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The impact of interest rate ceilings on households' credit access: Evidence from a 2013 Chilean legislation

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ABSTRACT

This study analyzes the impact of a legislation introduced in Chile in 2013, which gradually reduced the maximum legal interest rate for consumer loans from 54% to 36%. Using a representative sample of households that matches survey data and banking loan records, I compare consumers with risk-adjusted interest rates slightly above and slightly below the legal interest rate ceiling, two groups of similar characteristics but who are differently affected by the law. After accounting for both macroeconomic shocks and unobserved household heterogeneity, the results show that being above the interest rate cap reduces the probability of credit access by 8.7% on average. A counterfactual exercise shows that the new legislation excluded 9.7% of the borrowers from banking consumer loans. The law's impact was strongest on the youngest, least educated and poorest families. Finally, I show that the new law affected all lenders of consumer loans in Chile, not just banks.

1. Introduction

Usury laws are one of the most common credit market legislations, with many countries having interest rate ceilings (iff/ZEW, 2010),(Maimbo and Henriquez, 2014). Maximum legal interest rates have goals of consumer protection (Dewatripont and Tirole, 1994), defending inattentive, naive or desperate borrowers from the negative consequences of hazardous loans (Glaeser and Scheinkman, 1998), (Melzer, 2011). However, economic theory suggests that interest rate caps can have negative effects such as a reduction in credit, particularly among high-risk and low-income borrowers which may become unprofitable due to the inability of charging them a higher interest rate (Greer, 1975), (Villegas, 1989), (Zinman, 2010), (Rigbi, 2013). Empirical evidence for the United States suggests that access to some forms of high interest rate debt (such as payday loans) may help borrowers smooth negative shocks (Morse, 2011), (Morgan et al., 2012), although these are also associated with difficulties in paying for health care, mortgage, rent and utilities (Melzer, 2011). Other negative effects of interest rate ceilings may be an increased adoption of less regulated forms of credit as people search for loans outside of the banking system (iff/ZEW, 2010).

This paper analyzes the impact of an interest rate legislation introduced in Chile in December of 2013 (the Law Nr. 20715), which gradually reduced the maximum legal interest rate for consumer loans from a rate of 53.9% just before the law to 36.9% by June of 2015. This legislation represented a reduction of around 17% in the maximum legal interest rate over a period of less than two years. The legislation also changed the interest rate ceiling from a single cap for all consumer loans to two distinct caps for the segments of smaller (0–50 UF) and larger (50–200 UF) amounts[2] The segment for larger consumer loans had an even lower interest rate cap set around 30%, which was implemented gradually until December of 2015. Using a representative sample of 4,118 households I show that consumers with risk-adjusted interest rate profiles that are slightly above the interest rate caps have a lower credit access relative to peers with similar profiles just below the caps. After

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[2] UF is a real monetary unit applied in Chile, which is updated according to the official consumer price inflation (CPI) index. 1 UF was roughly equivalent to 40 USD during the sample period of 2013 to 2015. Therefore 0–50 UF and 50–200 UF would correspond roughly to loans between 0–2,000 USD and 2,000-8,000 USD, respectively.

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accounting for a wide range of macroeconomic shocks and different household characteristics that can impact the demand for credit, the results show that being slightly above the interest rate cap reduces the probability of bank credit access by 5.5% on average. After adding further controls for unobserved household heterogeneity, the estimated average reduction in bank credit access becomes 8.7%. A counterfactual exercise shows that the new law reduced the number of banking consumer borrowers by 9.7% by the end of 2015, which is equivalent to 197 thousand families.

To study the impact of the maximum legal interest rate change on the Chilean banking system I use a unique dataset, which matches the real identities of households interviewed in the Chilean Household Finance Survey (*Encuesta Financiera de Hogares*, hence on EFH) and their banking credit history from administrative records kept by the Chilean Banking and Financial Institutions Supervisor (*Superintendencia de Bancos e Instituciones Financieras*, hence on SBIF). This provides a dataset of households with their entire banking loan information for the period 2003 until 2015, and with cross-sectional information on the household demographic characteristics and income for one survey year (with survey years in 2007, 2008, 2009, 2010, 2011 and 2014). The sample of this matched EFH-SBIF dataset includes around 4118 households who had at least one banking consumer installment loan over the period 2003 to 2015, plus around 2,000 families who never had an installment credit during the same period (although they may have used other financial products such as credit cards, lines of credit or mortgages). The matched data includes the loan history in the banking system for the interviewed persons plus survey reported measures of income, age and education for both the interviewed person and its household members (partner/spouse, parents, children or siblings). This allows me to analyze all the banking loan contracts and payments of each borrower with a monthly frequency over the period 2003 to 2015.

To measure the impact of the law I apply a regression discontinuity design (Lee and Lemieux, 2010), (Dobbie and Skiba, 2013), which is induced by the inability to award credit above the interest rate cap. I estimate a risk-adjusted interest rate which includes the observable delinquency risk of each borrower plus the cost of bank capital and the loan's administrative costs (Edelberg, 2006), (Madeira, 2018). The empirical risk of consumer loan delinquency is positively associated with higher indebtedness, liquidity constraints, unemployment risk, low income, low education, young age and larger families (similar to Madeira (2018)). This risk-adjusted interest rate is not necessarily equivalent to the price each borrower would find in the market, since each bank may apply other criteria to screen customers and one would expect some heterogeneity of loan offers among lenders. However, the risk-adjusted interest rate can be used as a noisy measure of the actual offers that borrowers would find, which provides a noisy or fuzzy regression discontinuity design as long as consumers cannot perfectly control their risk and loan offers (Lee and Lemieux, 2010). Households with risk-adjusted interest rates slightly above the interest rate ceiling will find it much harder to get a loan relative to others with risk-adjusted interest rates slightly below the legal cap. Since the risk-adjusted interest rates used in this study are not perfectly measured, then this represents a standard problem of a mismeasured regressor and the econometrics literature suggests that the estimated results are a lower bound for the true impact (Wooldridge, 2010). Econometric theory therefore suggests that the qualitative conclusions of the analysis should be unaffected by the noisy measurement of the risk-adjusted interest rates (Wooldridge, 2010), (Lee and Lemieux, 2010).

After obtaining the risk-adjusted interest rates, I classify borrowers in each period according to 4 different ranges of proximity of the maximum legal interest rate: i) those far below the legal cap (therefore unaffected by the regulation), ii) slightly below the legal cap, iii) slightly above the legal cap, and iv) those far above the legal cap. It is the comparison of the second and third groups which yields the correct estimate for the impact of the maximum legal interest rate, since both groups are similar in characteristics but differ in the sense that only one group is affected by the regulation. Note that the same household may change its group over time for two reasons - first, indebtedness and unemployment risk change over time, affecting the risk-adjusted interest rates, and second, because the legal cap is changing over time (therefore the same person may be affected by the legal cap in one month even if he was unaffected in previous months and vice-versa). The changes over time in the credit worthiness of the same borrowers allows to identify the law's impact with controls for both aggregate time fixed-effects and household fixed-effects.

This paper fits into a larger literature that studies restrictions in the credit market (Jaffee and Stiglitz, 1990), (Dewatripont and Tirole, 1994). More recently, several studies use microdata to study household finance issues (Alessie et al., 2005), (Gerardi et al., 2018), (Christelis et al., 2017), (Madeira and Zafar, 2015), (Madeira, 2018), which are affected by over-borrowing and myopic decisions. Past studies have provided estimates of the impact of usury laws or interest rate ceilings across several countries (Maimbo and Henriquez, 2014), but these studies are mostly based on aggregate statistics from cross-country data, which can be affected by other differences in institutions or macroeconomic shocks[3] This paper improves upon the past literature (such as the official report on the impact of the 2013 Chilean law, SBIF, 2017) by using a carefully detailed regression discontinuity design in which two groups of very similar people are compared over time, but one group suffers most of the law's impact due to its borrower risk being unprofitable above the legal cap. Other ongoing studies of the Chilean 2013 interest rate legislation are now focusing on the consumer protection benefits of the legislation, with some structural models showing that the caps decreased the market power of banks (Hurtado, 2016), (Córdova and Toro, 2019), (Cuesta and Sepúlveda, 2019).

This paper is organized as follows. Section 2 summarizes the legislation about interest rate caps in Chile and the study dataset. Section 3 explains the empirical strategy. Section 4 summarizes the estimation results, while Section 5 shows the counterfactual simulations of how many households lost credit access with the legislation. Section 6 shows some evidence of the impact of the law on non-banking lenders. Finally, Section 7 concludes with implications for policy.

2. Data description and institutional setting

2.1. The interest rate cap legislation implemented in 2013

Two major changes were introduced by the new legislation (the Law Nr. 20715). First, the law established two distinct interest rate caps for loans with amounts between 0–50 UF and 50–200 UF, which previously had the same cap. The rate caps were set equal to the average interest rate of personal loans between 200 and 5000 UF (i.e., loans not affected by the interest rate caps of the legislation) in the preceding month plus an additive factor of 14% and 7%, respectively for the 0–50 UF and 50–200 UF segments. Second, the law would see the new caps implemented gradually until June and December of 2015, respectively for the segments of 0–50 UF and 50–200 UF loan amounts, with the larger loan segment seeing a larger reduction in the interest rate cap (from

[3] Christelis et al. (2017) show that there are huge unexplained differences in household debt levels across countries, even after taking education, age or income differences into account. This makes it difficult to compare the usury laws' impact based solely on aggregate statistics over time or cross-country data.

