual. Impacts on the other outcomes (loan contracts and overdue credit) occur only for Credit Card (negative sign) and Goods Financing (positive sign). However, the overdue rate related to the Credit Card is economically insignificant. The high significance of all baseline coefficients (y^{PRE}) suggests that ANCOVA is an appropriate model.

August 2011's lottery (Table 57) presents a negative impact of being drawn on Housing Financing and non-collateral loans such as Revolving Credit Card and Credit Card. There is again a strong, positive impact on Goods Financing and an increasing of being exposed to a Debt Credit Card, Credit Card and Goods Financing, showing evidence of financial inclusion from the program. In this sense, lottery winners may become less inhibited in demanding financial services. However, the lottery has a positive effect on the overdue rate only in the case for Goods Financing. Since half of the lottery applicants do not have a loan contract, its coefficients (Panel B) are low.

In contrast, November 2011's Lottery (Table 58) has only a positive impact on Goods Financing: those who win borrow 82,4 BRL more than those who do not win the lottery. Effects on the Household Credit exposure indicator (0.8% more if win the lottery) are only significant as a result of the My Better House Program (Panel D). Being drawn in a lottery seems to have low effects on overdue loan rates due to a low R^2. We thus confirm the relevance of baseline outcome for all credit types.

The September 2012 Lottery (Table 59) shows more evidence of wealth effects. With the exception of Automotive and Housing financing, significant and positive effects of the lottery on all other credit types are observed at 5% level. Lottery winners can borrow 412.6 BRL more than non-winners (160 BRL through the Payroll Credit). We also find positive effects on loan contracts of Credit Card (which is relevant to the level of exposure despite its low values), Goods Financing and all Household Credit, and find that being drawn can reduce overdue credit in 0.19% (Panel C) and increase the propensity to experience loan exposure in 2.6% (Panel D).

The fifth Lottery (Table 60) of October 2013 shows results similar to those of the previous lottery. We again find strong evidence of wealth effects on Goods Financing. Payroll Credit is the main channel through which this impact occur: lottery winners borrow 153.8 BRL more from this line. Being drawn is also related to lending more Personal Credit (41.3 BRL) and purchasing more through Credit Card (33.9 BRL). Lottery winners also show 4.2% higher chance of being exposed to a loan and of reducing the overdue rate by 0.27% relative to non-winners.

Last lottery (Table 61) from December 2013 still find evidence of wealth effects. Effects on Goods Financing are less significant for the 2013 lotteries because My Better House no longer existed when housing projects resulting from these lotteries were delivered to households. However, only for Automotive and Housing Financing is non-expressive impact of winning observed. This lottery presents the largest coefficient on household loan contracts (0.081), household loan exposure (3.5%) and overdue rate (-0.32%). Indeed, the increase in overdue credit rate on Goods Financing does not seem to contaminate other credit types in the short run.

Tables 62 to 67 contain instrumental variables procedure based on Equation (3.2). As another difference, only after housing projects are delivered and households sign a PMCMV contract is a post-treatment period entered.

First lottery (Table 62) had lottery winners signing the contract in March of 2012. Therefore, the beneficiaries borrowed 2,500 BRL less than non-beneficiaries. Naturally, the most negative effect resulted from Housing Financing since the PMCMV subsidy substitutes this loan. Positive effects of Goods Financing are more significant than those observed for lottery winners because the My Better House Program applies only to those who have signed the contract. In contrast, the beneficiaries are more likely to be exposed to credit due to Goods Financing, suggesting that a loan from My Better House Program led some individuals to enter a loan relationship with a financial institution.

Winners of the second lottery (Table 63) signed PMCMV contracts in June 2012. For those beneficiaries, we found a lower propensity to demand Automotive or Housing Financing or to purchase by Credit Card. The magnitude of effects observed for these lines is much larger than that observed for those winning the same lottery. On the other hand, these individuals tend to demand more Goods Financing (864.3 BRL) as observed for the previous lottery (866.2 BRL). We note a similar effect for those loan contracts. Except for the Goods Financing coefficient, we find no evidence of effects on overdue credit, although those who sign a PMCMV contract appear to be more likely to be exposed to a loan.

Lottery 3 (Table 64) had its beneficiaries being accepted in September 2012. In this case, we find a significant effect of signing the contract only in Goods Financing (789.1 BRL), leading these takers 5.9% more prone to being exposed to a Household Credit. As observed for other lotteries, estimations of overdue credit do not show strong evidence of impact with a low R-squared value.

The fourth lottery (Table 65) occurred in September 2012 but housing projects were delivered only in 2015. In this case, there is strong evidence of wealth effects related to Goods Financing and non-collateral lines: Revolving Credit Card (borrowing more 544 BRL), Credit Card (404.3 BRL), Overdraft (248.8 BRL) and Debt Credit Card (206.8 BRL). Effects on the Payroll Credit found for lottery winners are not as clear here. In addition, we find that signing a PMCMV contract can reduce overdue rates from Payroll Credit by 0.8%, suggesting that higher overdue rates from Goods Financing did not spread to the other credit types in the short run.

Fifth Lottery (Table 66) winners signed their PMCMV contracts in October 2014. With the exception of Automotive and Housing Financing, we find positive, significant effects of being a beneficiary of the program on credit types. The beneficiaries can borrow 6,252 BRL more, are 31% more likely to be exposed to at least one credit type or to enter 1.2 more loan contracts and present 4.8% lower overdue credit rates than non-takers. For this lottery, the main channels through wealth effects seem to include payroll credit (by amount) and Credit Card (by contracts). We thus regain the relevance of the baseline variable y_{PRE} on all credit types.

Last lottery (Table 67) delivered its housing projects in March 2015. We find evidence of significantly positive effects on Revolving Credit Card (the beneficiaries borrows 639 BRL more loans), Personal Credit (625 BRL) and Overdraft (341 BRL). However, the impact is less strong than those observed for the previous lottery. The strongest effects of PMCMV contracts on overdue credit (less 4.9%) occur in this lottery, although the R-squared value remains low. The beneficiaries are more exposed to all credit types (expect in the case of Automotive and Housing Financing) than non-beneficiaries.

Overall, we find differences in the effects of these lotteries. Although the earlier lotteries have neutral or even negative effects on credit, there are strong evidence of wealth effect for the later lotteries. In particular, this suggests that the Payroll Credit is the main channel of this impact. The results can be influenced by the particularities of lotteries. In India, distances between housing projects and city centers have frustrated effects of local housing lottery ((BARNHARDT; FIELD; PANDE, 2017)). This may explain the weaker impacts of some of the lotteries evaluated here given the distances between some housing projects and the Central Business District in Rio de Janeiro ((Da Mata; MATION, 2018)). As another point, lotteries held in 2011 delivered housing units to winners just one year later. According to the FipeZap Index, the city of Rio de Janeiro had a housing prices yearly growth levels of more than 15%[5] between 2008 and 2013, exceeding Brazilian CPI. It was a period of economic growth that facilitated the access of credit. After 2013, when the last lotteries delivered housing units and when applicants have signed the PMCMV

[5] Website: www.fipe.org.br/pt-br/indices/fipezap. Accessed on 18th March 2019.

contract, Brazil (and Rio de Janeiro in particular) began to suffer an economic crisis and entered a period of a low growth or even a real reduce in housing prices. Under such conditions, treated households borrowed more credit than non-treated households except in the realm of Automotive and Housing Financing.

Table 56 – Results from 1st Lottery (June 2011)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-305.41*	-13.50*	-0.87	-4.90	-49.65*	109.89***	11.20	-14.49	-25.79**	-305.24**
	(159.94)	(6.169)	(3.52)	(3.48)	(28.11)	(3.13)	(40.7)	(14.21)	(11.61)	(136.49)
Y_{PRE}	0.764***	0.185***	0.152***	0.222***	0.289***	0.145***	0.896***	0.348***	0.645***	0.784***
	(0.013)	(0.01)	(0.011)	(0.015)	(0.006)	(0.016)	(0.012)	(0.014)	(0.056)	(0.015)
R^2	0.165	0.015	0.010	0.029	0.063	0.012	0.294	0.080	0.128	0.102
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.035	-0.009	-0.001	-0.007*	-0.002	0.046***	-0.003	-0.010	-0.036**	-0.002*
	(0.028)	(0.008)	(0.007)	(0.004)	(0.001)	(0.002)	(0.007)	(0.006)	(0.014)	(0.001)
Y_{PRE}	1.382***	1.045***	0.587***	0.631***	0.493***	0.488***	1.327***	1.003***	2.048***	0.770***
	(0.009)	(0.014)	(0.02)	(0.013)	(0.004)	(0.085)	(0.01)	(0.017)	(0.036)	(0.005)
R^2	0.201	0.093	0.016	0.077	0.153	0.018	0.445	0.067	0.054	0.304
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.042	-0.086*	0.010	-0.021	0.004	0.076***	-0.016	-0.036	-0.006***	0.000
	(0.04)	(0.046)	(0.009)	(0.025)	(0.006)	(0.006)	(0.013)	(0.02)	(0.002)	(0.006)
Y_{PRE}	0.028***	0.014***	0.017***	0.010***	0.045***	0.016***	0.045***	0.015***	0.006***	0.017***
	(0.002)	(0.004)	(0.006)	(0.001)	(0.014)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
R^2	0.003	0.004	0.002	0.001	0.001	0.000	0.002	0.001	0.000	0.000
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.038***	0.003*	0.002	0.007***	0.000	0.024***	0.011	0.002*	0.009***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Y_{PRE}	0.094***	0.165***	0.079***	0.316***	0.080***	0.002***	0.304***	0.126***	0.191***	0.068***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.040	0.054	0.023	0.041	0.025	0.005	0.119	0.031	0.069	0.026
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472	6,946,472
Post-Treatment Periods	22	22	22	22	22	22	22	22	22	22

