Essays on High-Cost Consumer Credit

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Introduction

This dissertation studies high-cost consumer credit markets, and the welfare effects of current regulations. High-cost consumer lending, e.g., payday loans in the U.S., typically charge an APR of 322% for small, short-term loans. Often, policymakers and academia discuss whether they cause more harm than good. In Chapter 1, I make two contributions. Firstly, I document in a nationally representative survey that households that take out payday loans have: low-wealth and low-liquidity levels; relatively low income, although there are payday borrowers across the income distribution; high demand and rejection rates for traditional credit sources; and are more likely to experience expenditure shocks or unemployment spells. Secondly, I develop a model of banking and payday lending that delivers, in equilibrium, an interest rate and loan size spread between these lenders which we observe in the data.

In chapter 2, I study the welfare consequences of regulations on high-cost consumer credit in the US, such as borrowing limits and interest rate caps. For some borrowers, it is desirable to borrow at high interest rates when they experience adverse shocks (e.g., to their health). However, others have preferences with self-control issues that may induce them to overborrow. I estimate a heterogeneous-agents model with risk-based pricing of loans that features standard exponential discounters and households with self-control and temptation. I use transaction-level payday lending data and the literature's valuations of a no-borrowing incentive to identify different household types. I find that one-third of high-cost borrowers suffer from temptation. Although individually targeted regulation could improve the welfare of these households, I find that noncontingent regulatory borrowing limits and interest-rate caps—like those contained in typical regulations of payday loans—reduce the welfare of all types of households. The reason is that lenders offer borrowers tight individually-targeted loan price schedules that limit households' borrowing capacity so that noncontingent regulatory limits cannot improve welfare over them.

Chapter 1

Payday Lending: evidence and theory

1 Introduction

The payday lending industry is highly controversial due to the high cost of their loans compared to other sources of unsecured credit (e.g., credit cards). In this paper I develop a model of unsecured credit that delivers, in equilibrium, the interest rate spread between different lenders observed in the market for unsecured credit.

Payday loans are small, high-cost and short-term unsecured loans: typically, they charge an APR of 322% for a 14-day loan of $350 (CFPB 2013). These terms contrast with those of credit card debt, the most common source of unsecured credit.[1] The highest APR reported by a household for credit card debt is 36%; and, 98% of credit limits reported are greater than $500.[2]

This paper is motivated by the following two observations. Firstly, households that take payday loans have low wealth, in particular, low liquidity and relatively low income. Moreover, after controlling for these and age, households that took out a payday loan are more likely to have been late on their debt payments and more likely to have filed for bankruptcy. In addition, they have a high demand for credit during the time they took out a payday loan and are more likely to have been rejected by a lender compared to households that did not take a payday loan.[3]

Secondly, 80% of the observed interest rates can be explained by operational and default costs. Thus, payday lending is a costly way of providing unsecured credit.

Consistent with the evidence presented above, I develop a two-period model of unsecured credit with two financial intermediaries, banks and payday lenders, where consumers are heterogeneous in the probability of repayment (i.e., their risky type). The model has three key features. First, the banking sector can write contracts conditional

[1] I estimate that total loan volume of the payday lending industry is approximately between 1.6% and 3.2% of the credit used from credit cards.

[2] Survey of Consumer Finances, 2016.

[3] These correlations point in the same direction as those found in Bhutta, Skiba, and Tobacman 2015 using data from a payday lender.

on observables (i.e., the risk type of the agent) but the payday lender cannot distinguish between different borrowers. The model exaggerates the actual set of information that lenders have. For instance, banks make large investments in designing their products targeted at specific groups of clients as documented by Livshits, Gee, and Tertilt 2016. However, payday lenders offer the same loan contract to all of their clients but accept/reject applicants based on the Teletrack score. Second, banks face a search friction as in Nosal and Drozd 2008 and Raveendranathan 2018. They will target consumers depending on their type but will be able to extend a loan only if they are matched with a consumer. Once they are matched, they bargain over the terms of the loan. The search friction is key for the ability of the payday lenders to break even since it will allow them to have a mix of high and low-risk types in its pool of clients. Finally, less risky households are richer than high-risk households: the endowment in the high endowment state is correlated to the risk type of the agent. Without the relationship between endowment and probability of repayment, there is an indifferent consumer that would get the same interest rate at the bank and at the payday lender.

In a numerical example I show that a model with these features generates the relative interest rates and size of loans observed between payday lenders and banks. The key parameters that yield the results are those that govern the distribution of agents and the efficiency of the matching function. A distribution of consumers that is skewed towards low-risk types and low efficiency of the matching function allows the payday lender to break even since more non-matched low-risk consumers will come to the payday lender, compensating the expected losses from high risk types. Simulation results show that the spread in interest rates depends positively on the cost of defaulting and on the efficiency of the matching process.