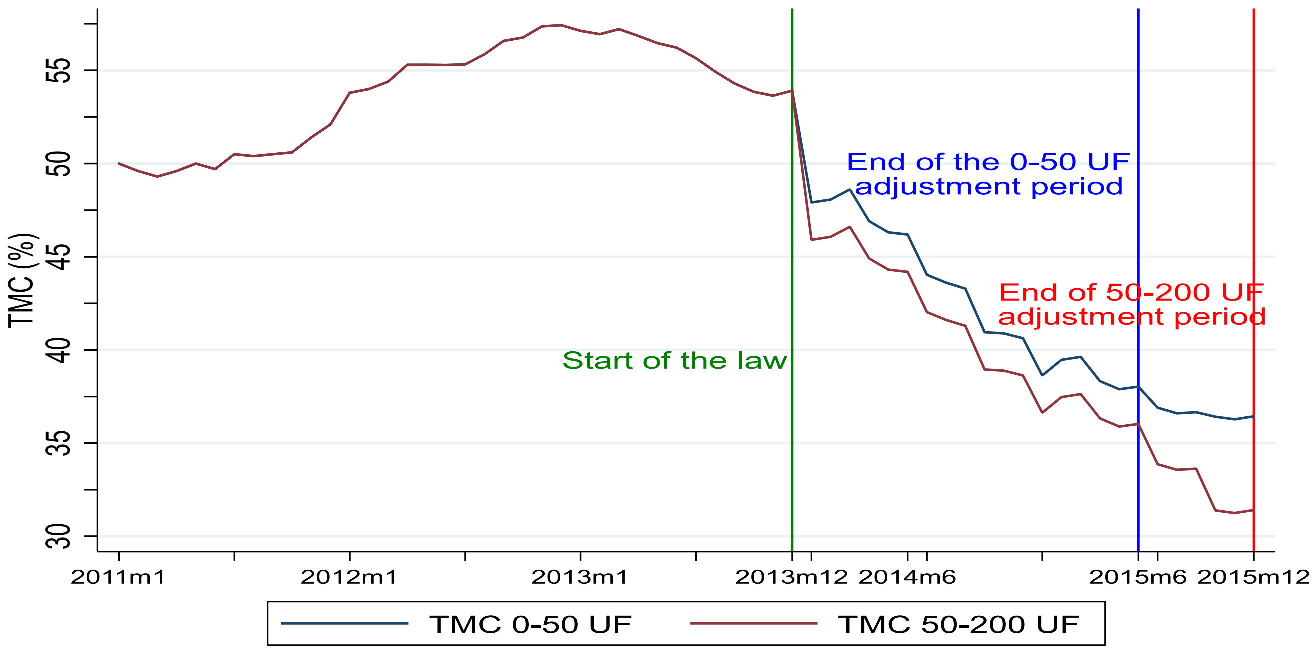

Fig. 1. Evolution of the interest rate caps (TMC) for the loan size segments 0–50 and 50–200 UF.

53.9% in December, 2013 to 30% by December, 2015) and a slower implementation schedule. Before the law, both segments had the same maximum legal interest rate which was equal to a multiple of 150% of the value of the average interest rate of loans in the 0–200 UF segment in the preceding month. Before the legislation was introduced, some simulation studies predicted that these formula changes would lead to a reduction in the maximum legal interest rate from around 50% to a steady-state value of 35% and 30% for the loan segments of 0–50 UF and 50–200 UF, respectively(SBIF, 2017).

Fig. 1 summarizes graphically these changes. It shows that the interest rate caps for the 0–50 UF and 50–200 UF segments changed suddenly and dropped from 53.9% to 47.9% and 45.9%, respectively, in December of 2013, which was the first month in which the new law was made applicable. Fig. 1 also shows that the interest rate cap for the smallest loan segment (those between 0–50 UF) fell to around 36% by June of 2015, which was the end of the adjustment period for this segment, while the largest loan segment (50–200 UF) fell to around 30% by December of 2015, which marked the end of the adjustment period for this segment. The interest rate caps for both segments implemented by the new law have remained stable since the end of 2015.

2.2. The Chilean Household Finance survey (EFH)

For this study I use the Chilean Household Finance Survey (in Spanish, *Encuesta Financiera de Hogares*, hence on EFH), which is a representative national survey with detailed information on assets, debts, income and financial behavior. The EFH is comparable to similar surveys in the United States and Europe, such as the Survey of Consumer Finances (SCF) and the Household Finance and Consumption Survey (HFCS). The six EFH survey waves (2007, 2008, 2009, 2010, 2011, 2014) covered 12,271 urban households, with an over representation of richer households. To adequately correct for the over representation of wealthier households, all the statistics in this article use expansion factors (or population weights), meaning each observation is weighted with a number f_i representing the statistical number of households equivalent to i (see Madeira, 2018, Madeira, 2019a). Since the survey sample was randomly selected according to a predetermined characteristic (the appraisal value of the household residence for tax purposes), then all the sample statistics are consistent once the sample expansion factors are applied (Madeira, 2019a). Also, note that the EFH sampling with over-representation of wealthier households is common in other countries.

Due to the absence of an administrative credit register that includes the loans of non-banking institutions, the EFH survey is the only micro data source in Chile with information on household loans from all types of lenders. The survey has detailed measures of income, assets (financial portfolio, vehicles and real estate) and debts, including mortgage, educational, auto, retail and banking consumer loans (whether in terms of credit cards, lines of credit or larger consumer loan contracts). In order to cover debts exhaustively, the survey elicits the loan terms (debt service, loan amount, maturity) for the 3 main loans in each category of debt (loan categories include credit cards and installment loans with banks, retail stores, labor and credit unions, auto loans, education loans, and informal lending). Each survey sample was collected over roughly an entire calendar year, with the EFH 2011 being collected between July of 2011 and May of 2012, while the EFH 2014 was collected between July of 2014 and March of 2015. However, for simplicity the survey waves are labelled as EFH 2011 and 2014, which corresponds to the year in which the largest portion of their respective samples was collected. Although the entire sample (waves 2007 to 2014) will be used in the data regressions of the following sections, in this data description I focus on the waves of 2011 and 2014, which correspond to the surveys before and after the new interest rate cap legislation.

Households can have consumer loans with many kinds of lenders. For summary purposes, I classify all the EFH households into 7 mutually exclusive categories of borrowers according to their largest consumer loan amount held: 1) households with consumer loans in Banks (but not in Retail Stores), 2) households with consumer loans both in Banks and Retail Stores, 3) households with consumer loans in Retail Stores (but not in Banks), 4) households with consumer loans in Labor and Credit Unions[4],

[4] Labor Unions in Chile can extend loans to their members, but have some restrictions relative to other lenders. In particular, unions cannot charge different interest rates according to the borrower profile (that is, union loans can have

Table 1
Debt share of motives by borrower type in 2011 (before the law) and 2014 (after the law).

Borrower type	Population	Consumer debt (mean)[a]	Consumption	Durables	Pay debts	Health
		EFH 2011				
Banks	8.5	103.7	57.8	21.7	14.0	6.5
Banks and Retail Stores	12.0	128.3	56.9	17.0	17.8	8.4
Retail Stores	25.9	19.9	90.2	2.9	3.1	3.8
Unions	8.2	56.8	44.3	17.0	20.6	18.1
Other Debts	5.2	208.2	78.5	8.9	9.2	3.5
No Desire for Debt	27.6					
No Access to Debt	12.5					
Total Borrowers	59.8	75.1	71.6	10.9	10.5	7.0
Bank Debtors 0-50UF	5.6	77.0	50.6	16.1	23.2	10.1
Bank Debtors 50-200UF	6.1	163.4	44.4	28.5	21.6	5.6
Bank Debtors 0-200UF	11.7	122.0	47.3	22.6	22.3	7.8
Non-Bank Debtors 0-50UF	14.1	64.5	56.6	14.8	16.4	12.2
Non-Bank Debtors 50-200UF	3.7	185.2	45.0	16.3	24.1	14.7
Non-Bank Debtors 0-200UF	17.8	89.6	54.2	15.2	18.0	12.6
		EFH 2014				
Banks	10.8	164.8	36.3	38.9	19.5	5.3
Banks and Retail Stores	16.8	185.7	42.4	30.9	20.4	6.3
Retail Stores	26.8	28.5	85.2	6.5	5.6	2.8
Unions	5.7	63.4	27.8	38.4	24.4	9.4
Other Debts	5.9	264.1	14.6	82.7	2.1	0.6
No Desire for Debt	23.2					
No Access to Debt	10.8					
Total Borrowers	66.0	112.5	55.0	27.5	12.9	4.5
Bank Debtors 0-50UF	5.4	93.7	31.0	35.3	29.2	4.6
Bank Debtors 50-200UF	6.2	194.9	26.8	42.0	22.0	9.2
Bank Debtors 0-200UF	11.6	147.7	28.8	38.9	25.4	7.0
Non-Bank Debtors 0-50UF	13.7	92.5	39.6	32.7	20.0	7.7
Non-Bank Debtors 50-200UF	4.3	219.4	17.7	50.8	27.2	4.3
Non-Bank Debtors 0-200UF	17.9	121.7	34.5	36.9	21.7	6.9

All the values are in percentage points, except *a*) which is in UF.

[a] Note that each household can have several loans of each type, therefore its overall consumer debt can be above 50 UF or above 200 UF even if it does not have any loan of 0–50 or 0–200 UF.

5) households with Other Loans (loans at car lenders, pawnshops, informal loans), 6) households with No Desire for Debt, and 7) households with No Access to Debt (either because their loan applications were rejected or because they expected the applications to be rejected). Since these borrower categories are mutually exclusive, their sum captures 100% of the sample. The EFH survey also has information on the motives why borrowers took their loans[5]

Table 1 summarizes the share of each borrower type as a percentage of the total household population, the total consumer debt amount per household, and the share that each loan motive represents as a percentage of the total consumer loan amount of each borrower type. The major lenders in Chile are Banks and Retail Stores, with 10.8%, 26.8% and 16.8% of the Chilean households in 2014 having loans with only Banks, with only Retail Stores, and with both Banks and Retail Stores, respectively. Also, 23% of the Chilean households have no consumer debt because they wish so, while over 10% do not have access to consumer loans although they would wish so. Although Retail Stores have more customers than Banks, their loan amounts are much smaller than for other lender types (such as Banks, Unions and Other Debts). In 2014 the mean debt of a borrower with Retail Stores is below 30 UF, while the mean debt of Bank, Union and Other Debt borrowers is above 150 UF, 50 UF and 250 UF, respectively. Therefore Banks capture around 60% of the total amount of the consumer loan market in Chile, even with fewer customers than Retailers.

The EFH survey includes measures of the households' delinquency behavior for each loan since 2010. Before 2010 the EFH survey recorded only a rough measure of whether the household was delinquent on any consumer loan in the previous year, but it did not measure delinquency on a loan-by-loan basis. For the case of credit cards there is not a standard measure of delinquency, since lenders can choose to turn the unpaid fraction of the credit as a revolving debt for the next month. However, the survey records whether households were unable to pay the minimum amount required by their credit cards, which is a rough measure of payment difficulties. Table 2 summarizes the delinquency and credit card payment difficulties in 2011 and 2014. The riskiest borrowers are those with major loans in Retail Stores or with both Banks and Retail Stores, while borrowers with Unions and Other Debts have lower delinquency rates. The consumer delinquency risk fell between 2011 and 2014 (after the 2013 interest rate cap law was introduced) for all types of borrowers.