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 57 – Results from 2nd Lottery (August 2011)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-240.64	-13.37**	-3.86	-1.36	-44.13	101.33***	46.66	-6.66	-29.27***	-271.14**
	(152.02)	(6.02)	(3.28)	(3.49)	(26.86)	(2.82)	(42.68)	(14.06)	(10.83)	(127.88)
Y_{PRE}	0.759***	0.161***	0.0163***	0.210***	0.283***	0.156***	0.893***	0.375***	0.666***	0.830***
	(0.017)	(0.015)	(0.016)	(0.013)	(0.007)	(0.013)	(0.013)	(0.014)	(0.023)	(0.013)
R^2	0.184	0.017	0.015	0.034	0.070	0.016	0.319	0.100	0.145	0.129
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.007	-0.010	-0.031	-0.004	-0.003**	0.042***	0.002	-0.009	-0.035**	-0.003**
	(0.002)	(0.007)	(0.027)	(0.004)	(0.001)	(0.002)	(0.007)	(0.006)	(0.014)	(0.001)
Y_{PRE}	0.335***	0.981***	1.386***	0.624***	0.492***	0.493***	1.309***	1.008***	1.990***	0.777***
	(0.001)	(0.011)	(0.007)	(0.01)	(0.004)	(0.063)	(0.008)	(0.013)	(0.03)	(0.004)
R^2	0.22	0.09	0.019	0.079	0.17	0.019	0.463	0.074	0.054	0.341
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.017	-0.064	0.006	-0.016	0.002	0.072***	-0.010	-0.030	-0.003*	-0.002
	(0.036)	(0.043)	(0.008)	(0.023)	(0.005)	(0.006)	(0.012)	(0.019)	(0.002)	(0.006)
Y_{PRE}	0.030***	0.023***	0.027***	0.011***	0.050***	0.015***	0.042***	0.023***	0.003***	0.031***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.01)	(0.002)	(0.002)	(0.003)	(0.001)	(0.004)
R^2	0.0024	0.0033	0.0027	0.0005	0.0014	0.0003	0.0021	0.0004	0.0002	0.0007
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.004	0.003*	0.003**	0.002	0.002*	0.024***	0.004*	0.003*	0.007***	0.002
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Y_{PRE}	0.132***	0.169***	0.077***	0.316***	0.081***	0.002***	0.307***	0.127***	0.187***	0.083***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.028	0.050	0.021	0.045	0.027	0.005	0.122	0.032	0.061	0.033
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175	8,131,175
Post-Treatment Periods	21	21	21	21	21	21	21	21	21	21

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 58 – Results from 3rd Lottery (November 2011)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	1.50 (183.12)	-8.32 (7.31)	0.02 (4.21)	5.15 (4.22)	-46.11 (30.86)	82.39*** (3.26)	96.11* (52.19)	1.85 (16.95)	-17.55 (12.14)	-71.85 (155.11)
Y_{PRE} dummy	0.768*** (0.015)	0.149*** (0.015)	0.221*** (0.014)	0.207*** (0.012)	0.271*** (0.006)	0.149*** (0.011)	0.904*** (0.011)	0.318*** (0.011)	0.696*** (0.012)	0.860*** (0.012)
R^2	0.202	0.017	0.022	0.036	0.072	0.013	0.337	0.103	0.193	0.151
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.010 (0.032)	-0.011 (0.008)	0.003 (0.009)	-0.003 (0.004)	-0.002 (0.001)	0.035*** (0.002)	0.009 (0.008)	-0.006 (0.007)	-0.020 (0.016)	-0.002 (0.001)
Y_{PRE}	1.195*** (0.007)	0.945*** (0.01)	0.408*** (0.01)	0.622*** (0.01)	0.502*** (0.003)	0.516*** (0.09)	1.333*** (0.008)	0.651*** (0.012)	1.339*** (0.016)	0.781*** (0.004)
R^2	0.204	0.088	0.014	0.080	0.188	0.018	0.488	0.063	0.060	0.367
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.031 (0.044)	-0.067 (0.052)	0.007 (0.009)	-0.020 (0.028)	0.003 (0.006)	0.052*** (0.007)	-0.008 (0.015)	-0.024 (0.023)	-0.006*** (0.001)	-0.005 (0.007)
Y_{PRE}	0.023*** (0.001)	0.019*** (0.001)	0.020*** (0.001)	0.013*** (0.001)	0.047*** (0.009)	0.002*** (0.001)	0.044*** (0.002)	0.016*** (0.001)	0.000*** (0.0002)	0.018*** (0.003)
R^2	0.0018	0.0026	0.0028	0.0003	0.0013	0.0001	0.0018	0.0003	0.0001	0.0003
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.008*** (0.003)	0.000 (0.002)	0.001 (0.002)	0.002 (0.002)	0.002 (0.001)	0.019*** (0.001)	0.000 (0.002)	0.001 (0.002)	0.002 (0.003)	0.001 (0.001)
Y_{PRE} dummy	0.133*** (0.003)	0.171*** (0.001)	0.082*** (0.001)	0.330*** (0.002)	0.084*** (0.001)	0.002*** (0.0002)	0.297*** (0.002)	0.128*** (0.001)	0.213*** (0.001)	0.086*** (0.001)
R^2	0.018	0.046	0.019	0.052	0.030	0.003	0.115	0.031	0.061	0.037
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328	8,429,328
Post-Treatment Periods	20	20	20	20	20	20	20	20	20	20

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 59 – Results from 4th Lottery (September 2012)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	412.63**	21.62***	10.14**	21.29***	41.29	18.25***	159.89***	33.12**	23.13*	177.74
	(199.07)	(7.7)	(4.46)	(4.38)	(33.92)	(2.43)	(47.96)	(15.03)	(11.89)	(174.75)
Y_{PRE}	0.519***	0.151***	0.218	0.203	0.287***	0.104***	0.927***	0.287***	0.710***	0.455***
	(0.006)	(0.007)	(0.011)	(0.014)	(0.005)	(0.005)	(0.011)	(0.01)	(0.012)	(0.007)
R^2	0.230	0.023	0.035	0.048	0.076	0.022	0.377	0.107	0.353	0.174
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.032***	-0.018	-0.005	0.004	0.001	0.008***	0.006	0.009	0.034**	0.001
	(0.03)	(0.007)	(0.005)	(0.003)	(0.001)	(0.002)	(0.006)	(0.006)	(0.015)	(0.001)
Y_{PRE}	0.443***	0.589***	0.694***	0.686***	0.495***	0.634***	1.066***	0.582***	0.210***	0.779***
	(0.003)	(0.003)	(0.009)	(0.005)	(0.003)	(0.037)	(0.005)	(0.022)	(0.003)	(0.004)
R^2	0.313	0.322	0.443	0.439	0.224	0.415	0.631	0.303	0.154	0.407
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.192***	-0.114*	0.001	0.007	0.016**	0.017**	-0.026	-0.016	-0.006**	0.003
	(0.049)	(0.058)	(0.008)	(0.031)	(0.007)	(0.007)	(0.016)	(0.025)	(0.002)	(0.008)
Y_{PRE}	0.017***	0.016***	0.019***	0.010***	0.043***	0.009***	0.037***	0.016***	0.000***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.002)	(0.001)	(0.0002)	(0.002)
R^2	0.0022	0.0029	0.0034	0.0003	0.0014	0.0002	0.0012	0.0005	0.0001	0.0004
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.026***	0.003	0.001	0.009***	0.005***	0.004***	0.004*	0.004**	0.013***	0.010***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Y_{PRE}	0.216***	0.178***	0.083***	0.287***	0.051***	0.002***	0.174***	0.091***	0.196***	0.050***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.040	0.057	0.024	0.081	0.015	0.000	0.061	0.022	0.061	0.016
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503	7,321,503
Post-Treatment Periods	17	17	17	17	17	17	17	17	17	17

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 60 – Results from 5th Lottery (October 2013)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	303.52*	20.67***	13.11***	20.44***	44.80	23.49***	153.75***	41.35***	33.88***	102.97
	(183.37)	(7.81)	(3.97)	(4.1)	(35.1)	(2.36)	(46.06)	(15.26)	(11.24)	(162.32)
Y_{PRE}	0.888***	0.156***	0.225***	0.266***	0.310***	0.010***	0.909***	0.332***	0.717***	0.997***
	(0.011)	(0.022)	(0.013)	(0.016)	(0.021)	(0.002)	(0.01)	(0.03)	(0.015)	(0.015)
R^2	0.352	0.031	0.057	0.070	0.073	0.001	0.447	0.137	0.394	0.319
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.062**	-0.013*	0.007	0.005*	-0.001	0.009***	0.012*	0.013**	0.041***	0.001
	(0.024)	(0.006)	(0.005)	(0.003)	(0.001)	(0.001)	(0.059)	(0.057)	(0.013)	(0.001)
Y_{PRE}	0.727***	0.600***	0.662***	0.710***	0.503***	0.601***	1.036***	0.644***	0.549***	0.796***
	(0.003)	(0.003)	(0.009)	(0.005)	(0.003)	(0.037)	(0.006)	(0.023)	(0.005)	(0.004)
R^2	0.448	0.330	0.424	0.468	0.260	0.383	0.683	0.405	0.239	0.500
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.271***	-0.183***	0.001	-0.034	0.011	0.025***	-0.008	-0.043*	-0.005***	0.001
	(0.05)	(0.06)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.001)	(0.01)
Y_{PRE}	0.022***	0.019***	0.001***	0.012***	0.061***	0.008***	0.042***	0.025***	0.004*	0.024***
	(0.001)	(0.001)	(0.0003)	(0.001)	(0.008)	(0.001)	(0.003)	(0.001)	(0.002)	(0.004)
R^2	0.0022	0.0025	0.0023	0.0003	0.0025	0.0001	0.0015	0.0008	0.0001	0.0004
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.032***	0.002	0.002	0.010***	0.003**	0.006***	0.010***	0.005***	0.015***	0.011***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Y_{PRE}	0.250***	0.198***	0.086***	0.349***	0.051***	0.002***	0.179***	0.095***	0.213***	0.051***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.0005)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.049	0.064	0.026	0.109	0.016	0.001	0.066	0.025	0.066	0.017
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982
Post-Treatment Periods	13	13	13	13	13	13	13	13	13	13

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 61 – Results from 6th Lottery (December 2013)