This paper is related to the literature on payday lending. The literature has mainly focused on empirically identifying the effect of taking a payday loan on the financial well-being of consumers; that is, the probability of being late in loans and other bills, and credit demand.[4]

The existing papers have not assessed the welfare effects of payday lending. This papers alerts us that we should interpret the empirical findings with caution. Concentrating on financial well-being is misleading with respect to welfare effects. For instance, the model predicts that the riskiest segment of the consumers will take a payday loan and default on it with certainty but will be better off compared to autarky. Observing default in isolation would lead to think that the consumer is actually worse off. Moreover, in my model there is an externality since consumers that are served by banks are also affected by the existence of the payday lender as it determines their option value in the bargaining with the bank. Thus, the aggregate welfare effect of regulating payday lenders will be a combination of how different types of consumers will be affected directly or indirectly by the payday lender.

2 Empirical findings

In this section, I document facts on households that have taken out payday loans. Additionally, I use payday lender data to calibrate a zero-profit interest rate to shed light on why interest rates are so high in the industry.

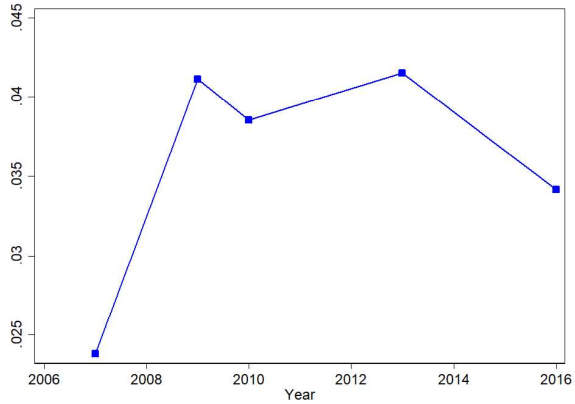
2.1 Who takes out payday loans?

I identify households that have taken a payday loan as households that respond that they took a loan in the previous 12 months in the SCF.[5] The proportion of households with a

[4]See Melzer 2011, Gathergood, Guttman-Kenney, and Hunt 2018, Bhutta, Skiba, and Tobacman 2015, Bhutta, Goldin, and Homonoff 2016. Skiba and Tobacman 2008 is an exception that estimates a structural model and finds that payday loan demand is consistent with naive quasi-hyperbolic discounting.

[5]There is a caveat regarding the timing of the variables in the SCF. Income refers to the year 2015 while assets and liabilities refer to the previous month of the survey.

Figure 1: Proportion of households with payday loans



Notes: Source: Survey of Consumer Finances, 2007, 2009, 2010, 2013, 2016. Households that have taken a payday loan are households that respond that they took a loan in the previous 12 months in the SCF.

payday loan has been on average 3.6% during the last decade as shown in Figure 1. It has a countercyclical behavior as more households took out loans during the Great Depression but to a lower extent in recent years.

Figure 2 plots the proportion of households with payday loans with respect to household wealth, liquidity, income and age. Having a payday loan is negatively correlated with household net worth as shown in the top-left panel. The two lowest deciles of net worth have the highest proportion of households with a payday loan. There are households with positive and relatively high net worth that still have some of these high-cost loans. If we look at their liquidity, top-right panel, households with payday loans appear more often in lower deciles of the liquidity distribution.[6] In fact, there is a sharp decline in the proportion of households with a payday loan at the median of the liquidity distribution. Thus, taking payday loans is correlated with low wealth but in particular with low liquidity. The relationship between having a credit card and wealth and liquidity is the opposite with respect to having a payday loan which highlights the substitutability between these credit products.

[6] Liquidity is defined as the sum of checking, saving and money market accounts, prepaid balances in debit cards and available credit in credit cards; minus, total monthly debt payments.

With respect to the income distribution, the proportion of households with a payday loan by income decile is hump-shaped: above-average use of payday loans concentrates between deciles 2 and 6.[7] The shape is preserved if I consider only households in which the head of household and spouse/partner were employed.[8] With respect to the distribution of normal income, which is the income that households report after recognizing that their income was unusually high or low, the mass of households with a loan is higher at lower deciles. Higher than expected income could be a driver of demand for payday loans.

Finally, younger households tend to have a higher demand for payday loans with respect to older households; the opposite pattern occurs for holding a credit card. This suggests a life cycle behavior of payday loans as they are taken more frequently when households are young which is when access to credit cards is at its minimum.

Now, I will look at several households characteristics to asses how different households that took out a payday loan are with respect to those that did not. I estimate the following regression for each characteristic y_i:

$$y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i \tag{1}$$

where i indexes a household in the SCF. $Payday_i$ is a dummy variable indicating whether a household took out a payday loan; and, $Controls_i$ includes net worth deciles, normal income per capita deciles and age groups.[9] I report the coefficient β, its standard error (SE) and p-value for each characteristic. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF with the STATA command developed by Collins 2015.

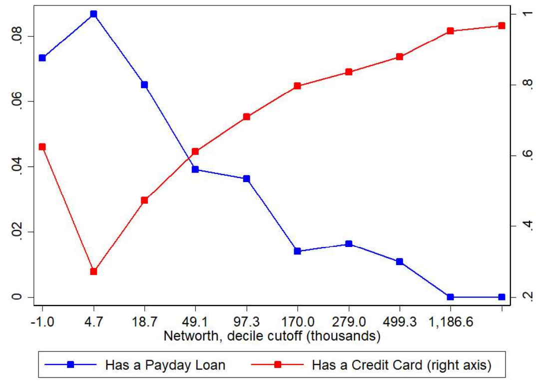
Demographics: Table 1 presents the results for this category of characteristics.