Table 1 and 2 show some evidence that the interest rate ceiling law of 2013 affected the loan market. Note that the overall number of consumer borrowers increased from 59.8% to 66% of

different interest rates according to its maturity and loan amount, but the same offer must be given to all borrowers). However, unions have the advantage that the credit can be paid directly from a fraction of the wage transfers of the employer, therefore unions will receive some payment even if the borrower chooses to engage in strategic default.

[5] The loan purposes are classified under 13 motives: 1) "Purchase of articles for the home and living expenses", 2) "To purchase clothes", 3) "To buy a vehicle or other means of transport, maintenance and repair expenses of vehicles", 4) "Vacations", 5) "To finance a business or professional activity", 6) "For investment in financial assets", 7) "To refurbish or renovate the residence", 8) "For education purposes", 9) "To purchase real estate assets", 10) "To provide funds or make a loan to another person or relative", 11) "To pay previous debts or consolidate other consumption debts", 12) "Medical treatment", 13) "Other". To summarize the loan motives in a better way, I aggregate the results into 4 larger categories, with category 1 being "Current consumption" (which aggregates purposes 1, 2, 13), category 2 being "Durable goods and investments" (which aggregates purposes 3 to 10), category 3 being "Pay other debts" (which includes purposes 11) and category 4 being "Health" (which includes purpose 12). Vacations represent an infrequent expenditure and a large item in households' budgets, therefore these are financed and classified as semi-durable expenditure goods for measurement purposes (United Nations, 2018), (Madeira, 2015b).

Table 2
Delinquency rates by borrower type.

Borrower type	Consumer debt delinquency (any loan)		Banks' consumer loan delinquency[a]		Credit card payment below minimum[a]	
	≥ 1 month	≥ 3 months	≥ 1 month	≥ 3 months	Banks	Retail Stores
EFH 2011						
Banks	19.7	12.1	19.3	11.2	8.7	
Banks and Retail Stores	22.5	14.3	20.9	12.7	14.0	18.2
Retail Stores	27.3	17.1				23.6
Unions	7.5	5.1	20.0	19.5	7.1	22.4
Other Debts	8.8	5.2	24.3	10.3	6.3	16.7
EFH 2014						
Banks	11.5	4.8	12.8	5.3	2.3	
Banks and Retail Stores	13.2	7.4	11.5	6.6	2.1	8.7
Retail Stores	15.6	7.8				10.8
Unions	6.8	4.0	16.3	7.4	3.8	6.5
Other Debts	3.1	1.3	3.9	3.1	1.3	1.4

All values are in percentage points.

[a] Note that the mutually exclusive categories of the borrowers are based on their largest debt amount. Therefore borrowers with their largest loans in Unions and Retail Stores may also have small loans and credit cards with Banks or Retail Stores.

the population between 2011 and 2014, while the average consumer debt also increased in real terms from 75 to 112 UF. However, the number of Bank Debtors with loans between 0–200 UF decreased slightly from 11.7% to 11.6%, while the number of Non-Bank debtors with 0–200 UF loans increased slightly from 17.8% to 17.9%. The loan motivations also changed significantly between 2011 and 2014, with the "Consumption" motive decreasing while the motive "Durables/Investments" increased among all borrower types. The motive of "Consumption purchases" for the total borrowers fell from over 70% of the consumer debt in 2011 to just 55% in 2014, while the motive of "Durables/Investments" increased from 10.9% to 27.5% and the motive of "Pay other debts" increased slightly from 10.5% to 12.9%. Therefore the 2013 interest rate ceiling law seems to have limited the growth of consumer loans between 0–200 UF (while loans of other amounts increased substantially), which affected mostly small loans destined to ordinary "Consumption" needs. Note that this same pattern would be clearly observed if Table 1 used the 2007 and 2017 EFH waves to compare the consumer borrowers before and after the 2013 law (results available upon request). Finally, Table 2 shows that the delinquency behavior (whether in terms of 30 or 90 days in arrears) for every loan type decreased between 2011 and 2014, which is consistent with the hypothesis that the 2013 legislation excluded some of the riskiest borrowers from the consumer credit market.

2.3. The matched Chilean EFH survey data and banking administrative records

The six EFH survey waves (2007, 2008, 2009, 2010, 2011, 2014) covered 12,271 urban households. These are cross-sectional surveys, with a small fraction of households participating in rotating samples and being interviewed for two different survey years. Overall, only 3505 households were interviewed for two different surveys and the household members may differ across the two interviews (due do divorce, separation, death or simply because they left to form a different household). Therefore the EFH does not have a strong panel data component.

To obtain a more accurate view of the evolution of each household's indebtedness over time, the Central Bank of Chile and the Chilean Banking Authority (SBIF) decided to build an EFH-SBIF dataset, where each survey respondent's information is linked to its monthly banking credit contracts over the period between January 2003 and December 2015. The link between each household's main member[6] on the survey dataset and its entire history of banking debt is made by using the Chilean national identity numbers. Chileans make regular use of their national id to obtain discounts in the supermarket chains, apply for loans, or to use the health system, therefore participating households are comfortable in providing their information during the survey interview (Madeira et al., 2019). This matched dataset has a few limitations: i) the universe is limited only to individuals who have ever applied for or used a banking product (such as a consumer loan, mortgage, credit card, or current account); ii) the monthly loan history is limited to banking loans of different types (consumer installment loans, credit cards, lines of credit, student loans, and mortgages), therefore it does not include loans from retail stores, unions or other lenders such as car dealers; and iii) the matched EFH-SBIF data provides information on the current loan amount, the original loan amount at the time the contract was made, the total payment made due to that loan in a certain month and whether the loan is in delinquency or not, but it does not include information on the renegotiation of loans[7], interest rates or on other fees and costs charged.

In the matched EFH-SBIF dataset there are 6242 households with monthly banking credit information between 2003 and 2015. In this study I focus on the banking loan access of 4118 households which contracted a banking consumer loan below 200 UF at some time in their history. This target universe has some limitations. For instance, we are unable to study the credit access of the flow of borrowers who are just starting their credit history, due to the small sample size. Since each household's banking loan history covers 156 periods, this makes for a dataset with a total of 642,408 observations (4118 households times 156 months). Due to the over-representation of richer families in the EFH survey, all the results in this paper use population weights (Madeira, 2019a).

The EFH survey has limited data on income volatility. For this reason I use the unemployment risks of the EFH workers based on the mean statistics for workers with similar characteristics from the Chilean Employment Survey (ENE), conditional on their education, age, industry, income quintile and region (Madeira, 2015a).

[6] This is the member with the greatest financial knowledge or the highest income in the family.

[7] The SBIF banking loan dataset is not a panel data of loans. It lists all the loans of each individual in a given month, but it is not possible to connect each loan with loans in other periods. If an individual renegotiates a loan, then it is not possible to establish whether the new loan was the result of a renegotiation of a prior loan.

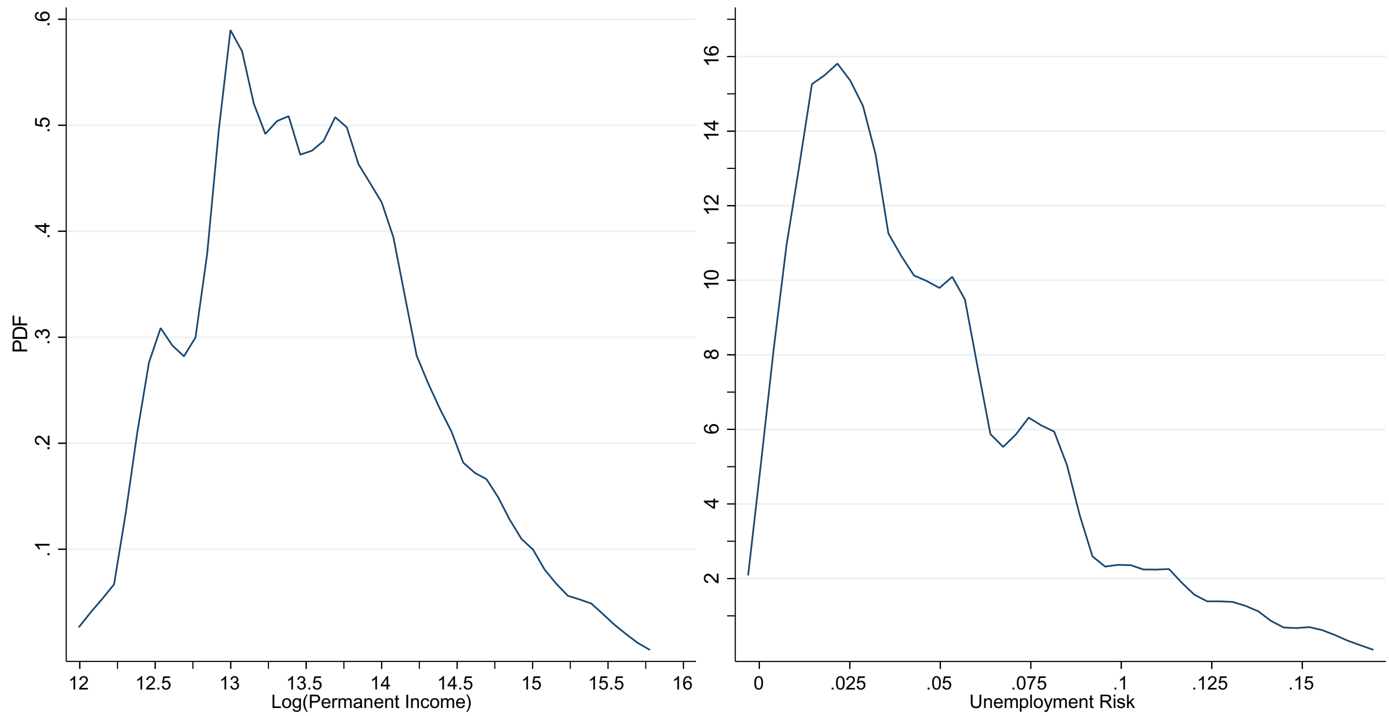

Fig. 2. Cross-sectional distribution (pdf kernel density) of the Households' Permanent Income (monthly, log) and Unemployment Risk of the EFH-SBIF sample in the year 2013.