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	304.62* (178.67)	24.38*** (8.1)	13.63*** (4.15)	23.01*** (4.18)	61.47* (35.63)	10.45*** (1.84)	141.46*** (46.71)	53.10*** (14.81)	23.67** (11.04)	89.78 (156.55)
Y_{PRE}	0.914*** (0.012)	0.140*** (0.026)	0.260*** (0.012)	0.273*** (0.011)	0.306*** (0.018)	0.214*** (0.013)	0.892*** (0.009)	0.350*** (0.036)	0.698*** (0.009)	1.039*** (0.015)
R^2	0.391	0.027	0.070	0.071	0.078	0.036	0.465	0.140	0.415	0.371
Panel B	Dependent Variable: credit contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.081*** (0.024)	-0.014** (0.007)	0.012** (0.005)	0.004 (0.003)	-0.001 (0.001)	0.005*** (0.001)	0.013** (0.006)	0.017** (0.006)	0.047*** (0.013)	0.0002 (0.001)
Y_{PRE}	0.711*** (0.003)	0.586*** (0.003)	0.685*** (0.008)	0.703*** (0.005)	0.485*** (0.003)	0.597*** (0.035)	0.998*** (0.004)	0.624*** (0.022)	0.532*** (0.005)	0.811*** (0.003)
R^2	0.459	0.327	0.434	0.467	0.276	0.389	0.695	0.411	0.240	0.531
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	-0.318*** (0.06)	-0.208*** (0.07)	0.003 (0.007)	-0.029 (0.03)	0.012 (0.008)	0.016** (0.008)	-0.010 (0.02)	-0.039 (0.03)	-0.005*** (0.001)	0.007 (0.009)
Y_{PRE}	0.023*** (0.001)	0.020*** (0.001)	0.011*** (0.003)	0.014*** (0.001)	0.053*** (0.007)	0.011*** (0.002)	0.051*** (0.003)	0.025*** (0.001)	0.004** (0.002)	0.026*** (0.003)
R^2	0.0022	0.0025	0.0024	0.0004	0.0023	0.0001	0.0026	0.0007	0.0001	0.0005
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Winner dummy	0.035*** (0.003)	0.003 (0.002)	0.003 (0.002)	0.010*** (0.002)	0.004*** (0.001)	0.003*** (0.001)	0.010*** (0.002)	0.006*** (0.002)	0.017*** (0.003)	0.012*** (0.002)
Y_{PRE}	0.262*** (0.001)	0.202*** (0.001)	0.086*** (0.001)	0.352*** (0.002)	0.051*** (0.0005)	0.002*** (0.0001)	0.177*** (0.001)	0.095*** (0.001)	0.214*** (0.001)	0.052*** (0.001)
R^2	0.052	0.066	0.026	0.117	0.016	0.000	0.065	0.025	0.067	0.018
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982	6,878,982
Post-Treatment Periods	12	12	12	12	12	12	12	12	12	12

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by Eq. 3.1. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit line. *Time FE* relates to the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the Lottery and 4Q2017.

Table 62 – 1st Lottery, IV Method

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-2507.2**	-88.32*	-9.23	-19.88	-462.11**	866.19***	-11.11	3.56	-169.48*	-2613.4***
	(1113.1)	(46.25)	(26.09)	(24.87)	(197.73)	(20.46)	(297.01)	(104.15)	(81.98)	(958.8)
Y_{PRE}	0.784***	0.122***	0.186	0.203***	0.276***	0.131***	0.913***	0.303***	0.611***	0.876***
	(0.013)	(0.017)	(0.025)	(0.016)	(0.007)	(0.011)	(0.018)	(0.011)	(0.014)	(0.017)
R^2	0.219	0.013	0.017	0.034	0.077	0.028	0.328	0.113	0.208	0.172
Panel B	Dependent Variable: loan contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-0.132	-0.036	-0.009	-0.045	-0.016*	0.360***	-0.042	-0.057	-0.238**	-0.021***
	(0.207)	(0.058)	(0.055)	(0.029)	(0.009)	(0.015)	(0.049)	(0.048)	(0.103)	(0.008)
Y_{PRE}	1.199***	0.762***	0.641***	0.660***	0.516***	0.489***	1.318***	0.701***	1.317***	0.784***
	(0.008)	(0.011)	(0.021)	(0.012)	(0.004)	(0.128)	(0.011)	(0.015)	(0.018)	(0.004)
R^2	0.201	0.081	0.017	0.079	0.201	0.024	0.502	0.064	0.065	0.386
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-0.367	-0.644*	0.051	-0.139	0.032	0.607***	-0.129	-0.284*	-0.040***	0.002
	(0.306)	(0.357)	(0.057)	(0.19)	(0.042)	(0.047)	(0.1)	(0.154)	(0.011)	(0.046)
Y_{PRE}	0.024	0.020	0.015	0.012	0.045	0.002	0.048	0.013	0.000	0.019
	(0.001)	(0.002)	(0.001)	(0.001)	(0.01)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
R^2	0.0019	0.0027	0.0022	0.0003	0.0011	0.0005	0.002	0.0003	0.0001	0.0004
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.058**	-0.024*	-0.018*	-0.011	-0.007	0.199***	-0.008	-0.012	-0.037**	-0.020***
	(0.018)	(0.014)	(0.01)	(0.011)	(0.007)	(0.005)	(0.013)	(0.011)	(0.017)	(0.007)
Y_{PRE}	0.429	0.328	0.254	0.325	0.389	0.053	0.685	0.292	0.443	0.787
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.002)	(0.004)
R^2	0.136	0.050	0.025	0.047	0.128	0.034	0.276	0.037	0.087	0.389
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956	6,144,956
Post-Treatment Periods	23	23	23	23	23	23	23	23	23	23

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

Table 63 – 2nd Lottery, IV Method

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-2066.8* (1149.6)	-72.68 (46.38)	-26.70 (26.28)	7.14 (25.91)	-504.02** (207.94)	864.28*** (19.91)	444.41 (326.19)	55.20 (115.46)	-218.16*** (72.32)	-2540.6*** (977.3)
Y_{PRE}	0.516*** (0.006)	0.154*** (0.011)	0.199*** (0.012)	0.205*** (0.011)	0.287*** (0.005)	0.123*** (0.005)	0.893*** (0.021)	0.297*** (0.01)	0.719*** (0.009)	0.447*** (0.007)
R^2	0.236	0.023	0.032	0.048	0.080	0.031	0.351	0.114	0.339	0.181
Panel B	Dependent Variable: loan contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-0.124 (0.196)	-0.062 (0.043)	-0.019 (0.037)	-0.025 (0.019)	-0.023** (0.009)	0.355*** (0.011)	-0.015 (0.053)	-0.045 (0.04)	-0.270*** (0.094)	-0.025*** (0.007)
Y_{PRE}	0.459*** (0.003)	0.610*** (0.003)	0.566*** (0.012)	0.699*** (0.005)	0.518*** (0.003)	0.656*** (0.038)	1.202*** (0.007)	0.606*** (0.015)	0.230*** (0.003)	0.771*** (0.004)
R^2	0.299	0.314	0.370	0.439	0.225	0.422	0.526	0.282	0.159	0.423
Panel C	Depedent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-0.148 (0.298)	-0.461 (0.354)	0.012 (0.053)	-0.091 (0.187)	0.023 (0.042)	0.602*** (0.046)	-0.109 (0.101)	-0.247 (0.153)	-0.016 (0.014)	-0.012 (0.046)
Y_{PRE}	0.019*** (0.001)	0.020*** (0.001)	0.011*** (0.001)	0.010*** (0.001)	0.064*** (0.011)	0.010*** (0.001)	0.029*** (0.002)	0.013*** (0.001)	0.002 (0.001)	0.018*** (0.002)
R^2	0.0019	0.0027	0.0026	0.0003	0.0023	0.0006	0.0007	0.0003	0.0001	0.0005
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.043*** (0.016)	-0.024* (0.013)	-0.028*** (0.009)	-0.008 (0.011)	-0.014* (0.007)	0.202*** (0.005)	-0.018 (0.014)	-0.013 (0.01)	-0.045*** (0.015)	-0.023*** (0.007)
Y_{PRE}	0.442*** (0.001)	0.309*** (0.002)	0.243*** (0.002)	0.299*** (0.002)	0.388*** (0.002)	0.075*** (0.003)	0.643*** (0.002)	0.273*** (0.002)	0.469*** (0.001)	0.776*** (0.003)
R^2	0.200	0.080	0.056	0.080	0.142	0.037	0.305	0.072	0.192	0.423
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434	7,155,434
Post-Treatment Periods	22	22	22	22	22	22	22	22	22	22

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

Table 64 – 3rd Lottery, IV Method

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-45.66 (1591.5)	-47.28 (61.8)	4.16 (37.01)	61.32* (34.9)	-446.62 (273.7)	789.08*** (24.81)	812.22* (428.49)	75.52 (153.05)	-145.23 (88.4)	-1018.4 (1369.7)
Y_{PRE}	0.522*** (0.006)	0.163*** (0.007)	0.220*** (0.012)	0.206*** (0.013)	0.288*** (0.005)	0.102*** (0.005)	0.893*** (0.018)	0.304*** (0.01)	0.701*** (0.011)	0.452*** (0.007)
R^2	0.243	0.027	0.037	0.052	0.079	0.027	0.390	0.126	0.357	0.182
Panel B	Dependent Variable: loan contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.140 (0.255)	-0.072 (0.057)	-0.039 (0.049)	-0.006 (0.025)	-0.020 (0.012)	0.337*** (0.015)	0.017 (0.058)	-0.049 (0.051)	-0.099 (0.122)	-0.014 (0.01)
Y_{PRE}	0.459*** (0.003)	0.595*** (0.003)	0.680*** (0.012)	0.683*** (0.005)	0.495*** (0.003)	0.635*** (0.036)	1.064*** (0.004)	0.610*** (0.021)	0.212*** (0.002)	0.779 *** (0.003)
R^2	0.329	0.328	0.432	0.442	0.229	0.411	0.637	0.339	0.162	0.437
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-0.306 (0.404)	-0.518 (0.483)	0.021 (0.065)	-0.122 (0.25)	0.003 (0.058)	0.510*** (0.06)	-0.140 (0.137)	-0.216 (0.207)	-0.043*** (0.012)	-0.044 (0.06)
Y_{PRE}	0.020*** (0.001)	0.018*** (0.001)	0.020*** (0.001)	0.011*** (0.001)	0.050*** (0.008)	0.009*** (0.001)	0.039*** (0.002)	0.016*** (0.001)	0.0001 (0.0001)	0.018*** (0.002)
R^2	0.0021	0.0028	0.0034	0.0003	0.0019	0.0004	0.0014	0.0005	0.0001	0.0004
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.059*** (0.021)	-0.001 (0.017)	-0.009 (0.013)	0.017 (0.014)	-0.015 (0.01)	0.182*** (0.006)	-0.002 (0.017)	-0.007 (0.014)	-0.009 (0.02)	-0.015* (0.009)
Y_{PRE}	0.465*** (0.001)	0.314*** (0.001)	0.268*** (0.002)	0.305*** (0.002)	0.378*** (0.002)	0.073*** (0.002)	0.646*** (0.001)	0.281*** (0.002)	0.479*** (0.001)	0.789*** (0.003)
R^2	0.225	0.093	0.065	0.092	0.145	0.025	0.380	0.088	0.207	0.440
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662	7,375,662
Post-Treatment Periods	21	21	21	21	21	21	21	21	21	21