[7] This is robust to considering income per capita and controlling by age.

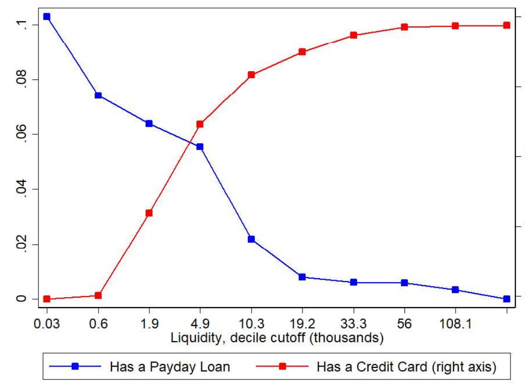
[8] Payday lenders require a pay stub from the borrower when applying for a loan.

[9] Income is divided by the square root of the number of members in the household

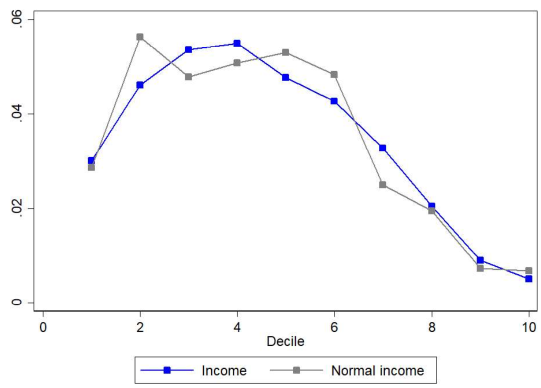
Figure 2: Proportion of households with payday loans



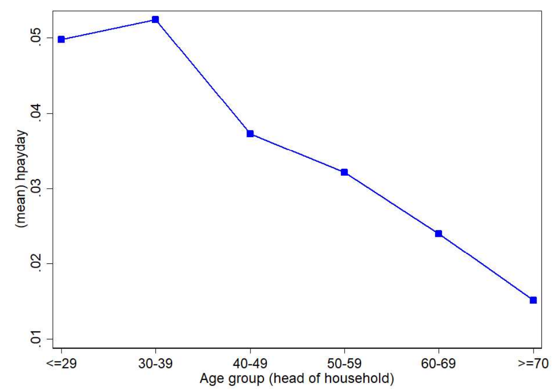
(a) Payday loans and credit cards by net worth



(b) Payday loans by liquidity



(c) Payday loans by income



(d) Payday loans by age group

Notes: Source: Survey of Consumer Finances, 2016. Liquidity is defined as the sum of checking, savings and money market accounts, prepaid balances in debit cards and available credit in credit cards; minus, total monthly debt payments. Normal income is different from income if households have responded that their income was unusually high or low with respect to what they would expect in a normal year.

Households that took out a payday loan are significantly larger households and have more children. The head of these households has a lower probability of being white non-Hispanic, a higher probability of completing college or completing an associate degree, while a lower probability of completing a bachelor's degree or higher. Interestingly, there is a higher probability that the head of household is not married or does not have a couple and has children.

Credit attitudes: Table 2 presents the results for this category of characteristics.

Table 1: Demographics

	Coefficient	SE	p-value
Married or living w/ partner	0.019	0.030	0.52
White non-hispanic	-0.066	0.028	0.02
Number of household memebrs	0.403	0.084	0.00
Number of kids	0.194	0.058	0.00
No high school diploma	0.013	0.021	0.52
High school diploma	-0.006	0.022	0.78
Some college or Assoc. degree	0.068	0.025	0.01
BA degree or higher	-0.075	0.018	0.00
Married/Partner, children	0.023	0.023	0.30
Married/Partner, no children	-0.004	0.019	0.81
Not married/partner, children	0.074	0.029	0.01
Not married/partner, no children	-0.093	0.025	0.00

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF with the STATA command developed by Collins 2015.

The first three rows cannot reject the hypothesis that households with and without a payday loan are not different in how knowledgeable they are about their personal finances, whether they think it is a good idea to buy things with credit and how much they search for the best terms when looking for credit.

The remaining rows confirm the findings in Bhutta, Skiba, and Tobacman 2015: households that took a payday loan have a higher probability of having applied for additional credit through applications for new accounts or extensions of credit limits; a higher probability of being turned down or obtaining less credit; and, higher riskiness as they are more likely to have been late with payments and filed for bankruptcy.