Each household i's permanent income is obtained as the sum of its non-labor income (a_i) plus the labor earnings of each labor force member k: $P_{i,t} = a_i + \sum_k (Y_{k,i}(1 - u_{k,i,t}) + Y_{k,i}RR_{k,i}u_{k,i,t})$, where $Y_{k,i}$ is worker k's earnings when in employment, $u_{k,i,t}$ is its probability of being in an unemployment spell, and $RR_{k,i}$ is its replacement ratio of income during unemployment relative to the earnings while working (Madeira, 2015a), (Madeira, 2018). Also, the unemployment risk of the household is estimated as a weighted average of the unemployment risk of its labor force members, using each member's permanent income as a weight: $\bar{u}_{i,t} = \sum_k \frac{P_{k(i),t}}{P_{i,t} - a_i} u_{k(i),t}$.

Note that both the household's permanent income and its unemployment risk differ over time, because the unemployment probabilities of different workers change with each period (at a year-quarter frequency). Also, since the permanent income is the expected value of the income between working or not, then it differs from the household's current income.

Fig. 2 shows the pdf of the log monthly permanent income ($\ln(P_{i,t})$) and unemployment risk ($\bar{u}_{i,t}$) for the year 2013 (the year of the new law) of the 4118 household sample of our study. There is a significant heterogeneity among banking borrowers in Chile, with the logarithm of the permanent income ranging between 12 and 15.75 and unemployment risk ranging between almost 0 to above 15% for some borrowers. Therefore our sample includes many types of borrowers, from those with high income and low unemployment to those with lowest income and higher unemployment risk.

3. Empirical strategy

3.1. Modeling the discrete outcome of obtaining a loan

The empirical strategy implies classifying households according to how close their risk-adjusted interest rates ($tar^S_{i,t}$, with tar being the abbreviation of "tasa ajustada por riesgo" in Spanish) are from the Maximum Interest Rate (TMC^S_t, with TMC being the abbreviation of "Tasa Máxima Convencional" in Spanish) at time t for each loan size segment S (with S being 0-50UF or 50-200UF loan amounts). The intuitive mechanism of the identification strategy is that households who are slightly above and slightly below the TMC are two similar groups, having similar risk profiles and reacting in the same way to macroeconomic shocks, but these groups are treated differently by lenders because the law prevents them from giving credit slightly above the TMC.

Each household i in period t is classified in four groups according to whether their risk-adjusted interest rate ($tar^S_{i,t}$) is within or outside a Bandwidth interval (BW) from the Maximum Legal Interest Rate (TMC^S_t): Well above the TMC ($1(tar^S_{i,t} > TMC^S_t + BW)$); Slightly above the TMC ($1(tar^S_{i,t} \in (TMC^S_t, TMC^S_t + BW])$); Almost in the TMC ($1(TMC^S_t - BW \leq tar^S_{i,t} \leq TMC^S_t)$); and Well Below the TMC ($1(tar^S_{i,t} < TMC^S_t - BW)$). This classification depends crucially on how big the bandwidth is, therefore the next section shows the main results with a bandwidth BW of 5% first and then with a tighter value of 2.5%.

Using dummies for the distance to the TMC and other observable characteristics $X_{i,t}$, it is possible to estimate a discrete choice model (such as a probit or logit) for the probability of whether a household i had or not a new consumer loan ($NC_{i,t} = 1$ or 0):

1) $\Pr(NC_{i,t} = 1 \mid X_{i,t}, \text{dummies for distance to } TMC^S_{i,t}) = \Lambda(\theta(X_{i,t}, distance\_TMC^S_{i,t}))$, with Λ representing the traditional logit functional form ($\frac{e^{\theta x}}{1+e^{\theta x}}$).

It is possible that households' debts above or below the interest rate caps (TMC^S_t) are a function of factors which affect both the risk-adjusted interest rate profile ($tar^S_{i,t}$) and the demand for credit ($X_{i,t}$). For instance, age and education could affect financial knowledge and also affect delinquency risk. Aggregate shocks can also affect the demand for credit and the risk profile, such as a labor market expansion in Chile after 2010 and a reduction in economic growth in 2014 and 2015. However, the key identification assumption (Lee and Lemieux, 2010) is that the interest rate cap ($distance\_TMC^S_{i,t}$) is the only discontinuous factor affecting credit in a nearby bandwidth around the cap ($TMC^S_t \pm BW$). Financial knowledge (as given by age and education), delinquency risk (as given by income and unemployment) or aggregate shocks (labor market expansions, shocks to banks' supply of credit) can affect households' demand for credit. However, the interest rate cap creates a discontinuous treatment between those slightly below and above the cap, therefore this discontinuous effect can be consistently estimated even after including all the other variables that affect the households (such as $X_{i,t}$) and all other aggregate shocks (such as time dummies).

In the empirical estimation the control vector $X_{i,t}$ includes variables such as time fixed-effects, age bracket dummies of the household head (20-25 years, 25–30 years, ...), the household's permanent income ($\ln(P_{i,t})$) and a quadratic function of the risk-adjusted interest rate ($tar^S_{i,t}$). The control vector can be interpreted as factors affecting household demand for credit. One should expect that the risk-adjusted interest rate is a proxy for the liquidity constraints of the household (Attanasio et al., 2008), (Attanasio and Weber, 2010), since households with higher risk profiles experience more expenditures and income shocks and typically face more adverse events that lead them to demand credit. I model the demand for credit as a quadratic function of the $tar^S_{i,t}$, since one expects that riskier households demand more credit but with a decreasing marginal effect for each unit of additional risk. Also, one could expect that households with higher permanent income may demand more credit, because they can afford more needs and may have more complex finances.

3.2. Calibrating the households' risk-adjusted interest rates

The risk-adjusted interest rate $tar^S_{i,t}$ is obtained in each period as the rate that gives lenders an expected zero profit between making the loan or not. The costs of making a loan are a fixed administrative cost (AC^S) and the opportunity cost which is equal to the capital (standardized as one) and the banking sector's one-year deposit rate (DR_t): $(1+AC^S+DR_t)$. The gains of making a loan are the capital plus the interest rate $(1+tar_{i,t})$ weighted by the probability of repayment $(1-\Pr(Df_{i,t}=1))$ and a fraction of the amount owed $(1-LGD)$ given by the Loss-Given-Default (LGD) parameter, weighted by the probability of loan delinquency ($\Pr(Df_{i,t}=1)$). Equating expected gains to costs then gives us the risk-adjusted interest rate $tar_{i,t}$:

2) $(1+AC^S+DR_t)=(1+tar^S_{i,t})[(1-\Pr(Df_{i,t}=1))+(1-LGD)\times\Pr(Df_{i,t}=1)]$

$$\Rightarrow tar^S_{i,t}=\frac{AC^S+DR_t+LGD\times\Pr(Df_{i,t}=1)}{1-LGD\times\Pr(Df_{i,t}=1)}.$$

The calibration of the $tar^S_{i,t}$ uses a Loss-Given-Default parameter equal to fifty percent in annualized rate ($LGD=0.50$, which is similar to parameters used in studies for Chile and the US, see Madeira, 2019b). The administrative cost parameter is set as 7.5% for loans of larger amounts ($AC^{S=50-200UF}=0.075$) and 10% for loans of smaller amounts ($AC^{S=0-50UF}=0.10$), which represents the average non-capital costs reported in the Chilean banking system for loans of these amounts (Madeira, 2018). The reason why loans of smaller amounts have a larger administrative cost as a percentage is due to fixed-cost fees such as checking the borrowers' credit history or the time spent screening a loan application. However, results remain qualitatively similar even if one repeats the empirical analysis with six different calibrated values of $AC^S\in\{6\%, 8\%, 9\%, 10\%, 11\%, 12\%\}$.

Lenders estimate borrowers' risk from a delinquency regression model for whether households missed any contract payment over the last 12 months ($Df_{i,t}=1$), using the information set $Z_{i,t}$: $\Pr(Df_{i,t}=1\mid Z_{i,t})=\Phi(\beta Z_{i,t})$, with $Z_{i,t}$ including both fixed demographic characteristics and time-varying risk-factors. For the empirical estimation I choose $Z_{i,t}=\{$ Santiago Metropolitan resident or not, number of household members, gender, marriage status, age and education dummies of the household head, household's log-income, consumer debt to annual permanent income ratio $\frac{D_{i,t}}{12\times P_{i,t}}$, total debt service to monthly income $\frac{DS_{i,t}}{Y_{i,t}}$, and the household's unemployment probability $\bar{u}_{i,t}$ }. $\frac{D_{i,t}}{12\times P_{i,t}}$ can be understood as a measure of household solvency, while $\frac{DS_{i,t}}{Y_{i,t}}$ measures households' liquidity risk due to high immediate payments.

Table 3
Probit Regression of the Delinquency risk model for the pooled cross-section waves of 2007 to 2011, the 2011 wave and the 2014 wave.