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

Table 65 – 4th Lottery, IV Method

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-1002.4	544.01***	206.76**	248.80***	634.67	107.56***	-54.39	287.01	404.32**	-868.22
	(2928.7)	(186.65)	(92.47)	(88.94)	(794.72)	(27.77)	(790.43)	(298.13)	(197.23)	(2463.36)
Y_{PRE}	0.986***	0.242***	0.315***	0.304***	0.494***	0.265***	1.014***	0.440***	0.731***	1.030***
	(0.009)	(0.011)	(0.011)	(0.012)	(0.007)	(0.014)	(0.006)	(0.016)	(0.007)	(0.012)
R^2	0.599	0.052	0.100	0.089	0.158	0.083	0.624	0.177	0.498	0.604
Panel B	Dependent Variable: loan contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.653	-0.129	0.083	0.021	0.001	0.059*	0.108	0.126	0.593**	-0.038**
	(0.447)	(0.141)	(0.113)	(0.059)	(0.025)	(0.031)	(0.088)	(0.109)	(0.262)	(0.016)
Y_{PRE}	0.762***	0.565***	0.697***	0.730***	0.566***	0.644***	0.977***	0.686***	0.623***	0.908***
	(0.005)	(0.004)	(0.009)	(0.005)	(0.003)	(0.069)	(0.003)	(0.021)	(0.006)	(0.002)
R^2	0.548	0.323	0.412	0.492	0.383	0.431	0.831	0.480	0.336	0.719
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-1.874	1.010	0.031	0.351	0.343*	0.401**	-0.842**	-0.414	-0.034**	0.238
	(1.402)	(1.676)	(0.206)	(0.827)	(0.197)	(0.17)	(0.382)	(0.633)	(0.016)	(0.227)
Y_{PRE}	0.049***	0.045***	0.020***	0.017***	0.037***	0.041***	0.066***	0.026***	0.030***	0.101***
	(0.001)	(0.001)	(0.006)	(0.001)	(0.005)	(0.006)	(0.004)	(0.002)	(0.007)	(0.009)
R^2	0.0027	0.0026	0.0021	0.0003	0.0012	0.0014	0.0045	0.0009	0.0032	0.0098
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.114**	0.147***	0.026	0.079**	0.014	0.044***	0.032	0.057*	0.145***	-0.047***
	(0.046)	(0.044)	(0.032)	(0.033)	(0.021)	(0.009)	(0.029)	(0.031)	(0.047)	(0.016)
Y_{PRE}	0.570***	0.405***	0.357***	0.443***	0.492***	0.321***	0.780***	0.422***	0.568***	0.890***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)
R^2	0.335	0.148	0.105	0.189	0.293	0.127	0.592	0.192	0.297	0.677
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430	3,486,430
Post-Treatment Periods	10	10	10	10	10	10	10	10	10	10

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

Table 66 – 5th Lottery, IV Method

	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
Panel A	Dependent Variable: amount of credit									
PMCMV taker	6252.7**	531.07***	219.44***	331.72***	793.69	553.24***	1798.6**	562.41**	576.19***	3118.5
	(3134.4)	(160.27)	(83.03)	(78.96)	(719.74)	(43.73)	(853.92)	(272.16)	(200.72)	(2700.3)
Y_{PRE}	0.876***	0.213***	0.261***	0.278***	0.401***	0.202***	0.931***	0.409***	0.723***	0.899***
	(0.011)	(0.02)	(0.01)	(0.009)	(0.006)	(0.012)	(0.007)	(0.014)	(0.008)	(0.016)
R^2	0.513	0.046	0.078	0.081	0.086	0.055	0.532	0.181	0.462	0.501
Panel B	Dependent Variable: loan contracts									
PMCMV taker	1.227***	-0.335***	0.187*	0.075	-0.015	0.192***	0.130	0.143	0.775***	-0.012
	(0.456)	(0.128)	(0.098)	(0.057)	(0.025)	(0.025)	(0.101)	(0.107)	(0.26)	(0.019)
Y_{PRE}	0.691***	0.512***	0.670***	0.689***	0.532***	0.697***	1.011***	0.631***	0.526***	0.822***
	(0.003)	(0.002)	(0.01)	(0.005)	(0.003)	(0.049)	(0.004)	(0.02)	(0.006)	(0.004)
R^2	0.478	0.327	0.414	0.470	0.323	0.474	0.762	0.440	0.253	0.599
Panel C	Dependent Variable: % overdue credit									
PMCMV taker	-4.857***	-1.783	0.027	-0.342	0.241	0.563***	-0.599*	-0.707	-0.058***	0.203
	(1.181)	(1.392)	(0.157)	(0.684)	(0.163)	(0.159)	(0.333)	(0.532)	(0.02)	(0.191)
Y_{PRE}	0.035***	0.033***	0.020***	0.015***	0.042***	0.020***	0.053***	0.029***	0.015***	0.027***
	(0.001)	(0.001)	(0.006)	(0.001)	(0.004)	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)
R^2	0.0024	0.0026	0.0024	0.0005	0.0019	0.0004	0.0031	0.0011	0.0009	0.0009
Panel D	Dependent Variable: indicator of credit exposure									
PMCMV taker	0.310***	0.113***	0.070**	0.165***	0.006	0.141***	0.073**	0.125***	0.263***	-0.023
	(0.046)	(0.04)	(0.029)	(0.032)	(0.02)	(0.012)	(0.03)	(0.03)	(0.045)	(0.016)
Y_{PRE}	0.525***	0.358***	0.321***	0.384***	0.439***	0.221***	0.726***	0.364***	0.532***	0.857***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)
R^2	0.283	0.119	0.092	0.147	0.227	0.051	0.505	0.143	0.262	0.590
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398	5,260,398
Post-Treatment Periods	13	13	13	13	13	13	13	13	13	13

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

Table 67 – 6th Lottery, IV Method

Panel A	Dependent Variable: amount of credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	1871.2 (2922.2)	639.02*** (177.65)	228.22*** (86.88)	340.86*** (82.84)	715.23 (764.89)	157.98*** (29.59)	836.60 (796.51)	625.77** (304.04)	336.86* (189.88)	1086.9 (2468.5)
Y_{PRE}	0.920*** (0.01)	0.224*** (0.009)	0.314*** (0.012)	0.274*** (0.012)	0.478*** (0.007)	0.324*** (0.04)	0.968*** (0.008)	0.415*** (0.014)	0.631*** (0.006)	0.947*** (0.014)
R^2	0.569	0.046	0.099	0.070	0.131	0.181	0.613	0.175	0.503	0.564
Panel B	Dependent Variable: loan contracts									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.589 (0.44)	-0.503*** (0.139)	0.102 (0.107)	0.088 (0.06)	-0.011 (0.025)	0.060** (0.025)	0.198** (0.093)	0.158 (0.113)	0.667*** (0.254)	-0.034** (0.016)
Y_{PRE}	0.744*** (0.003)	0.565*** (0.004)	0.698*** (0.01)	0.723*** (0.005)	0.554*** (0.003)	0.674*** (0.058)	0.967*** (0.003)	0.660*** (0.019)	0.583*** (0.006)	0.900*** (0.002)
R^2	0.532	0.320	0.415	0.480	0.364	0.451	0.814	0.460	0.314	0.685
Panel C	Dependent Variable: % overdue credit									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	-4.922*** (1.346)	-1.629 (1.586)	0.060 (0.192)	0.014 (0.783)	0.266 (0.185)	0.348** (0.174)	-0.445 (0.375)	-0.325 (0.6)	-0.032 (0.021)	0.216 (0.213)
Y_{PRE}	0.034*** (0.001)	0.032*** (0.001)	0.025*** (0.007)	0.016*** (0.001)	0.035*** (0.003)	0.042*** (0.006)	0.050*** (0.003)	0.020*** (0.001)	0.010** (0.004)	0.055*** (0.007)
R^2	0.0021	0.0022	0.0023	0.0004	0.0012	0.0012	0.0028	0.0007	0.0004	0.0026
Panel D	Dependent Variable: indicator of credit exposure									
	Household Credit	Revolving Credit Card	Debt Credit Card	Overdraft	Automotive Financing	Goods Financing	Payroll Credit	Personal Credit	Credit Card	Housing Financing
PMCMV taker	0.279*** (0.047)	0.112*** (0.043)	0.064** (0.032)	0.177*** (0.034)	0.008 (0.021)	0.055*** (0.009)	0.096*** (0.03)	0.119*** (0.031)	0.224*** (0.046)	-0.0281* (0.016)
Y_{PRE}	0.556*** (0.001)	0.384*** (0.001)	0.342*** (0.002)	0.419*** (0.002)	0.472*** (0.002)	0.308*** (0.006)	0.759*** (0.001)	0.393*** (0.002)	0.562*** (0.001)	0.880*** (0.002)
R^2	0.317	0.1317	0.0971	0.1544	0.2671	0.103	0.5583	0.1601	0.2954	0.639
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840	4,602,840
Post-Treatment Periods	11	11	11	11	11	11	11	11	11	11

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parenthesis are clustered at the individual level. Estimations were provided by the Equation 3.2. Each panel represents one type of outcome. Each column represents one specific credit type. Y^{PRE} refers to the panel's past outcome of the column's credit type. *Time FE* represents the quarterly fixed effects. *Post-Treatment period* ranges the time between the quarter immediately after the signature of PMCMV related to this lottery and 4Q2017.

3.6 Supplementary Analysis

Our concern in this section is to investigate if the above results are robust. As indicated in the Figure 26, two changes in the lower bound limit of reported loans (2012 and 2016) affected outcomes in distinct periods. Indeed, these 'jumps' may bias the results since each lottery draw occurred in distinct quarters.

We then transform the Equation (3.1) into the Equation (3.3) applying an event-study methodology. This estimation provides reactions to the intention-to-treatment over time and thus reveals differences extending beyond thresholds.

$$Y_{it}^{POS} = \alpha + \sum_{t=l+2}^{4Q2017} D_t + \gamma Z_i + \sum_{t=l+2}^{4Q2017} \beta(Z_i * D_t) + \delta Y_{il}^{PRE} + e_{it}, \tag{3.3}$$

where D_t denotes indicators of each quarter (as a period fixed effects) and β captures the interaction between D_t and the indicator of being a lottery winner Z_i for one semester after the lottery ($t = l + 2$) to the last quarter of 2017. Quarter $t = l + 1$ is the dummy basis for each lottery organized at a quarter l. Variables Y_{il}^{PRE} and e_{it} are the same as those used in Equation (3.1).

Our focus in this section is on the four outcomes that appear to be affected by winning the lottery: the amount of the Household Credit, the amount of Goods Financing, the exposure of Household Credit and the overdue rate of Goods Financing.

The lines on the next graphs represent the β values of (3.3) over time for each lottery. We plotted only two lotteries per graph (3 graphs per variable) for superior visualization. Shaded areas denote the confidence interval of the coefficient measured at the 95%-level.