Income, expenses and savings: Results for this part are presented in Table 3. The first panel shows that the saving habits for households with a payday loan are more likely to be zero or negative savings. Furthermore, looking at the previous 12 months, which is when households took a payday loan, it is more likely that they effectively had negative savings during that period. When asked to exclude purchases of cars or houses,

Table 2: Credit attitudes

	Coefficient	SE	p-value
Knowledgeable personal finances (-1 to 10)	0.003	0.116	0.981
Good idea to buy things with credit	-0.018	0.027	0.498
Searching best terms credit (scale -1 to 10)	-0.046	0.185	0.804
Apply credit card (prev. 12m)	0.111	0.026	0.000
Request increase limit in card (prev. 12m)	0.064	0.015	0.000
Apply mortgage/home-based loan (prev. 12m)	0.015	0.020	0.437
Request refinance mortgage (prev. 12m)	0.015	0.015	0.317
Apply auto loan (prev. 12m)	0.101	0.024	0.000
Apply student loan (prev. 12m)	0.008	0.020	0.695
Apply other consumer credit (prev. 12m)	0.127	0.020	0.000
Request increase limit other loans (prev. 12m)	0.076	0.018	0.000
Turned down/less credit wrt applied, prev. 12m	0.288	0.025	0.000
Any late payments last year?	0.203	0.028	0.000
Any payments > 60 days past due last year?	0.112	0.019	0.000
Filed bankruptcy last 5 years	0.035	0.016	0.031

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF with the STATA command developed by Collins 2015.

it is still the case but to a lower extent. Thus, taking a payday loan is correlated with purchases of durable goods.

Looking at expenditures, households that took out a payday loan are more likely to have unusually high expenses. With respect to income, we cannot reject that there are no differences between households with respect to income being unusually low. Interestingly, there is no evidence that the households have different health insurance coverage although they are less likely to own their home. Finally, there is a significant correlation between having a payday loan and the head of household being unemployed.

Credit cards: Related to credit card access and use, which could be considered as a substitute for payday loans, results are presented in Table 4. Households with payday loans are less likely to have a credit card, and if they do have, they have a lower number of them. Additionally, their credit limit is lower and so is the availability of

Table 3: Income, expenses and savings

	Coefficient	SE	p-value
Saving habits: spending>income	0.097	0.023	0.000
Saving habits: spending=income	0.118	0.026	0.000
Saving habits: some saving	-0.213	0.026	0.000
Spending>income (prev. 12m)	0.190	0.036	0.000
Spending=income (prev. 12m)	-0.003	0.034	0.926
Spending<income (prev. 12m)	-0.186	0.020	0.000
Spending>income (prev. 12m, ex. assets)	0.031	0.012	0.011
Spending=income (prev. 12m, ex. assets)	-0.008	0.006	0.150
Spending<income (prev. 12m, ex. assets)	0.007	0.006	0.286
Expenses unusually high (prev. 12m)	0.076	0.025	0.002
Everyone covered by health insurance	-0.022	0.021	0.293
Owns home	-0.099	0.020	0.000
(Food+Rent+Debt Payments)/Income	-0.068	0.021	0.001
Income unusually low (previous year)	0.000	0.019	0.982
Head: unemployed prev. 12m?	0.067	0.027	0.012
Spouse: unemployed prev. 12m?	0.044	0.035	0.209
Head: years worked full-time	0.654	0.643	0.309
Spouse: years worked full-time	1.676	0.732	0.022
Head: years worked part-time	-0.453	0.223	0.042
Spouse: years worked part-time	0.091	0.275	0.740

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF with the STATA command developed by Collins 2015.

credit. Interest rates are significantly higher for households that took out a payday loan.

Table 4: Credit cards

	Coefficient	SE	p-value
CC, can carry balance: has?	-0.117	0.028	0.00
How many?	-0.050	0.023	0.03
CC, store branded: has?	-0.022	0.003	0.00
How many?	-0.178	0.116	0.12
CC, pay balance: has?	-0.168	0.067	0.01
How many?	-0.023	0.004	0.00
Credit limit to income	-1.792	0.284	0.00
Credit limit-Utilization	-1.581	0.235	0.00
Interest rate on highest balance CC	1.289	0.640	0.04

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF with the STATA command developed by Collins 2015.

2.2 Why are interest rates so high?

Finally, I look at data on payday lenders to explain the observed interest rates in the industry. Specifically, how much of the observed interest rates are explained by operating costs and default? In Equation 4 I write an expression for the zero profit interest rate for a typical payday loan, $\bar{R^P}$:

$$\Pi = \rho \bar{R^P} L - \kappa - RL = 0 \tag{2}$$

$$\Rightarrow \bar{R^P} = \frac{1}{\rho}\left[R + \frac{\kappa}{L}\right] \tag{3}$$

where, ρ is the probability of repayment; κ are fixed costs of the payday lender (wages, occupancy costs, advertising, corporate expenses), L is the total amount loaned; and, R is the rate at which the lender borrows the funds that it lends. I use store-level data from Flannery and Samolyk 2005 and K-10 forms for two public payday lenders to calibrate these parameters.[10]

Results are shown in Table 5. Comparing the zero profit interest rate and the effective interest rate that these lenders charge, the former explains, on average, 80% of the interest rates charged by lenders which indicates that payday lending is a very costly activity.