$\Pr(Df_{i,t}=1\mid z_{i,t})$	2007-11	2011	2014
Log Income $\ln(Y_{i,t})$	-0.144***	-0.163***	-0.110***
	(0.0240)	(0.0442)	(0.0416)
$\frac{D_{i,t}}{12\times P_{i,t}}$	0.915***	0.746***	1.634***
	(0.132)	(0.239)	(0.153)
$\frac{DS_{i,t}}{Y_{i,t}}$	0.439***	0.747***	0.131
	(0.151)	(0.243)	(0.180)
Number of Members	0.104***	0.0898***	0.123***
of the Household	(0.0131)	(0.0220)	(0.0226)
Age (years)	-0.00680***	-0.0115***	-0.00881***
	(0.00158)	(0.00273)	(0.00247)
Household Head	-0.174***	-0.158	-0.0601
is a Married Man	(0.0652)	(0.125)	(0.110)
Household Head	0.0845	0.0349	0.0496
is Female	(0.0603)	(0.106)	(0.0906)
Technical education	0.0495	-0.273**	0.000762
	(0.0666)	(0.118)	(0.0961)
College education	-0.202***	-0.471***	-0.321***
	(0.0622)	(0.110)	(0.0904)
Unemployment risk $\bar{u}_{i,t}$	2.073***	3.208***	0.771
	(0.488)	(0.787)	(0.888)
Metropolitan Region	-0.0843*	0.0148	0.0246
	(0.0506)	(0.0800)	(0.0718)
Dummy for County	0.0419	0.0330	0.0140
of High Income	(0.0597)	(0.0945)	(0.104)
Constant	0.596*	1.062*	0.116
	(0.329)	(0.598)	(0.578)
N (Observations)	5696	2111	2892

Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

Table 3 shows the estimates of the delinquency risk model. It is important for the calibration of the $tar^S_{i,t}$ that the risk model includes the data before 2013. The reason is that after 2013 the legislation may have excluded some high-risk borrowers from the credit market, but these borrowers represent exactly the risk that one wants to include in the model. Therefore the empirical model is estimated with the Chilean Household Finance Survey (EFH) for three sample options, using all its waves prior to 2014 (waves of 2007, 2008, 2009, 2010 and 2011), just the wave of 2011 (the last data wave before the 2013 legislation), and the 2014 wave. The estimates show that delinquency is correlated with youth, lower education and larger families, lower income, higher debt amounts ($\frac{D_{i,t}}{12\times P_{i,t}}$) and debt service ($\frac{DS_{i,t}}{Y_{i,t}}$), and unemployment risk ($\bar{u}_{i,t}$). The coefficients for unemployment ($\bar{u}_{i,t}$) and debt service liquidity risk ($\frac{DS_{i,t}}{Y_{i,t}}$), however, are not statistically significant in 2014 (after the legislation), which could happen because some high risk borrowers were no longer having credit after the law. The calibration of the risk-adjusted interest rates ($tar^S_{i,t}$) of the following sections uses the risk model ($\Pr(Df_{i,t}=1\mid z_{i,t})$) from the waves 2007 to 2011, but the results remain similar if one uses the calibration coefficients from the wave 2011 only. Note that the risk-adjusted interest rates ($tar^S_{i,t}$) are time-varying for each household, since unemployment risk changes over time for each worker (according to its education, age, industry, income quintile and region). The distribution of risk-adjusted interest rates is realistic in the sense that it coincides with the mode interest rates of the main consumer loan products of the Chilean banks (Madeira, 2018).

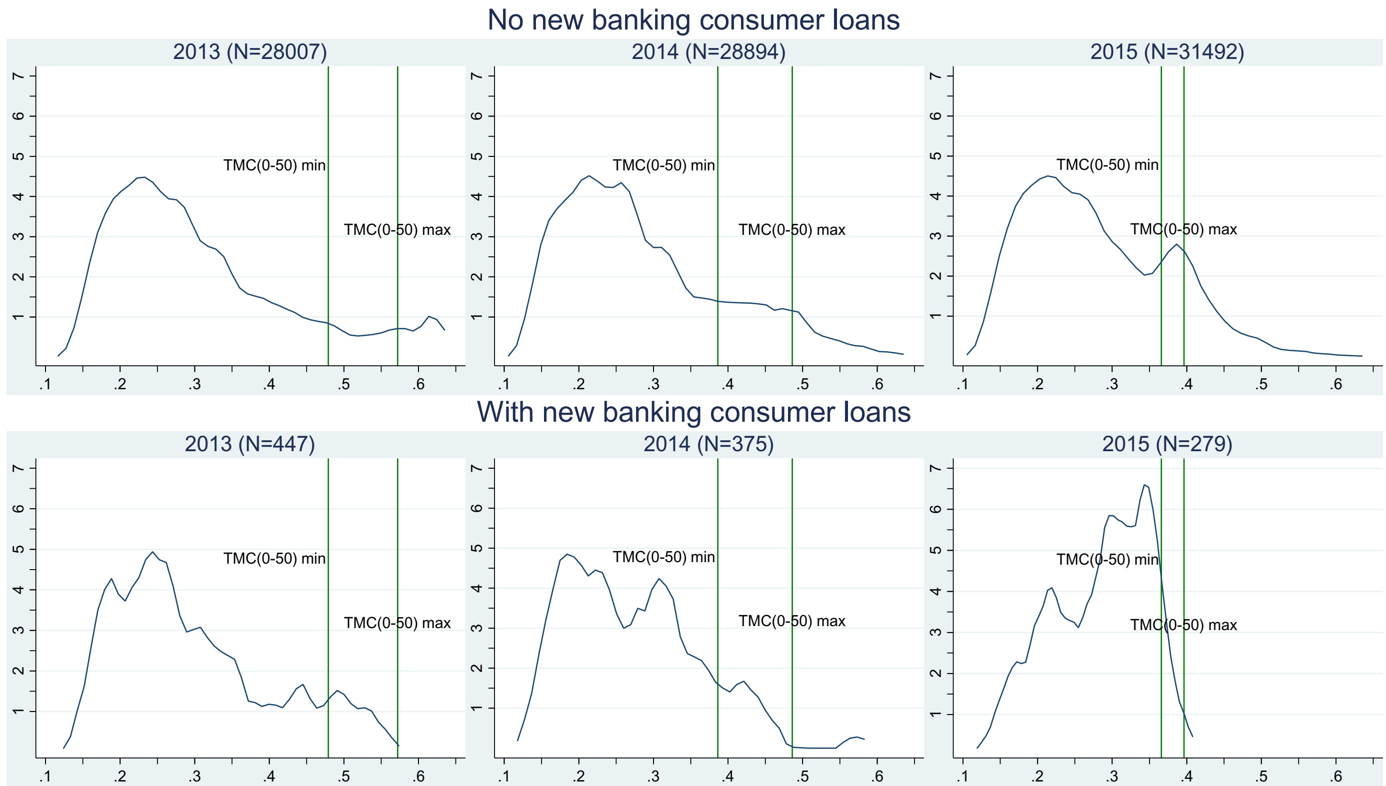

Fig. 3. Distribution (pdf) of the Risk adjusted interest rates (0–50 UF segment) in 2013, 2014 and 2015. Minimum and Maximum values for the TMC 0–50 UF of each year in vertical lines.

4. Results

Fig. 3 shows the distribution of the risk-adjusted interest rates ($tar^S_{i,t}$) for the segment of smaller consumer loans ($S = 0 - 50UF$)[8] for the years 2013, 2014 and 2015. All the households in this sample have obtained at least one banking consumer loan contract during the period 2003 until 2015. Some of these borrowers obtain a new banking consumer loan contract ($NC_{i,t} = 1$) while others do not ($NC_{i,t} = 0$). The year 2013 represents a period almost unaffected by the new legislation (except for the last 15 days of the year), while 2014 was a period in which the Maximum Legal Interest Rate for the loans of 0-50UF was gradually lowered from 47.9% to 40.6%, and the year 2015 was finally the year in which the Maximum Legal Interest Rate was fully implemented with its value lowering from 38.6% until 36.4%[9]

The distribution of $tar^S_{i,t}$ for the sample of borrowers who received a new loan has a range between 10% and 55% in the year 2013, with a substantial proportion of borrowers having risk-adjusted interest rates between 40% and 55%. However, in 2014 there are few new loans with risk-adjusted interest rates above 45% and in 2015 there are almost no borrowers with risk-adjusted interest rates above 36%. This is consistent with the Maximum Legal Interest Rate gradually excluding the high-risk borrowers from access to new loans. Fig. 3 also shows that the risk-adjusted interest rates in 2014 and 2015 fell a bit relative to 2013, which can be explained by a strong reduction in unemployment rates during this period (Madeira, 2015a). However, Fig. 3 also shows that the risk-adjusted interest rates for the sample who did not get a new consumer loan always have a substantial proportion of values between 40% and 65% in every year, therefore the results cannot be entirely explained by a general reduction in the risk for all borrowers.

Table 4 shows the main estimates of the impact on new loans, according to whether households are slightly close or above the Maximum Legal Interest rate (equation 1 in the previous section): $\Pr(NC_{i,t} = 1) = \Lambda(\theta(X_{i,t}, distance\_TMC^S_{i,t}))$. All regressions include age bracket dummies of the household head (20–25 years, 25–30 years, ...), household permanent income ($\ln(P_{i,t})$) and a quadratic function of the risk-adjusted interest rate ($tar^S_{i,t}$). These regressions help to control for other characteristics of the household that affect its demand for credit. There are five different models estimated: the first and third regressions only include a time dummy for the entire period before the law, while the second, fourth and fifth model include time dummies for each month-year period. Furthermore, the third and fourth regressions also include fixed-effects for each household. Finally, the fifth version of the model has both time fixed-effects and random effects for each household. The model can be estimated with household fixed-effects, because each borrower's risk changes over time (due to time-varying changes in unemployment risk and permanent income) and the maximum legal interest rate also fluctuates over time (therefore some high risk-borrowers can have credit in one period and then lose credit access). The logit model is used in all regressions, because it is consistent with either household or time fixed-effects, while other non-linear estimators such as the probit are inconsistent with fixed-effects (Wooldridge, 2010).

The regressions in Table 4 show that being slightly above or far above the Maximum Legal Interest Rate (TMC in Spanish, due to the text of the Chilean law) has a strong negative impact on the probability for getting a new banking consumer loan. Furthermore, it does not matter much if one is just slightly above or far above the law in order to lose credit, which should be expected if the

[8] Remember, however, that the risk-adjusted interest rates for the larger loan segment (50–200 UF) only differ in terms of the administrative cost parameter (which is slightly lower, being 7.5% instead of 10%).

[9] In the same period the Maximum Legal Interest rate for loans of 50-200UF was lowered from 45.9% to 38.6% in 2014 and from 36.6% to 29.7% in 2015.

Table 4
Probability (Logit) of a new banking consumer loan (2003–2015, monthly).