Figure 29 shows the coefficients of the interaction over time for Household Credit. There is no evidence that the report changes in the Credit Registry Data impact the value of the coefficients: no jumps in these lines occur in June-2012 or March-2016. Again, each lottery seems to present its own dynamics. After 2015, the wealth effect appears to lose power from the coefficients on the first lotteries, suggesting that the wealth effect is not relevant over the long run.

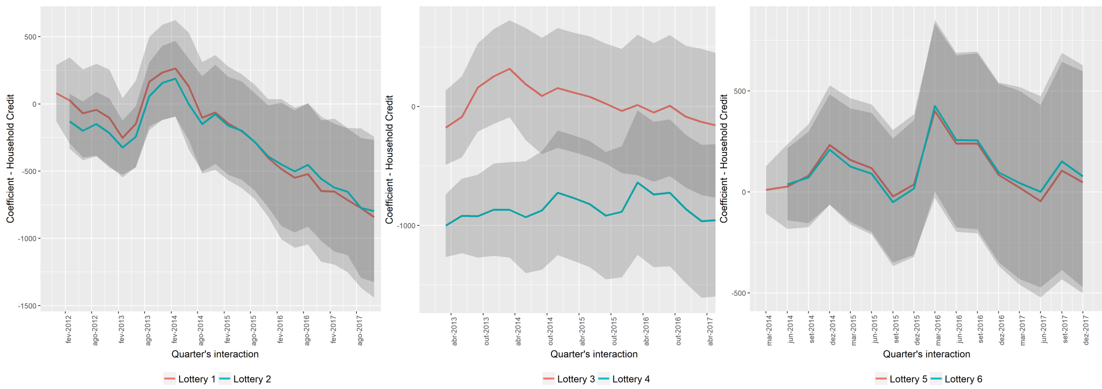

Figure 29 – Interaction Coefficients for Household Credit

Note: Red line represents β coefficients of the Equation (3.3) for Lotteries 1, 3 and 5, respectively, when the outcome is the amount of the Household Credit. Blue line represents β coefficients for Lotteries 2, 4 and 6, respectively. Shadows are the Confidence Intervals of those coefficients at 95% level.

Figure 30 charts coefficients derived when the outcome is the level of Goods Financing. The first three lotteries show an expansion of the coefficient between September 2013 and June 2014. This suggests that this difference is more closely related to the provision of the resources through My Better House Program because only the beneficiaries of the first lotteries received this loan. For the last lotteries, the magnitude of the coefficient has risen in 2015. As the My Better House Program does not apply to these lotteries, beneficiaries may purchase goods for a new home by themselves. We find no evidence of an impact of changes in credit registry data on these coefficients.

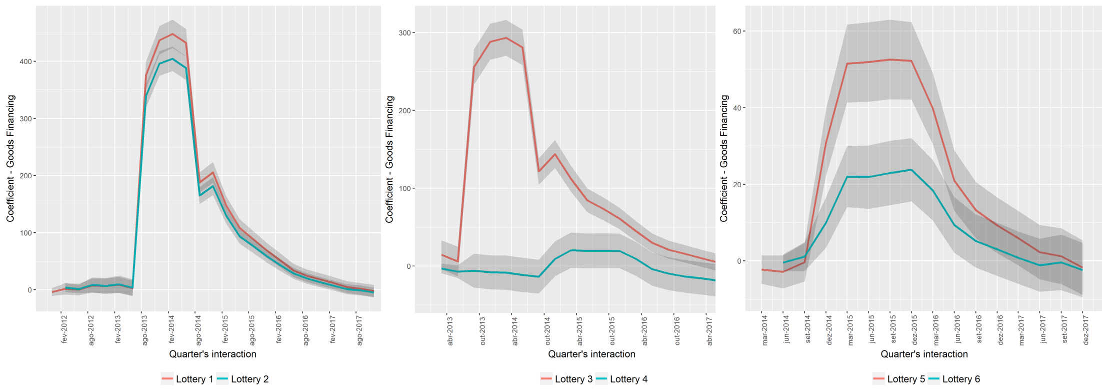

Figure 30 – Interaction Coefficients for Goods Financing

Note: Red line represents β coefficients of the Equation (3.3) for Lotteries 1, 3 and 5, respectively, when the outcome is the amount of Goods Financing. Blue line represents β coefficients for Lotteries 2, 4 and 6, respectively. Shadows are the Confidence Intervals of those coefficients at the 95% level.

The coefficients predicted for the exposure to the household credit are reported in Figure 31. Similarities to the previous figure are observed. Since the magnitude of the coefficients rises at the end of 2013 and in the beginning of 2014, it provides more evidence that the My House Better Program led individuals to begin engaging with financial institutions. The coefficients' lines follow different curves on last lotteries when My House Better Program does not apply. However, the decline of β values from 2016 may be related to the reduction in the thresholds of the credit registry data.

In contrast, we observe a clear change in the coefficients of Equation (3.3) when the overdue rate of Goods Financing is the outcome. Figure 32 plots the results. We see again an increase in β magnitudes for 2011 lotteries with beneficiaries eligible for My House Better Contracts. As the numerator of the overdue rate reports credit given in arrears over three months, variation in the coefficients occurs one quarter after the previous charts. Although the impact of being drawn is less significant after 2015, for all lotteries the coefficient does not return to its values before the draw, which may suggest a long-term impact on the overdue rates.

3.7 Conclusion

We here exploit the effects of housing lotteries for lower-income households in Rio de Janeiro, Brazil, on loans related to household consumption. We compared the outcomes (amounts borrowed, number of

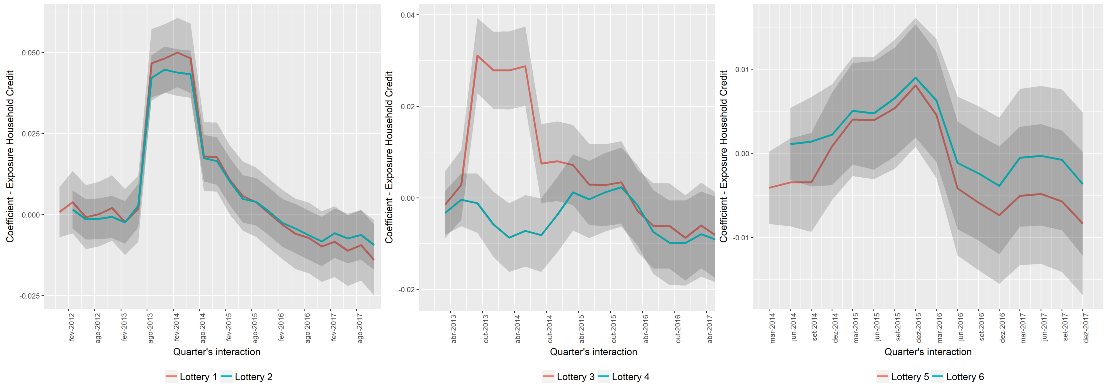

Figure 31 – Interaction Coefficients for exposure of Household Credit

Note: Red line represents β coefficients of the Equation (3.3) for Lotteries 1, 3 and 5, respectively, when the outcome is the exposure of the Household Credit. Blue line represents β coefficients for Lotteries 2, 4 and 6, respectively. Shadows are the Confidence Intervals of those coefficients at the 95% level.

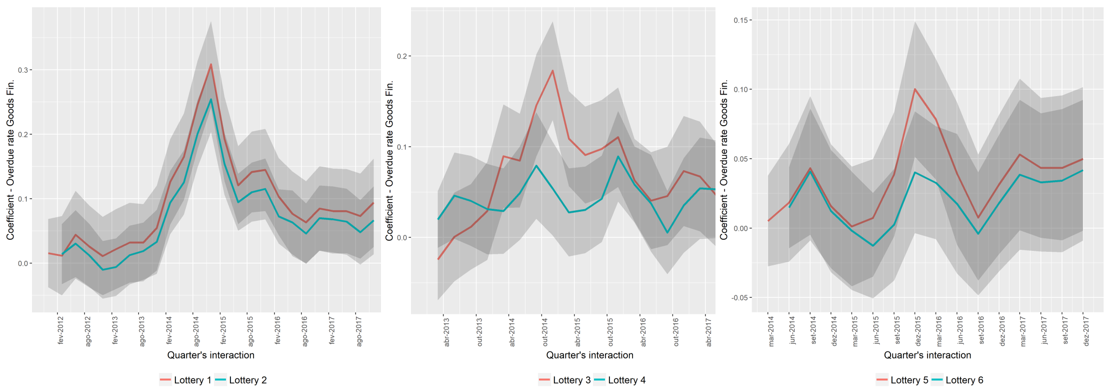

Figure 32 – Interaction Coefficients for the overdue rate of Goods Financing

Note: Red line represents β coefficients of the Equation (3.3) for Lotteries 1, 3 and 5, respectively, when the outcome is the overdue rate of Goods Financing. Blue line represents β coefficients for Lotteries 2, 4 and 6, respectively. Shadows are the Confidence Intervals of those coefficients at the 95% level.

contracts, overdue credit rates and loan exposure) of different credit types for treated and non treated populations.

Each lottery shows its own dynamics. Styles, locations and supplies of housing projects for each draw can influence the demand for housing and the effects of being treated by the policy. For lotteries occurring in 2011 with housing units delivered in 2012 amidst growing housing prices and economic development, we note that treated individuals exhibited the same behaviors or even borrowed less credit than non-treated individuals.

In contrast, lotteries occurring in 2012 and 2013 and had its housing projects delivered in 2014 and 2015 amidst the start of an economic crisis show strong evidence of wealth effects. Owning a secure asset such as real estate can increase demand for credit and consumption and can raise the probability of having that demand accepted by the financial institution, even if the house is not considered as collateral. These results support robustness tests and endorse a hypothesis given in the literature showing that owning a house can change the investment decisions of households ((FLAVIN; YAMASHITA, 2002)).

However, we observe an overall effect of the examined program on borrowing for Goods Financing and mostly as a result of the My Better House Program. Exposition and overdue rates for this credit type were also increased. Financial inclusion may constitute a unique factor that shapes lotteries. Almost half of low-income applicants did not experience any loan exposure throughout the whole period. Even though, we found being treated to affect exposure to loans across almost all draws. The results suggest that this process begins with Goods Financing line.

Impacts of lotteries on overdue credit are less significant, except in the case of the rise of credit in arrears observed in My Better House Program. However, we did not not find this symptom to spread to other types of credit. Possible effects may include migration to non-collateral lines and a rise in interest rates after being in arrears. Since a large proportion of PMCMV beneficiaries defaulted as a result of My Better House loans, a reduction in credit rates for these defaulters may limit access to credit over the long run.