Table 5: Calibration of zero-profit payday lending interest rate

	Calibration	Flannery et al.	AEA	QCCO
$\frac{\kappa}{L}$	(Operating+Corp. expenses)/ Loans	0.12	0.10	0.093
R	Federal Funds Rate	1.015	1.002	1.002
ρ	Provisions/Loans	0.98	0.97	0.96
$\bar{R}^P$		1.156	1.140	1.145
R^P		1.176	$\leq$ 1.22	1.15-1.20

Notes: Flannery et al. uses data from Flannery and Samolyk 2005; the remaining columns uses data from K-10 forms for Advance America Cash Advance Centers Inc. and QC Holdings, Inc., between 2009 and 2011. R^P is the interest rate charged by payday lenders on a typical loan, not annualized.

3 Model

This section develops a simple two-period model of banking and payday lending that reproduces the observed spread in interest rate and loan size between banks and payday lenders for unsecured loans.

3.1 Environment

There are two periods. The economy is an endowment economy: y_1 is deterministic and homogeneous across consumers, while $y_2 = \rho > 0$ with probability ρ and $y_2 = 0$ with probability $1 - \rho$. That is, consumers with a higher probability of getting the high

[10] I use financial statements from Advance America Cash Advance Centers Inc. and QC Holdings, Inc., between 2009 and 2011, because payday lending is their only product or represents more than 70% of total revenues.

endowment get a higher endowment[11]. In period 1, banks target consumers and the payday lender posts its contract. Consumers decide if they will borrow and from whom. In period 2, consumers decide if they repay or default and consume.

3.2 Consumers

There is a continuum of consumers heterogeneous in $\rho \in [0, 1]$ which is drawn from a distribution $\mathcal{F}$. ρ is private information known exclusively by consumers. Lifetime utility is $c_1 + \beta \, \mathbb{E} \, c_2$.

3.3 Financial sector

There are two financial intermediaries: banks and a payday lender. They have access to a competitive financial sector with risk-free interest rate of 0. There is limited commitment. If a consumer defaults on its loan he will lose a fraction γ of y_2.

3.3.1 Banks

Banks face a search friction as in Nosal and Drozd 2008 and Raveendranathan 2018. They can observe the type of each consumer and can target each segment of the market by paying a fixed cost of χ per offer sent. Once they are matched with a consumer they will bargain over the terms of the contract. I follow Raveendranathan 2018 closely: matches between consumers and banks are produced by a Cobb-Douglas technology given by Equation 4.

$$M(u(\rho), v(\rho)) = Au(\rho)^{\alpha} v(\rho)^{1-\alpha} \tag{4}$$

[11]The crucial feature here is the correlation between probability and endowment. The endowment can be a more general function of ρ but I am assuming they are identical for simplicity.

where u = mass of consumers, v = mass of offers sent by firms; α and A are parameters.

Define the probability that an offer from a bank gets to a consumer, P_M, and the probability that a consumer gets a credit offer, P_A. Then, I can write P_A as in Equation 5.

$$P_A(\rho) = A\Big(\frac{A}{P_M(\rho)}\Big)^{\frac{1-\alpha}{\alpha}} \tag{5}$$

Banks will send offers until they make zero expected profit. Equation 6 will pin down $P_M(\rho)$ and, thus, $P_A(\rho)$.

$$P_M(\rho)\Big[\rho - q(\rho)\Big]L(\rho) = \chi \tag{6}$$

where $q(\rho)$ is the per-unit price of the loan and $L(\rho)$ is the size of the loan. A low probability of getting a match with the consumer type ρ implies a high probability of access to a credit offer by that consumer. This is due to, given the mass of consumers $u(\rho)$, banks will strongly target consumer types that are very profitable which reduces the probability that a banks is matched with that type. This will in turn increase the probability of access to a credit offer by consumers of that type. Banks and consumers only bargain over $q(\rho)$, since $L(\rho)$ will be pinned down by linearity of the utility function as shown below. I assume that the total surplus from the transaction is split between bank and consumer according to a fixed rule. The bank obtains a proportion δ of the surplus and the consumer obtains the remaining $1 - \delta$.

3.3.2 Payday Lender

The payday lender cannot observe ρ and makes a unique credit offer of (q^P, L^P). Any consumer can obtain this loan. However, in the design of its contract the lender will anticipate the expected pool of applicants. The payday lender is assumed to be a monopolist for simplicity[12].

3.4 Equilibrium

3.4.1 Definition

An equilibrium consists of a set of loan contracts between banks and matched consumers $\{q(\rho), L(\rho)\}_{\rho \in (\bar{\rho},1)}$; and, a unique contract available to all consumers offered by the payday lender (q^P, L^P) such that:

1. Given consumer policy rules, banks will maximize profits by: i) choosing which consumer types to target; ii) bargaining over the terms of the contract with matched consumers.

2. Given consumer policy rules, the payday lender will choose (q^P, L^P) that maximizes its expected profits.

3. Each consumer of type ρ, will maximize lifetime utility by choosing: i) in period 1, between contract $(q(\rho), L(\rho))$, (q^P, L^P) or autarky if it was matched with a bank; or, between (q^P, L^P) or autarky if it was not matched; ii) in period 2, whether to repay or default.