Logit ($NC_{i,t}=1$)	M1	M2	M3	M4	M5
Well above $TMC^{0-50}_{i,t}$	-2.430***	-2.742***	-5.958***	-5.996***	-3.690***
	(0.229)	(0.231)	(0.261)	(0.261)	(0.176)
Slightly above $TMC^{0-50}_{i,t}$	-2.823***	-3.007***	-6.027***	-6.047***	-3.667***
	(0.217)	(0.215)	(0.235)	(0.234)	(0.163)
Almost in $TMC^{0-50}_{i,t}$	0.401***	0.217***	0.0644	-0.0339	0.0494
	(0.0778)	(0.0800)	(0.0616)	(0.0621)	(0.0554)
Dummy Before the Law_t	0.578***		0.0951*		
	(0.0603)		(0.0514)		
$tar^{0-50}_{i,t}$	-11.19***	-1.981*	-7.853***	14.18***	-7.208***
	(1.147)	(1.194)	(1.594)	(1.649)	(0.930)
$(tar^{0-50}_{i,t})^2$	16.73***	7.256***	2.800	-19.99***	14.41***
	(1.783)	(1.913)	(2.302)	(2.350)	(1.453)
$\ln(P_{i,t})$	-0.0341	0.151***	-0.123	0.135	0.142***
	(0.0275)	(0.0270)	(0.204)	(0.206)	(0.0224)
Other controls:	Constant, Household head's 5-year age dummies				
Fixed effects: Time		Yes		Yes	Yes
Fixed effects: Household			Yes	Yes	RE
N (Observations)	374,710	374,710	374,379	374,379	374,710
Nr of Households	4118	4118	3994	3994	4118
	Average marginal effects				
Well above $TMC^{0-50}_{i,t}$	-0.047***	-0.050***	-0.238*	-0.173*	-0.088***
Slightly above $TMC^{0-50}_{i,t}$	-0.054***	-0.055***	-0.241*	-0.175*	-0.087***
Almost in $TMC^{0-50}_{i,t}$	0.008***	0.004***	0.003	-0.001	0.001
$\ln(P_{i,t})$	-0.001	0.003***	-0.005	0.004	0.003***
	Conditional marginal effects (at the means)				
Well above $TMC^{0-50}_{i,t}$	-0.036***	-0.033***	-0.061*	-0.086*	-0.060***
Slightly above $TMC^{0-50}_{i,t}$	-0.042***	-0.036***	-0.062**	-0.086**	-0.060***
Almost in $TMC^{0-50}_{i,t}$	0.006***	0.003***	0.001	-0.001	0.001
$\ln(P_{i,t})$	-0.001	0.002***	-0.001	0.002	0.002***

Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

legislation is effective and lenders base their decisions mostly on risk profiles similar to the one used in our model. Finally, being slightly below the Maximum Legal Interest Rate has no negative effect on receiving a new banking loan, as one would expect. These results are robust to including time fixed-effects (which control for any unspecified aggregate shock) and household fixed or random effects (which control for fixed unobservable characteristics of each family). The regressions (except for model M4) also show that the demand for credit is quadratic in the risk-adjusted interest rate, which is to be expected: demand for a consumer credit increases for borrowers with a higher risk profile, although with a declining marginal effect[10]

Table 4 also reports the Average Marginal Effects (AME) and the Conditional Marginal Effects with the control variables at the means (CME) of each model for the dummy variables of the distance to the TMC and the household permanent income. The AME and CME estimates for both the "Well above the TMC" and the "Slightly above the TMC" dummies are similar when each model is considered separately. Note that the AME estimates are always a bit larger than the CME ones, which shows that the average consumer is less sensitive to the interest rate ceiling legislation than the average across all consumers. This makes sense because the average impact across all consumers includes the effects on lower income and more desperate borrowers. The AME estimates differ substantially across models, with the effect of being above the interest rate ceiling (whether well above or slightly above) ranging from 4.7% to 24.1%. However, the AME values of 17% and 24% only appear with the models that have household fixed-effects (models M3 and M4), which give higher weight to the observations of households that change their decisions more frequently (Wooldridge, 2010). Also, the AME and CME estimates for the household fixed-effects models (M3 and M4) have larger standard-deviations and are statistically significant only at a 10% level. For the CME estimates the models report a range of values between 3.6% to 8.6%.

As a robustness check I also estimate three models with additional controls that affect the loan decision of the borrower and the aggregate credit environment. As additional controls at the household level I include the time period (in months) in which the household took its last consumer loan, the highest value of its banking consumer debt in the previous periods, and the highest number of missed payments in the past[11] To represent the aggregate credit environment I use the Senior Loan Officers Survey (SLOS) for the Chilean banking system, which is a quarterly survey of senior loan managers of commercial banks[12] The survey answers are used to build two perception indicators of

[10] In the case of model M4 the two coefficients for the quadratic function of the risk-adjusted interest rate reverse their sign. This difference could be due to the model M4 being over-parameterized, since it includes a large number of coefficients by having both time and household fixed-effects.

[11] This goes from 0 to 7 payments, since afterwards banks typically move a loan to debt collection.

[12] The Chilean SLOS survey is similar to the ones implemented in the USA, Japan, Canada, Europe and other countries. The SLOS asks specifically about the perceptions of how market conditions changed compared to the previous quarter, in terms of supply lending standards (with five options: strongly loosened, moderately loosened, unchanged, moderately tightened, strongly tightened) and credit demand (with five options: strongly higher, moderately higher, unchanged, moderately weaker, strongly weaker). Bank managers answer their perceptions in terms of different supply factors and demand factors for each market segment: corporate loans (for large companies, small and medium companies, and the construction sector), consumer loans, and household mortgages. Consumer loans' supply conditions are measured for the following aspects: Risk of the loan portfolio (delinquency, loan loss provisions), Competition from other banks and non-banking lenders, Regulatory changes, Loan terms (which includes the maximum size of the loan and credit lines, highest maturity, loan spread relative to banks' funding costs, lowest credit score standards, minimum required payment relative to total revolving debt,

Table 5
Probability (Logit ($NC_{i,t}=1$)) of a new consumer loan with additional supply and demand controls (2003–2015, monthly).

Exogenous variables	M6	M7	M8	Exogenous variables	M6	M7	M8
Well above $TMC^{0-50}_{i,t}$	-2.310***	-2.938***	-2.866***	Banks' consumer loan supply$_t$	0.405***	0.156**	
	(0.230)	(0.233)	(0.234)		(0.0662)	(0.0701)	
Slightly above $TMC^{0-50}_{i,t}$	-2.750***	-3.150***	-3.074***	Banks' consumer loan demand$_t$	-0.399***	-0.354***	
	(0.220)	(0.222)	(0.216)		(0.0466)	(0.0493)	
Almost in $TMC^{0-50}_{i,t}$	0.450***	0.201***	0.181**	Last consumer loan (months)$_{i,t}$		-0.0204***	-0.0183***
	(0.0801)	(0.0780)	(0.0795)			(0.00122)	(0.00124)
Dummy Before Law$_t$	0.692***	0.0171		Highest past consumer debt$_{i,t}$		1.5e-08***	2.0e-08***
	(0.0618)	(0.0687)				(4.60e-09)	(4.17e-09)
$tar^{0-50}_{i,t}$	-10.61***	-12.60***	-1.839	Highest nr of past missed payments$_{i,t}$		-0.161***	-0.155***
	(1.148)	(1.174)	(1.223)			(0.0111)	(0.0115)
$(tar^{0-50}_{i,t})^2$	15.58***	20.54***	7.637***	$\ln(P_{i,t})$	-0.0319	-0.0576**	0.119***
	(1.803)	(1.838)	(1.951)		(0.0275)	(0.0278)	(0.0272)
Other controls:	Constant, 5-year age dummies			Fixed Eff.: Time	No	No	Yes
N / Households	374,710 / 4,118			FE: Household	No	No	No
	Average marginal effects				Conditional marginal eff.: at means		
Well above $TMC^{0-50}_{i,t}$	-0.044***	-0.056***	-0.052***	Well above TMC	-0.034***	-0.035***	-0.029***
Slightly above $TMC^{0-50}_{i,t}$	-0.053***	-0.060***	-0.055***	Slightly above TMC	-0.041***	-0.037***	-0.031***
Almost in $TMC^{0-50}_{i,t}$	0.009***	0.004***	0.003**	Almost in TMC	0.007***	0.002**	0.002**
$\ln(P_{i,t})$	-0.001	-0.001**	0.002***	$\ln(P_{i,t})$	-0.001	-0.001**	0.001***

Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

Table 6
Probability (Logit) of a new consumer loan for three different segments of borrowers: those who only used loans between 0-50UF, those who used only 50-200UF loans, and those who used loans of both segment sizes[a] (2003–2015, monthly).

Logit ($NC_{i,t}=1$)	M2 Only 0–50 UF	M5	M2 Only 50–200 UF	M5	M2 Both[b]	M5
Well above $TMC^S_{i,t}$	-2.513***	-3.183***	-3.735***	-3.948***	-2.306***	-3.308***
	(0.482)	(0.350)	(0.513)	(0.364)	(0.297)	(0.243)
Slightly above $TMC^S_{i,t}$	-2.440***	-2.691***	-4.592***	-4.585***	-2.941***	-3.555***
	(0.395)	(0.269)	(0.608)	(0.520)	(0.288)	(0.228)
Almost in $TMC^S_{i,t}$	0.540***	0.423***	0.0777	0.0134	0.168	-0.0989
	(0.148)	(0.109)	(0.175)	(0.118)	(0.117)	(0.0794)
$tar^S_{i,t}$	-3.202	-10.81***	-2.011	-8.862***	0.369	-4.309***
	(2.545)	(1.717)	(1.920)	(1.409)	(1.792)	(1.325)
$(tar^S_{i,t})^2$	7.006*	18.33***	9.587***	19.39***	3.421	9.772***
	(3.871)	(2.663)	(3.319)	(2.418)	(2.905)	(2.073)
$\ln(P_{i,t})$	0.0594	0.0459	0.291***	0.265***	0.188***	0.137***
	(0.0609)	(0.0377)	(0.0490)	(0.0392)	(0.0365)	(0.0317)
Other controls:		Constant, Household head's 5-year age dummies				
Fixed Effects: Time	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects: Household		RE		RE		RE
N	116,196		122,264		136,250	
Households	930		1,397		1,791	
	Average marginal effects					
Well above $TMC^S_{i,t}$	-0.031***	-0.043***	-0.056***	-0.081***	-0.058***	-0.106***
Slightly above $TMC^S_{i,t}$	-0.030***	-0.036***	-0.069***	-0.094***	-0.074***	-0.114***
Almost in $TMC^S_{i,t}$	0.007***	0.006***	0.001	0.0003	0.004	-0.003
$\ln(P_{i,t})$	0.001	0.001	0.004***	0.006***	0.005***	0.004***
	Conditional marginal effects (at the means)					
Well above $TMC^S_{i,t}$	-0.018***	-0.029***	-0.029***	-0.051***	-0.038***	-0.074***
Slightly above $TMC^S_{i,t}$	-0.017***	-0.025***	-0.036***	-0.059***	-0.048***	-0.079***
Almost in $TMC^S_{i,t}$	0.004***	0.004***	0.0006	0.0002	0.0027	-0.0022
$\ln(P_{i,t})$	0.0004	0.0004	0.002***	0.003***	0.003***	0.003***