3.A Credit types

Table 68 – Composition of Credit Types

Credit Types	Aggregation (In Portuguese)	SCR Lines	Exposure Individuals	Lottery Winners	Demands Collateral
(1)	(2)	(3)	(4)	(5)	(6)
Overdraft	Cheque Especial + Adiantamento a Depositantes	101+201+213	1,633,609	82,336	No
Payroll credit	Crédito Consignado	202	2,145,943	110,050	Yes
Personal credit	Crédito Pessoal	203	1,420,029	70,008	No
Automotive Financing	Financiamento Automotivo	401	639,054	30,255	Yes
Other goods Financing	Financiamento Outros bens	402	104,068	19,741	No
Housing Financing	Financiamento Imobiliário	901+902+990	451,872	26,096	Yes
Revolving Credit Card	Cartão de Crédito rotativo	204 + 218	2,712,667	141,122	No
Credit Card Debt	Cartão de Crédito parcelado	210 + 406	1,351,690	70,630	No
Credit Card (Consuming)	Cartão de Crédito: compra à vista e parcelado lojista	1304	3,864,116	195,337	No
Household Credit	**Crédito Pessoa Física**	**All**	3,731,263	315,228	

Note: Columns (2) and (3) represent specifications from SCR available on Attachment 3 of <www.bcb.gov.br/fis/crc/ftp/SCR3040_Leiaute.xls>. Columns (4) and (5) include individuals registered in all 29 quarters of data. Household Credit includes all nine credit types listed above plus other credit types related to individuals with short number of contracts.

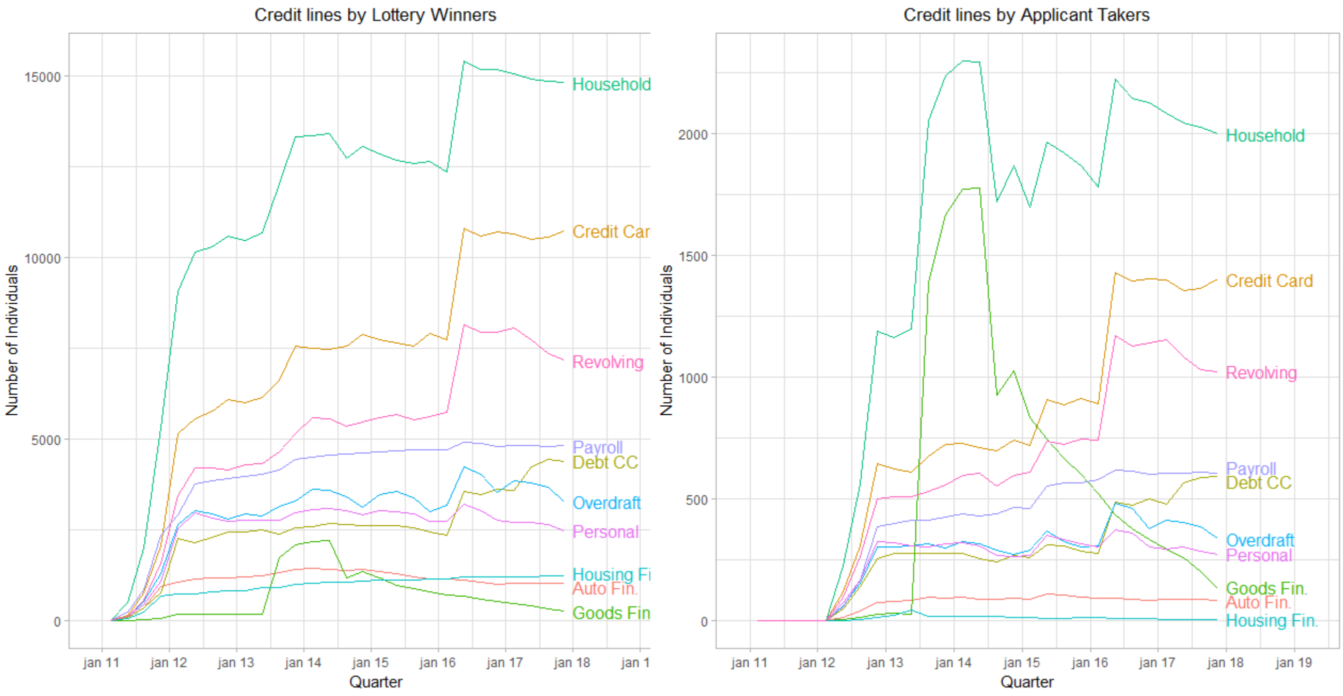

Figure 33 – credit types by selected individuals

Note: each line corresponds to the number of the lottery winners or the beneficiaries that are exposed to that credit type, respectively. Jumps in 2012 and 2016 occurred due to the changes on the minimum value of total loan obligation reported to the Credit Registry Data.

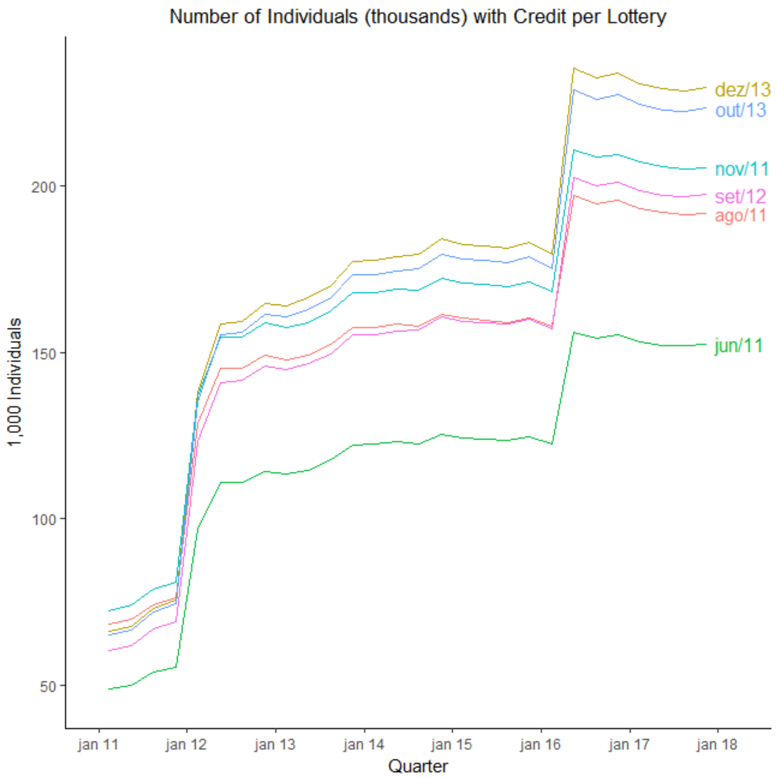

Figure 34 – Individuals by Lottery

Note: this graph represents number of applicants that are exposed to at least one credit for each lottery. Jumps in 2012 and 2016 occurred due to the changes on the minimum value of total loan obligation reported to the Credit Registry Data.

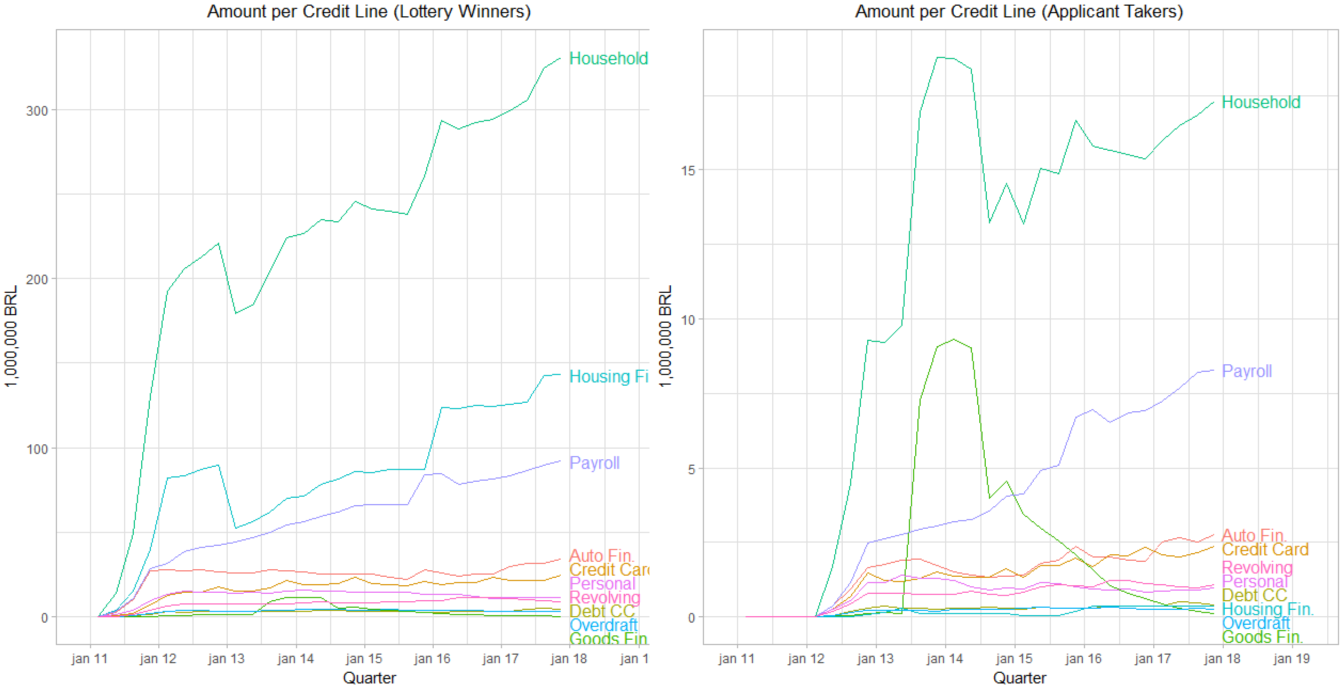

Figure 35 – Amount of Credit by selected individuals

Note: each line corresponds to the total amount of that credit type borrowed by the lottery winners or the beneficiaries, respectively. Jumps in 2012 and 2016 occurred due to the changes on the minimum value of total loan obligation reported to the Credit Registry Data.