3.4.2 Repayment/Default

There is no risk-free contract with positive loan amount since the lowest realization of the endowment is zero. Consumers will repay if consumption given repayment is greater than consumption after defaulting on their loans. That is, there is a maximum loan size that prevents default in the high endowment state: $L \leq \gamma y_h$. Since consumers are

[12] In reality, payday lenders are atomistic and offer many combinations of loan price and size (see Figure 9). These are features that should be taken into account in a quantitative model.

risk neutral, if they are willing to accept a price of a loan they will want the largest loan possible. Using $y_h = \rho$, there is a unique loan size for risky contracts for each ρ, $L(\rho) = \gamma\rho$. All loans made by the bank will be risky contracts that will be repaid in high endowment state and defaulted in low endowment state.

3.4.3 Borrowing decisions

This section and the following one are summarized in Figure 4. I characterize borrowing decisions as a function of the price of the payday lender.

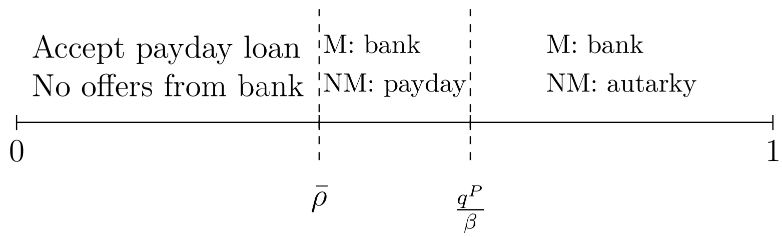


Figure 4: Equilibrium characterization with respect to ρ

Consumers with $\rho > \frac{q^P}{\beta}$ will prefer autarky with respect to a loan from the payday lender. This segment of consumers will be served by banks exclusively. However, consumers with $\rho < \frac{q^P}{\beta}$ are willing to accept a payday loan versus autarky. This segment will be served, potentially, by banks and payday lenders. Within the latter case there are two sub cases: consumers with type $\rho \geq \frac{LP}{\gamma}$ will repay their payday loan; however, those with $\rho < \frac{LP}{\gamma}$ will default on their payday loan. Hence, the option value in each case is different.

3.4.4 Financial contracts

Consumers with $\rho > \frac{q^P}{\beta}$: banks will target these consumers. Bank, consumer and total surplus is given by Equation 7, Equation 8 and Equation 9 respectively.

$$S_B = (\rho - q(\rho))\gamma\rho \tag{7}$$

$$S_C = (q(\rho) - \beta\rho)\gamma\rho \tag{8}$$

$$S = S_B + S_C = (1 - \beta)\gamma\rho^2 \tag{9}$$

Since the bank gets δS_B, we can solve for the per-unit price of the loan which is given by Equation 10. Consumers accept this offer if $\delta < 1$. Consumers that are not matched will prefer autarky over the payday loan.

$$q(\rho) = \rho[1 - \delta(1 - \beta)] \tag{10}$$

Consumers with $\rho < \frac{q^P}{\beta}$: banks will send offers but now consumers are willing to accept the payday loan. I distinguish between consumers that are below or above $\frac{L^P}{\gamma}$, since this threshold determines if the consumer defaults on the payday loan or not.

$\underline{\rho > \frac{LP}{\gamma}}$: matched consumers will bargain with an option value of going to the payday lender and repaying. The consumer and total surplus are:

$$S_C = (q(\rho) - \beta\rho)\gamma\rho - (q^P - \beta\rho)L^P \tag{11}$$

$$S = S_B + S_C = \rho^2\gamma(1 - \beta) - (q^P - \beta\rho)L^P \tag{12}$$

Similarly as before, we can solve for $q(\rho)$:

$$q(\rho) = \rho(1 - \delta(1 - \beta)) + \frac{(q^P - \beta\rho)L^P}{\gamma\rho} \tag{13}$$

Matched consumer will prefer the bank loan with respect to the payday loan if $\delta \leq 1$. However, banks will not send offers to consumers that yield negative profits. Define $\hat{\rho}$

as the lowest consumer type that will receive offers from banks in this segment of the market. That is, $\hat{\rho}$ satisfies condition in Equation 14.

$$\hat{\rho}^2(1-\beta)\delta\gamma + L^P\beta\hat{\rho} - q^P L^P = 0 \tag{14}$$

$\underline{\rho \leq \frac{L^P}{\gamma}}$: Matched consumers will bargain with an option value of going to the payday lender and defaulting. The consumer and total surplus are:

$$S_C = q(\rho)\gamma\rho - q^P L^P \tag{15}$$

$$S = S_B + S_C = \rho^2\gamma - q^P L^P \tag{16}$$

Similarly as before, we can solve for $q(\rho)$:

$$q(\rho) = \rho(1-\delta) + \frac{\delta q^P L^P}{\gamma\rho} \tag{17}$$

Matched consumer will prefer the bank loan with respect to the payday loan if $\delta \leq 1$. As above, banks will not send offers to segments of the market that yield negative profits. Notice that the bank surplus is negative at $\rho = \frac{L^P}{\gamma}$, and it is increasing in ρ. So, the segment of the market below $\frac{L^P}{\gamma}$ will not be targeted by banks.