[a] This sample differs from Table 4 (which uses borrowers of loans from either segment size), because the borrowers of both loans used at least one loan of 0-50UF and one loan of 50–200 UF.
[b] The ceiling (TMC^S) and risk-adjusted rates (tar^S) applied to the sample borrowing in both segments are the same as for the segment of 0–50 UF, since that is the least restrictive TMC rate.
Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

composite supply and demand conditions for each bank, with positive values implying, respectively, looser supply conditions and higher credit demand. The aggregate banking system indicators are given by the sum of each Chilean bank weighted by its market share and with aggregate conditions being the cumulative level until the current period (see Jara et al., 2017, for details). Table 5 shows the logit model estimates with these additional controls. Model M6

number of loans granted to subprime customers). Consumer loans' demand factors measure the following aspects: Income and employment conditions of the borrowers, Ease of substitution between bank and non-bank lending.

has the aggregate banking consumer loans' demand and supply indicators. Model M7 has both the banking aggregate indicators plus the controls for the household's past debt behavior (in terms of the most recent loan taken, largest past debt, and longest delinquency payment period). Neither models M6 nor M7 have time fixed-effects, since the aggregate banking indicators cannot be identified with time dummies for all periods. Model M8 has the time-fixed effects and the controls for the household's past debt behavior, but does not include the banking supply and demand indicators.

The results in Table 5 show that households are more likely to get a new loan when there is a positive shock to banking loan supply, but that probability decreases when there is a positive shock to loan demand (models M6 and M7). This makes sense, since a higher loan supply makes it easier for customers to get a loan, but a higher loan demand could imply that some households have to compete for loans with better customers. In terms of the other controls, models M7 and M8 show that households with a large past debt are more likely to get a new loan, while households that took their last consumer loan a long time ago are less likely to take a new loan now. This could indicate that there are "habit" effects (Attanasio and Weber, 2010) in terms of the households' debt behavior, with some consumers taking loans more frequently and in large amounts. Models M7 and M8 also show that households with a past delinquency history are less likely to get a new banking loan, since banks would be more reluctant to lend to them. Finally, note that the TMC distance dummy' coefficients and their AME and CME effects in models M6, M7 and M8 are relatively close to the same values in models M1 and M2 (Table 4).

Although all models provide similar qualitative results, I take models M2 (with time fixed-effects) and M5 (with time fixed-effects and household random effects) as the baseline regressions, because household fixed-effects exclude consumers who only applied for one credit contract in their history.

Now I analyze separately the two interest rate caps imposed for the loan segments of 0-50UF and 50-200UF. Table 6 shows the estimates of the two main models (M2 and M5) for three mutually exclusive population groups: the consumers who only had loans of 0-50UF during the entire period of 2003 until 2015, those who had only loans of size 50-200UF, and those who have used both kinds of loans. The first two groups are subject to the interest rate ceiling imposed on the segments 0-50UF and 50-200UF, respectively, while the third one is also affected by the interest rate ceiling of 0-50UF since it includes the largest range of affected individuals. The estimates show a similar impact of the interest rate ceiling for all the three groups. People slightly above the interest rate ceiling cap experience a drop in their probability of getting a loan as much as those far above the cap, while people slightly below the cap suffer from no downside effects despite having similar risk profiles. The AME and CME effects are more negative for the borrowers of 50–200 UF loans and even more negative for borrowers of both loan types, therefore the legislation had a higher impact on the borrowers of large loans (which experience a stronger decrease in the legal interest rate cap).

It is possible that the results could be affected by a bandwidth around the legal cap that is too wide (BW=5% in Tables 4, 5 and 6). However, as shown in Table 7, the results are qualitatively similar for each borrower group (all borrowers, those who use loans of 0-50UF, those who use loans of 50-200UF, and those who use both kinds of loans) if one uses a bandwidth of just 2.5% for determining the loans slightly above and below the legal cap restriction. Similar results are found if one uses a bandwidth of just 1% (results available from the author upon request). Another robustness check considers different values for the administrative cost parameter (AC). Table 8 considers the estimation of model M2 (with time fixed effects) with different values of the AC parameter

Table 7
Probability (Logit) of a new consumer banking loan using a bandwidth of 2.5% around the Maximum Legal Interest Rate (2003–2015, monthly).

Logit ($NC_{i,t}=1$)	M2 (BW=2.5%)			
	All	Only 0–50	Only 50–200	Both
Well above $TMC^S_{i,t}$	-2.848***	-3.022***	-3.844***	-2.312***
	(0.192)	(0.393)	(0.426)	(0.235)
Slightly above $TMC^S_{i,t}$	-3.341***	-2.397***	-4.847***	-3.951***
	(0.286)	(0.435)	(1.005)	(0.362)
Almost in $TMC^S_{i,t}$	0.176*	0.382**	0.146	0.236
	(0.0971)	(0.167)	(0.210)	(0.147)
$tar^S_{i,t}$	-2.063*	-4.295*	-2.016	0.681
	(1.194)	(2.522)	(1.864)	(1.766)
$(tar^S_{i,t})^2$	7.781***	9.862***	9.610***	3.054
	(1.892)	(3.775)	(3.109)	(2.819)
$\ln(P_{i,t})$	0.153***	0.0585	0.291***	0.190***
	(0.0269)	(0.0607)	(0.0489)	(0.0364)
Other controls:	Constant, Household head's 5-year age dummies			
Fixed Effects: Time	Yes	Yes	Yes	Yes
Fixed Effects: Household	No	No	No	No
N	374,710	116,196	122,264	136,250
Households	4118	930	1397	1791
	Average marginal effects			
Well above $TMC^S_{i,t}$	-0.052***	-0.037***	-0.058***	-0.058***
Slightly above $TMC^S_{i,t}$	-0.061***	-0.030***	-0.073***	-0.099***
Almost in $TMC^S_{i,t}$	0.003*	0.005**	0.002	0.006
$\ln(P_{i,t})$	0.003***	0.0007	0.004***	0.005***
	Conditional marginal effects (at the means)			
Well above $TMC^S_{i,t}$	-0.034***	-0.022***	-0.030***	-0.036***
Slightly above $TMC^S_{i,t}$	-0.040***	-0.017***	-0.038***	-0.062***
Almost in $TMC^S_{i,t}$	0.002*	0.003**	0.001	0.004
$\ln(P_{i,t})$	0.002***	0.0004	0.002***	0.003***

Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

(6%, 8%, 9%, 10%, 11%, 12%), showing similar results as the baseline (AC=10%). The coefficients for the other models are also similar if one changes the AC parameter (results available from the author upon request). The intuition of why the TMC effects are insensitive to the administrative costs is that these coefficients are mostly affected by high risk borrowers, for whom the administrative cost is a smaller factor compared to their delinquency risk.

Finally, although Tables 4, 5, 6, 7 and 8 were estimated with the entire household sample between 2003 to 2015, all the results would be qualitatively similar if estimated with just the period between 2013 to 2015. This makes sense, because that is the period in which the interest rate ceiling experienced more fluctuations and therefore corresponds to the data period with higher identification power. These results are available from the author upon request.

5. Counterfactual analysis of the impact of the new legislation

Using model M2 (Tables 4 and 6) I simulate a counterfactual analysis of the credit access if there was no maximum legal interest rate. The model can be used to estimate for each household in every period the counterfactual probability of getting a new loan with or without the interest cap, $\Pr(NC_{i,t}=1 \mid x_{i,t}, TMC^S_t)$ and $\Pr(NC_{i,t}=1 \mid x_{i,t}, no\_TMC^S_t)$, which is done by assuming all households have null values for the distance to TMC dummies. I then estimate an Exclusion Ratio given by $\frac{\Pr(NC_{i,t}=1 \mid x_{i,t}, no\_TMC^S_t)}{\Pr(NC_{i,t}=1 \mid x_{i,t}, TMC^S_t)} - 1$. This indicator gives the ratio of people that are not getting a new loan due to the interest cap (as a fraction of the population of

Table 8
Probability (Logit) of a new consumer banking loan, with alternative values of the administrative cost of making a loan (baseline is 10%): 2003–2015, monthly.

Logit ($NC_{i,t}=1$)	M2 (BW=5%): All loans between 0–200 UF					
	$AC=6\%$	8%	9%	base 10%	11%	12%
Well above $TMC_{i,t}^{0-50}$	-2.404***	-2.740***	-2.661***	-2.742***	-2.707***	-2.559***
	(0.262)	(0.248)	(0.235)	(0.231)	(0.218)	(0.216)
Slightly above $TMC_{i,t}^{0-50}$	-3.152***	-2.971***	-2.825***	-3.007***	-2.958***	-2.926***
	(0.288)	(0.240)	(0.225)	(0.215)	(0.206)	(0.190)
Almost in $TMC_{i,t}^{0-50}$	0.330***	0.167*	0.268***	0.217***	0.297***	0.376***
	(0.0915)	(0.0860)	(0.0830)	(0.0800)	(0.0753)	(0.0729)
$tar_{i,t}^{0-50}$	-0.505	-1.271	-1.387	-1.981*	-2.456**	-2.250*
	(0.957)	(1.041)	(1.111)	(1.194)	(1.249)	(1.333)
$(tar_{i,t}^{0-50})^2$	4.264**	6.159***	6.062***	7.256***	7.732***	7.171***
	(1.676)	(1.745)	(1.821)	(1.913)	(1.947)	(2.037)
$\ln(P_{i,t})$	0.162***	0.160***	0.155***	0.151***	0.144***	0.140***
	(0.0268)	(0.0268)	(0.0269)	(0.0270)	(0.0271)	(0.0272)
Other controls:	Constant, Household head's 5-year age dummies					
Fixed Effects: Time	Yes					
Fixed Effects: Household	No					
N	374,710					
Households	4,118					
	Average marginal effects					
Well above $TMC_{i,t}^{0-50}$	-0.044***	-0.050***	-0.048***	-0.050***	-0.049***	-0.046***
Slightly above $TMC_{i,t}^{0-50}$	-0.057***	-0.054***	-0.051***	-0.055***	-0.054***	-0.053***
Almost in $TMC_{i,t}^{0-50}$	0.006***	0.003*	0.005***	0.004***	0.005***	0.007***
$\ln(P_{i,t})$	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	Conditional marginal effects (at the means)					
Well above $TMC_{i,t}^{0-50}$	-0.030***	-0.034***	-0.033***	-0.0328***	-0.032***	-0.029***
Slightly above $TMC_{i,t}^{0-50}$	-0.040***	-0.037***	-0.035***	-0.0359***	-0.035***	-0.034***
Almost in $TMC_{i,t}^{0-50}$	0.004***	0.002*	0.003***	0.003***	0.004***	0.004***
$\ln(P_{i,t})$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***

Robust Standard-errors in (), ***, **, * denote 1%, 5% and 10% statistically significance.