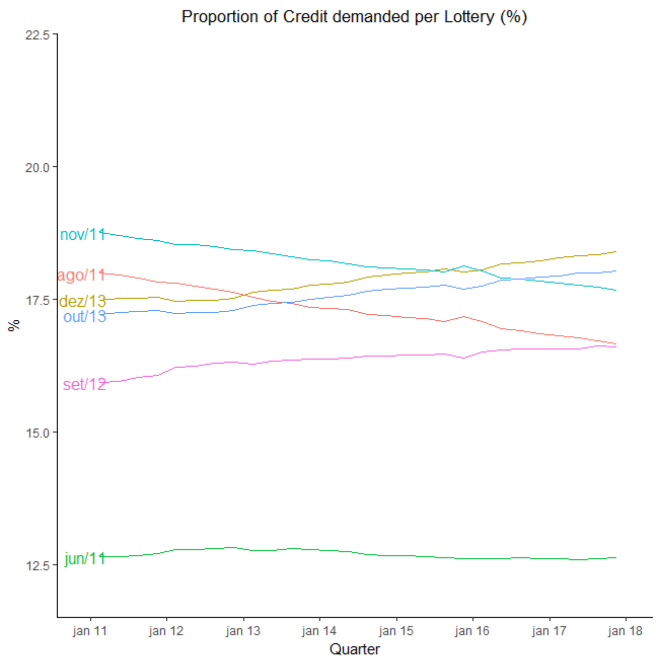

Figure 36 – Amount of Credit by Lottery
Note: each line corresponds to the proportion of the whole amount of credit borrowed by the applicants of each lottery.

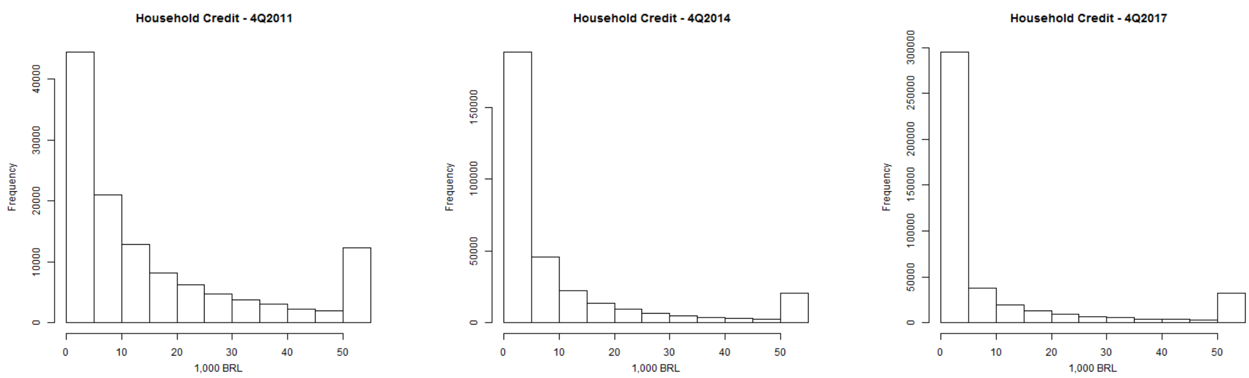

Figure 37 – Histogram of all household credit in distinct thresholds
Note: This graph shows the distribution of values of exposition to a credit type in specific periods. Bin selection was 5,000 BRL.

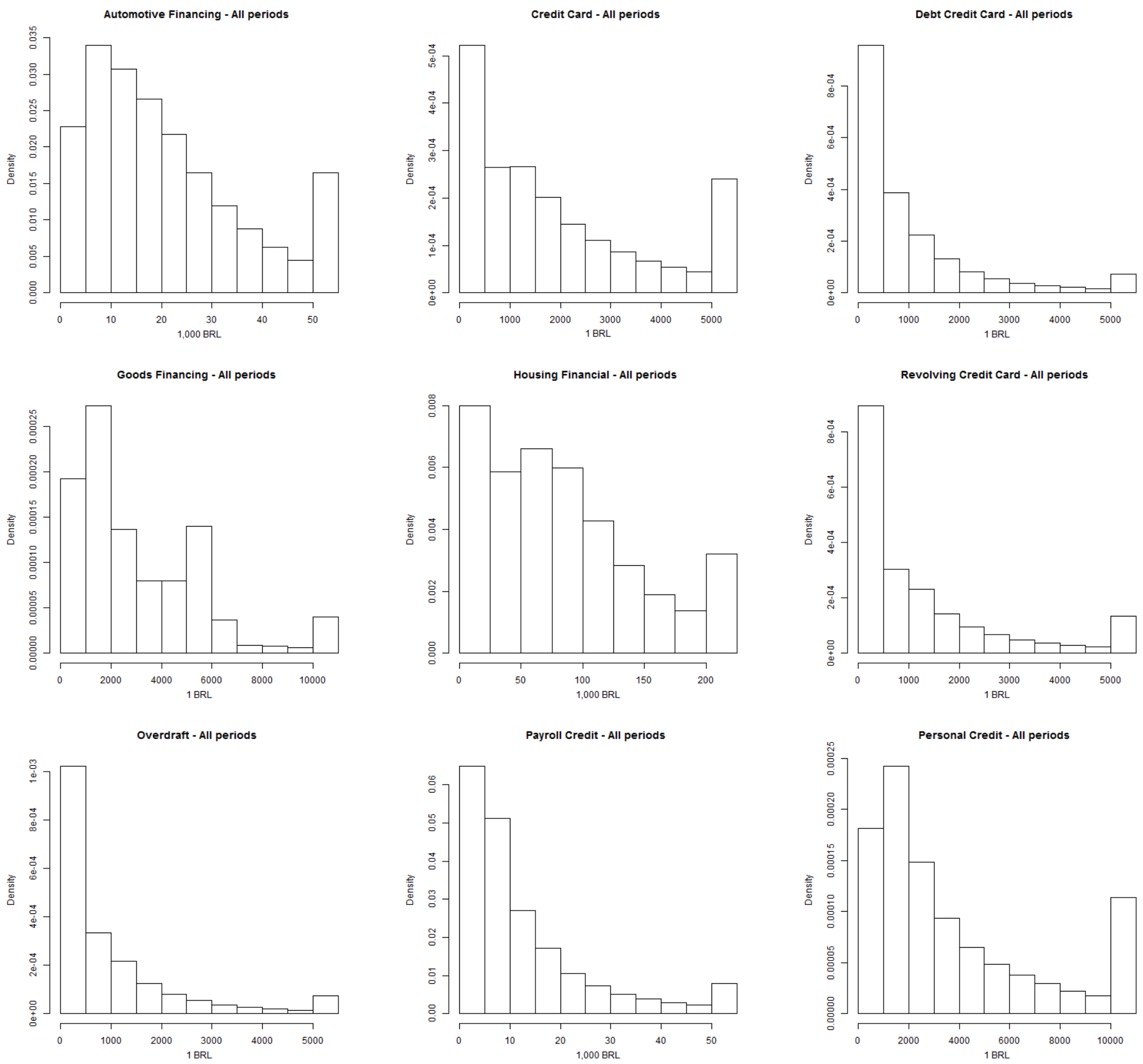

Figure 38 – Histogram of per credit types

Note: Those graphs show the distribution of values of exposition to each credit type in the whole period 2010-2017. Bin selection was 5,000 BRL.

Bibliography

ADELINO, M.; SCHOAR, A.; SEVERINO, F. *Credit supply and house prices: evidence from mortgage market segmentation*. [S.l.], 2012. Citado na página 15.

AGARWAL, S.; QIAN, W. Access to home equity and consumption: Evidence from a policy experiment. *Review of Economics and Statistics*, MIT Press, v. 99, n. 1, p. 40–52, 2017. Citado na página 55.

ALADANGADY, A. Housing wealth and consumption: Evidence from geographically-linked microdata. *American Economic Review*, v. 107, n. 11, p. 3415–46, November 2017. Disponível em: <http://www.aeaweb.org/articles?id=10.1257/aer.20150491>. Citado na página 93.

ALESSANDRINI, P.; PRESBITERO, A. F.; ZAZZARO, A. Banks, distances and firms' financing constraints. *Review of Finance*, Oxford University Press, v. 13, n. 2, p. 261–307, 2009. Citado na página 56.

ALLEN, J. et al. The impact of macroprudential housing finance tools in canada. 2017. Citado na página 15.

ANDRADE, R. A. S. d. *Creditor's protection and bank loans: lack of competition hampers bankruptcy reform's effects*. Tese (Doutorado) — Fundação Getúlio Vargas, 2015. Citado 2 vezes nas páginas 57 and 82.

ANSELIN, L. *Spatial econometrics: methods and models*. [S.l.]: Springer Science & Business Media, 1988. v. 4. Citado 2 vezes nas páginas 76 and 79.

ARAUJO, D. K. G. de et al. *Loan-To-Value Policy and Housing Loans: Effects on constrained borrowers.* [S.l.], 2016. Citado 3 vezes nas páginas 15, 18, and 29.

BARNHARDT, S.; FIELD, E.; PANDE, R. Moving to opportunity or isolation? network effects of a randomized housing lottery in urban india. *American Economic Journal: Applied Economics*, v. 9, n. 1, p. 1–32, 2017. Citado na página 105.

BERNANKE, B. S.; GERTLER, M. *Inside the black box: the credit channel of monetary policy transmission*. [S.l.], 1995. Citado na página 55.

BESLEY, T.; MEADS, N.; SURICO, P. The incidence of transaction taxes: Evidence from a stamp duty holiday. *Journal of Public Economics*, Elsevier, v. 119, p. 61–70, 2014. Citado na página 16.

BEST, M. C.; KLEVEN, H. J. Housing market responses to transaction taxes: Evidence from notches and stimulus in the uk. *The Review of Economic Studies*, Oxford University Press, v. 85, n. 1, p. 157–193, 2017. Citado 2 vezes nas páginas 16 and 46.

BLACK, L. K.; HANCOCK, D.; PASSMORE, S. W. The bank lending channel of monetary policy and its effect on mortgage lending. 2010. Citado na página 55.

BOSTIC, R.; GABRIEL, S.; PAINTER, G. Housing wealth, financial wealth, and consumption: New evidence from micro data. *Regional Science and Urban Economics*, Elsevier, v. 39, n. 1, p. 79–89, 2009. Citado na página 93.

BRAZIL, C. B. of. *Financial Stability Report*. [S.l.], 2018. Disponível em: <https://www.bcb.gov.br/ingles/estabilidade/2018_10/fsrFullRep.pdf>. Citado na página 97.

BREVOORT, K. P.; WOLKEN, J. D. Does distance matter in banking? In: *The changing geography of banking and finance*. [S.l.]: Springer, 2009. p. 27–56. Citado na página 56.

BROWNING, M.; GØRTZ, M.; LETH-PETERSEN, S. Housing wealth and consumption: a micro panel study. *The Economic Journal*, Wiley Online Library, v. 123, n. 568, p. 401–428, 2013. Citado na página 93.

CAMPBELL, J. Y.; COCCO, J. F. How do house prices affect consumption? evidence from micro data. *Journal of monetary Economics*, Elsevier, v. 54, n. 3, p. 591–621, 2007. Citado na página 55.