In summary, banks will target consumers between $(\bar{\rho} = \hat{\rho}, 1)$.

3.4.5 Payday lender problem

The payday lender maximizes profits given by Equation 18. Profits are zero when $\frac{q^P}{\beta} < \frac{L^P}{\gamma}$ because all consumers would default the payday loan, so the lender would not extend loans.

To find the optimal contract (q^P, L^P), I assume $\rho \sim Beta(a, b)$ and find the maximum of the objective function for the payday lender for a given (a, b), using Pattern Search optimizer. In the appendix, Figure 10 plots the profit function for the payday lender.

$$\Pi(q^P, L^P) = \begin{cases} \int_0^{\frac{L^P}{\gamma}} (-L^P) f(\rho) d\rho + \int_{\frac{L^P}{\gamma}}^{\hat{\rho}} (\rho - q^P) L^P f(\rho) d\rho & \\ + \int_{\hat{\rho}}^{\frac{q^P}{\gamma}} (1 - P_A(\rho, q^P))(\rho - q^P) L^P f(\rho) d\rho & \text{if } \frac{q^P}{\beta} \geq \frac{L^P}{\gamma}, \\ 0 & \text{if } \frac{q^P}{\beta} < \frac{L^P}{\gamma} \end{cases} \tag{18}$$

3.5 Results

The model presented above predicts a negative spread in the per-unit price of loans between the payday lender and banks for consumers with $\rho \in (\hat{\rho}, \frac{q^P}{\beta})$ as shown in Figure 5. In terms of interest rates, the inverse of the price of the loan, there is a positive spread. With respect to loan size, Figure 6 shows that banks will offer larger loans than the payday lender. The probabilities of getting a match for banks and consumers are shown in the appendix in Figure 11. Together, these predictions are in line with the contracts observed in the data: payday lenders offer small and high-cost loans compared to credit card terms.

It is interesting to decompose the expected profits of the payday lender. As shown in Figure 7, profits are a combination of: i) losses from consumers below $\frac{L^P}{\gamma}$; ii) expected losses from all the consumers in the segment $(\frac{L^P}{\gamma}, q^P)$; iii) expected profits from serving all consumers in the segment $(q^P, \bar{\rho})$; iv) expected profits from serving consumers that where not matched in the segment $(\bar{\rho}, \frac{q^P}{\beta})$.

$$spread = \frac{1}{q^P} - \mathbb{E}\left[\frac{1}{q(\rho)} | \hat{\rho} \leq \rho \leq \frac{q^P}{\beta}\right] \tag{19}$$

Finally, I look at how the interest rate spread between the payday lender and the banks depends on the key parameters of the model. I define the interest rate spread