Table 9
Households excluded from new consumer banking loans (percentage of the population of borrowers with new loans).

Year	Quarter	All borrowers	0–50 UF borrowers	50–200 UF borrowers	Borrowers in both segments	Maximum Legal Rate (TMC)	
		Exclusion Ratio (fraction of the total flow of borrowers)					
Flow		Model with time fixed-effects (M2)				0–50 UF	50–200 UF
2013	3	12.7%	8.6%	18.0%	9.5%	53.9%	53.9%
2013	4	15.3%	11.2%	20.9%	11.8%	50.0%	48.6%
2014	1	14.8%	10.6%	19.9%	11.9%	47.3%	45.3%
2014	2	16.0%	11.5%	20.2%	13.2%	44.6%	42.6%
2014	3	18.2%	12.6%	22.6%	15.7%	41.7%	39.7%
2014	4	19.9%	14.4%	23.5%	17.9%	39.6%	37.6%
2015	1	24.5%	18.2%	28.4%	22.2%	38.6%	36.6%
2015	2	22.4%	16.4%	26.1%	20.8%	37.2%	34.5%
2015	3	22.8%	17.1%	28.9%	21.4%	36.5%	32.1%
2015	4	22.4%	16.7%	30.3%	21.0%	36.7%	30.4%
2015Q4-2013Q3		9.7%	8.0%	12.3%	11.5%		

borrowers that currently got a new loan), which is the indicator documented in official reports (SBIF, 2017)[13]

Table 9 shows the estimates of the exclusion ratio for each quarter from 2013-Q3 (the last period with the old law) until 2015-Q4 (the last period in our data) for each group of consumers: all borrowers, those who use loans of 0-50UF, those who use loans of 50-200UF, and those who use both kinds of loans. The last two columns show the value of the Maximum Legal Interest Rate (TMC) for the segments of 0-50UF and 50-200UF for each period. The results of the exclusion ratio show that around 12.7% of all consumers were already excluded from loan access due to the 54% interest rate cap that already existed in 2013. However, the fraction of excluded consumers had increased to 22.4% by the end of 2014, which represents an additional 9.7% of the potential banking loan customers that were excluded from consumer credit by the new legislation. Looking at different groups one finds that the legislation excluded 8% of the population from the use of 0-50UF loans. The law's impact was even higher for the segment of 50–200 UF

[13] One can also compute the Increase of Excluded Borrowers $\left(\frac{\Pr(NC_{i,t}=0 \mid x_{i,t}, TMC_t^S)}{\Pr(NC_{i,t}=0 \mid x_{i,t}, no\_TMC_t^S)}-1\right)$, which is the ratio of people that are not getting a loan due to the interest rate ceiling (as a fraction of the total population of borrowers that would not get a loan even with no legislation restrictions). Note that the denominator of this ratio is different and harder to interpret than the previous indicator, since authorities measure the number of consumers that are currently with loans, but not the number of people without access. Calculating the Increase of Excluded Borrowers indicator gives an increase in the number of non-borrowers of 4.2% by the end of 2015.

Table 10
Heterogeneity of the Exclusion Ratio (fraction of the total flow of borrowers) before and after the legislation.

Model with time fixed-effects (M2): All borrowers								
Household's Income Quintile			Household head's age			Household head's education		
Quintile	2013-Q3	2015-Q4	Age	2013-Q3	2015-Q4	Degree	2013-Q3	2015-Q4
1	54.1%	82.9%	18–34	8.9%	30.6%	Elementary	16.5%	27.4%
2	12.2%	29.4%	35–44	11.0%	24.5%	High school	13.2%	28.4%
3	4.8%	18.0%	45–54	17.3%	22.9%	Technical university	8.7%	14.0%
4	3.3%	12.0%	55–64	11.4%	20.4%	Incomplete college	0.2%	5.3%
5	1.7%	3.8%	+65	11.3%	20.4%	College (5 years)	5.7%	8.6%

Table 11
Panel EFH households' credit access in 2014 by borrower type in 2011.

All households		Unrestricted household[b]	Restricted household[a]	N Panel
Debtor type in 2011	(% of restricted households[a]): 2014	No Access to Debt: 2014	No Access to Debt: 2014	sample size
Banks	3.4%	4.1%	100.0%	197
Banks and Retail	1.6%	1.5%	36.5%	266
Retail Stores	3.4%	8.9%	64.8%	404
Unions	0.9%	12.9%	16.9%	160
Other Debts	1.8%	5.1%	100.0%	102
No Desire for Debt	2.4%	12.4%	40.2%	463
No Access to Debt	10.1%	20.6%	88.9%	168

Sample size for the EFH 2011–2014 common sample is 1760 households.
[a] Restricted household is defined as $1(TMC^{0-50}_{i,t=2014,m} > tar^{0-50}_{i,t=2014,m}) = 1$.
[b] Unrestricted household is defined as $1(TMC^{0-50}_{i,t=2014,m} > tar^{0-50}_{i,t=2014,m}) = 0$.

or the consumers of both segment sizes, with 12.3% and 11.5% of the consumers excluded from access.

Table 10 reports the heterogeneity of the Exclusion Ratio impact of the law across different household types, in terms of the household's income (given by the national income quintile, with 1 being the poorest 20% and 5 the richest 20% households), the household head's age bracket and its education. The results show that, in terms of the fraction of excluded households, the law had a more negative impact on the credit access of the poorest households (those of quintiles 1 and 2), the youngest (those of age 18–34) and the least educated (those who completed just a High school degree or less). In terms of the relative rate of increase of excluded households (that is the ratio of the fraction of households excluded after the law relative to before the law), then there was a stronger increase among households with an incomplete college degree (whose exclusion rate increased from a low value of 0.2% to 5.3%) and among the middle class (with the income quintile 3 increasing its rate of exclusion more than 3 times over, from 4.8% to 18.0%).

6. The interest rate ceiling cap's impact across different lenders

As shown in Section 2 (Tables 1 and 2), several households in Chile have access to non-banking lenders. It is difficult to study the law's impact on other lenders due to the lack of credit history data on households' non-banking loans. However, due to the rotating sample design of the EFH survey, there were 1760 households interviewed for both the 2011 (before the law) and the 2014 (after the law) waves. Using this small Panel EFH sample, I estimate how many households in 2014 had a risk-adjusted interest rate profile that could lead them to being credit restrained or not ($1(TMC^{0-50}_{i,t=2014,m} > tar^{0-50}_{i,t=2014,m}) = 1$ or 0). I also report how many households in 2014 had "No Access to Debt" either because all of their loan applications were denied or because they did not apply for a loan due to the fear of being denied credit. Table 11 shows that the highest fraction of credit restricted households in 2014 were those that in 2011 had "No Access to Debt". Also, across all debtor types (except borrowers with Unions), a high fraction of the borrowers with credit restricted profiles ($1(TMC^{0-50}_{i,t=2014,m} > tar^{0-50}_{i,t=2014,m}) = 1$) had "No Access to Debt" in 2014. This makes sense, since Labor Unions must offer the same conditions to all their members and are partially protected from delinquency risk due to direct payroll discounts made by the employers to the lending union. Also, the unrestricted households show very low rates of "No Access to Debt" in 2014, as expected. These results are based on a limited sample size (as shown in the last column in Table 11), but they confirm that Chilean households' credit access suffered after the 2013 law and this loan access was not replaced by non-banking lenders.

7. Conclusions

Using a representative sample of Chilean households I find that the reduction in the maximum legal interest rate decreased the number of borrowers with new loans in 9.7% by the end of 2015, which is roughly equivalent to 197 thousand consumers (consistent with the range of 151 to 227 thousand consumers excluded from credit in official estimates, SBIF (2017)). The analysis of this article improves upon the official estimates, because the aggregate credit statistics can be affected by other macroeconomic shocks, such as changes to economic growth, employment and wages that occurred in the same period. Using a unique microdataset I compare consumers whose risk-adjusted interest rates were just slightly below the maximum legal interest rate in relation to similar ones slightly above the legal cap. Although both groups are similar in characteristics, I show that the group of borrowers just above the legal interest rate cap was the most affected by the 2013 legislation. This discontinuous regression methodology is valid for any period and it is robust to all sorts of macro shocks (which are controlled with time fixed-effects).

One implication of the new legislation was that the maximum legal interest rate was implemented differently for the segments of smaller loans (0-50UF) and larger loans (50-200UF), with smaller loans being allowed a higher interest rate cap. The results show that the segment of users of smaller loans (0–50 UF) had a lower increase in exclusion in terms of the population of consumers. In particular, after accounting for both macroeconomic shocks and unobserved household heterogeneity, being above the interest rate ceiling reduces the estimated average probability of credit access by 3.6%, 9.4% and 11.4%, respectively for the segments of borrowers that shop exclusively for small loans (0–50 UF), those that shop exclusively for larger loans (50–200 UF), and those that shop for both small and large loans. Therefore the law appears to have had a higher impact on the fraction of large consumer loans that high-risk borrowers could access from banks.

The article shows that the legislation caused a significant reduction in loan access, with the credit exclusion being stronger among the young, the less educated and the poorest families. Furthermore, the decline in consumer debt access affected all loan types, including non-banking lenders.

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