CAMPBELL, J. Y.; RAMADORAI, T.; RANISH, B. The impact of regulation on mortgage risk: Evidence from india. *American Economic Journal: Economic Policy*, American Economic Association, v. 7, n. 4, p. 71–102, 2015. Citado 2 vezes nas páginas 15 and 20.

CATTANEO, M. D.; IDROBO, N.; TITIUNIK, R. A practical introduction to regression discontinuity designs: Volume ii. 2018. Citado na página 27.

CERUTTI, E.; DAGHER, J.; DELL'ARICCIA, G. Housing finance and real-estate booms: a cross-country perspective. *Journal of Housing Economics*, Elsevier, 2017. Citado na página 15.

CHIODA, L.; MELLO, J. M. D.; SOARES, R. R. Spillovers from conditional cash transfer programs: Bolsa família and crime in urban brazil. *Economics of Education Review*, Elsevier, v. 54, p. 306–320, 2016. Citado na página 65.

CHO, S. Housing wealth effect on consumption: Evidence from household level data. *Economics Letters*, Elsevier, v. 113, n. 2, p. 192–194, 2011. Citado na página 93.

CLAESSENS, S. An overview of macroprudential policy tools. Annual Reviews, 2015. Citado na página 15.

Da Mata, D.; MATION, L. Labor market effects of public housing: Evidence from large-scale lotteries. Unpublished paper, 2018. Citado 3 vezes nas páginas 96, 103, and 105.

Da Mata, D.; RESENDE, G. Changing the climate for banking: The economic effects of credit in a climate-vulnerable area. 2015. Citado na página 56.

DEATON, A. *Understanding consumption*. [S.l.]: Oxford University Press, 1992. Citado na página 60.

DIX-CARNEIRO, R.; SOARES, R. R.; ULYSSEA, G. *Economic Shocks and Crime: Evidence from the Brazilian Trade Liberalization*. [S.l.], 2017. Citado na página 65.

DONG, Y. Regression discontinuity applications with rounding errors in the running variable. *Journal of Applied Econometrics*, Wiley Online Library, v. 30, n. 3, p. 422–446, 2015. Citado na página 24.

DONG, Z.; HUI, E. C.; JIA, S. How does housing price affect consumption in china: Wealth effect or substitution effect? *Cities*, Elsevier, v. 64, p. 1–8, 2017. Citado na página 93.

FERRO, L. P. de M. et al. *Crédito e Formação de Domicílios no Brasil*. [S.l.], 2016. Citado 4 vezes nas páginas 56, 60, 62, and 93.

FLAVIN, M.; YAMASHITA, T. Owner-occupied housing and the composition of the household portfolio. *American Economic Review*, v. 92, n. 1, p. 345–362, March 2002. Disponível em: <http://www.aeaweb.org/articles?id=10.1257/000282802760015775>. Citado 2 vezes nas páginas 94 and 122.

FRANCIS, N.; OWYANG, M. T.; SEKHPOSYAN, T. The local effects of monetary policy. *The BE Journal of Macroeconomics*, v. 12, n. 2, 2011. Citado na página 56.

GARBER, G. et al. *Household Debt and Recession in Brazil*. [S.l.], 2018. (Working Paper Series, 25170). Disponível em: <http://www.nber.org/papers/w25170>. Citado 2 vezes nas páginas 97 and 98.

GOMES, F. A. R. Evolução do consumo de duráveis e não duráveis: existe ajustamento lento no caso brasileiro? *Economia Aplicada*, SciELO Brasil, v. 17, n. 2, p. 275–294, 2013. Citado 2 vezes nas páginas 57 and 60.

GONZALEZ, L.; ORTEGA, F. Immigration and housing booms: Evidence from spain. *Journal of Regional Science*, Wiley Online Library, v. 53, n. 1, p. 37–59, 2013. Citado na página 36.

HADDAD, E.; MEYER, J. The financial crisis and brazil's expanding housing market. *Global Housing Markets: Crises, Policies, and Institutions*, Wiley Online Library, p. 491–510, 2011. Citado 2 vezes nas páginas 16 and 94.

HAHN, J.; TODD, P.; KLAAUW, W. Van der. Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, Wiley Online Library, v. 69, n. 1, p. 201–209, 2001. Citado na página 23.

HALLISSEY, N. et al. *Macro-prudential tools and credit risk of property lending at Irish banks*. [S.l.], 2014. Citado na página 15.

HIROMOTO, M. H. *Análise de três dimensões do Programa Minha Casa Minha Vida: Expansão Urbana, infraestrutura de saneamento e emprego*. Tese (Doutorado) — Fundação Getúlio Vargas, 2018. Citado na página 95.

IACOVIELLO, M.; MINETTI, R. The credit channel of monetary policy: Evidence from the housing market. *Journal of Macroeconomics*, Elsevier, v. 30, n. 1, p. 69–96, 2008. Citado 2 vezes nas páginas 15 and 55.

IMBENS, G.; ZAJONC, T. Regression discontinuity design with multiple forcing variables. *Report, Harvard University.[972]*, 2011. Citado na página 23.

IMBENS, G. W.; RUBIN, D. B.; SACERDOTE, B. I. Estimating the effect of unearned income on labor earnings, savings, and consumption: Evidence from a survey of lottery players. *The American Economic Review*, American Economic Association, v. 91, n. 4, p. 778–794, 2001. ISSN 00028282. Disponível em: <http://www.jstor.org/stable/2677812>. Citado na página 94.

KEELE, L. J.; TITIUNIK, R. Geographic boundaries as regression discontinuities. *Political Analysis*, Oxford University Press, v. 23, n. 1, p. 127–155, 2014. Citado 2 vezes nas páginas 20 and 23.

KHALIFA, S.; SECK, O.; TOBING, E. Housing wealth effect: Evidence from threshold estimation. *Journal of Housing Economics*, Elsevier, v. 22, n. 1, p. 25–35, 2013. Citado na página 93.

KLEVEN, H. J.; WASEEM, M. Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from pakistan. *The Quarterly Journal of Economics*, MIT Press, v. 128, n. 2, p. 669–723, 2013. Citado 2 vezes nas páginas 44 and 46.

KROTH, D. C.; DIAS, J. et al. A contribuição do crédito bancário e do capital humano no crescimento econômico dos municípios brasileiros: uma avaliação em painéis de dados dinâmicos. *ENCONTRO NACIONAL DE ECONOMIA*, v. 34, 2006. Citado na página 56.

KUMAR, A. et al. *Assessing financial access in Brazil*. [S.l.]: World Bank Publications, 2005. Citado 2 vezes nas páginas 55 and 63.

KUTTNER, K.; SHIM, I. et al. Taming the real estate beast: the effects of monetary and macroprudential policies on housing prices and credit. *of: Heath, Alexandra, Packer, Frank, & Windsor, Callan (eds), Property Markets and Financial Stability. Sydney: Reserve Bank of Australia*, p. 231–259, 2012. Citado na página 15.

MARTINS, B.; LUNDBERG, E.; TAKEDA, T. Housing finance in brazil: Institutional improvements and recent developments. 2011. Citado na página 16.

MCKENZIE, D. Beyond baseline and follow-up: The case for more t in experiments. *Journal of development Economics*, Elsevier, v. 99, n. 2, p. 210–221, 2012. Citado na página 102.

MELLO, L. C. d. *Desenvolvimento financeiro e econômico-social nos municípios brasileiros*. Tese (Doutorado) — Universidade de São Paulo, 2014. Citado na página 56.

MIAN, A.; RAO, K.; SUFI, A. Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, Oxford University Press, p. qjt020, 2013. Citado 2 vezes nas páginas 15 and 55.

MIAN, A.; SUFI, A. *House price gains and US household spending from 2002 to 2006*. [S.l.], 2014. Citado 2 vezes nas páginas 15 and 55.

MILLER, S.; SOO, C. K. *Do Neighborhoods Affect Credit Market Decisions of Low-Income Borrowers? Evidence from the Moving to Opportunity Experiment*. [S.l.], 2018. (Working Paper Series, 25023). Disponível em: <http://www.nber.org/papers/w25023>. Citado na página 93.

MILLS, G. et al. Effects of individual development accounts on asset purchases and saving behavior: Evidence from a controlled experiment. *Journal of Public Economics*, v. 92, n. 5, p. 1509 – 1530, 2008. ISSN 0047-2727. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0047272707001570>. Citado na página 94.

MUSSA, A.; NWAOGU, U. G.; POZO, S. Immigration and housing: A spatial econometric analysis. *Journal of Housing Economics*, Elsevier, v. 35, p. 13–25, 2017. Citado na página 36.

National Monetary Council. *Resolution n. 2,640*. 1999. Dispõe sobre a contratação de correspondentes no País. Citado na página 64.

National Monetary Council. *Resolution n. 3,706*. 2009. Dispõe sobre a concessão de financiamentos imobiliários, o direcionamento dos recursos captados em depósitos de poupança pelas entidades integrantes do Sistema Brasileiro de Poupança e Empréstimo (SBPE), a realização de operações de microcrédito destinadas à população de baixa renda e a microempreendedores e altera a Resolução nº 2.828, de 2001, que trata da constituição e do funcionamento de agências de fomento. Citado na página 18.

National Monetary Council. *Resolution n. 4,271*. 2013. Dispõe sobre os critérios de concessão de financiamento imobiliário e dá outras providências. Citado na página 18.

National Monetary Council. *Resolution n. 4,537*. 2016. Altera o Regulamento anexo à Resolução nº 3.932, de 16 de dezembro de 2010, que consolida as normas sobre direcionamento dos recursos captados em depósitos de poupança pelas entidades integrantes do Sistema Brasileiro de Poupança e Empréstimo (SBPE). Citado na página 18.

PASCALI, L. Banks and development: Jewish communities in the italian renaissance and current economic performance. *Review of Economics and Statistics*, MIT Press, v. 98, n. 1, p. 140–158, 2016. Citado na página 56.

PONTICELLI, J.; ALENCAR, L. S. Court enforcement, bank loans, and firm investment: evidence from a bankruptcy reform in brazil. *The Quarterly Journal of Economics*, Oxford University Press, v. 131, n. 3, p. 1365–1413, 2016. Citado na página 56.

SERRANO, F. M. *Impacto regional da política monetária no Brasil: uma abordagem Bayesiana*. Tese (Doutorado) — Universidade de São Paulo, 2014. Citado na página 56.

SILVA, M. A. d.; BRITO, G.; MARTINS, T. C. Default contagion among credit types: evidence from brazilian data. *Journal of Credit Risk*, v. 14, n. 3, p. 31–48, 2018. Citado na página 97.

UN-HABITAT. *Scaling-Up Affordable Housing Supply in Brazil: The 'My House My Life'Programme*. [S.l.]: United Nations Human Settlements Programme Nairobi, 2013. Citado na página 94.