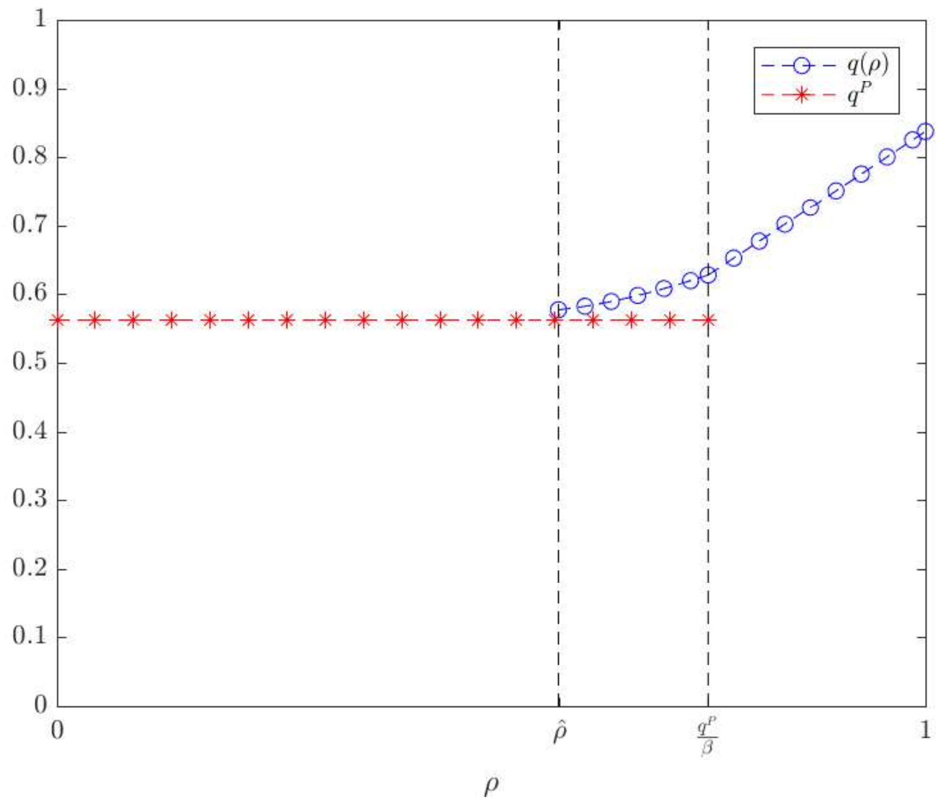


Figure 5: $q(\rho)$ and q^P

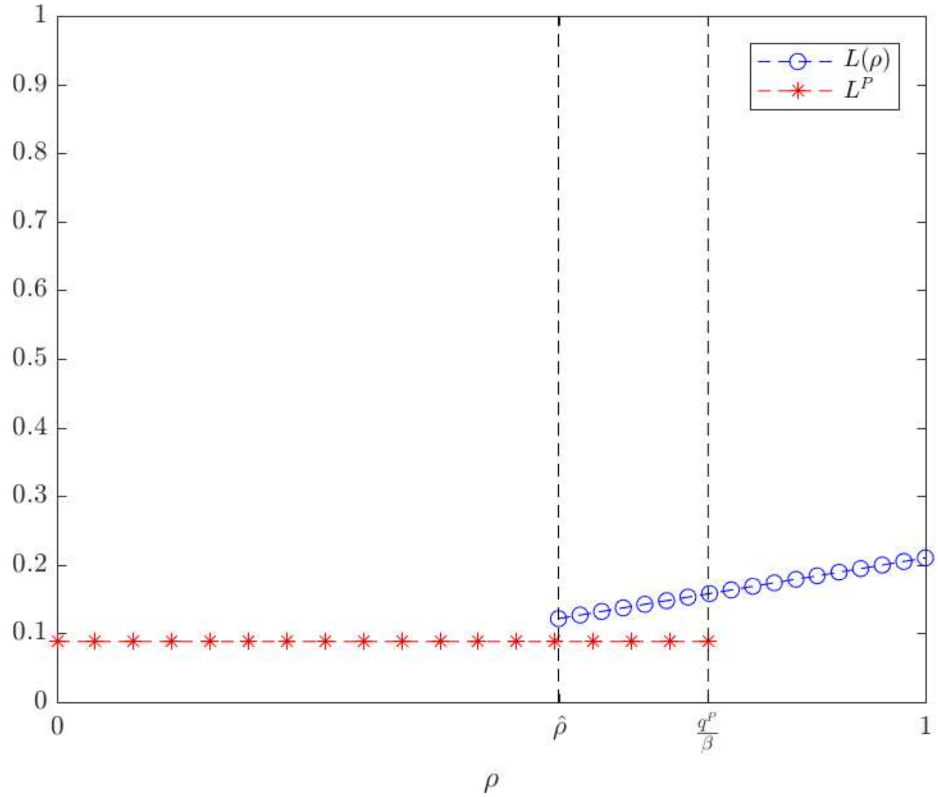


Figure 6: $L(\rho)$ and L^P

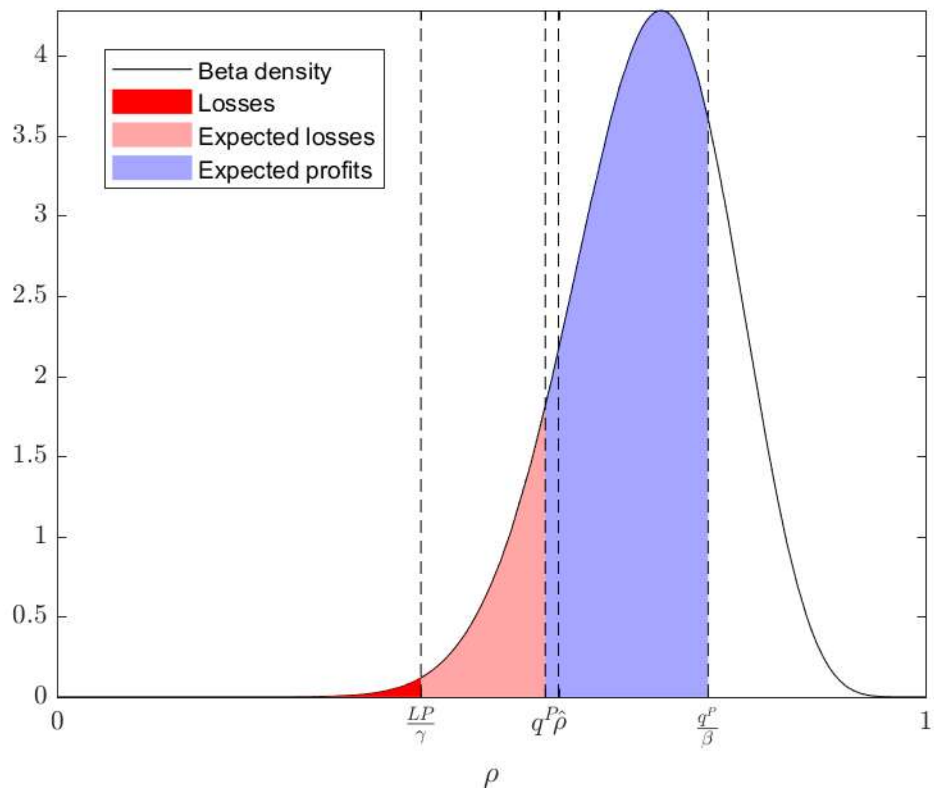
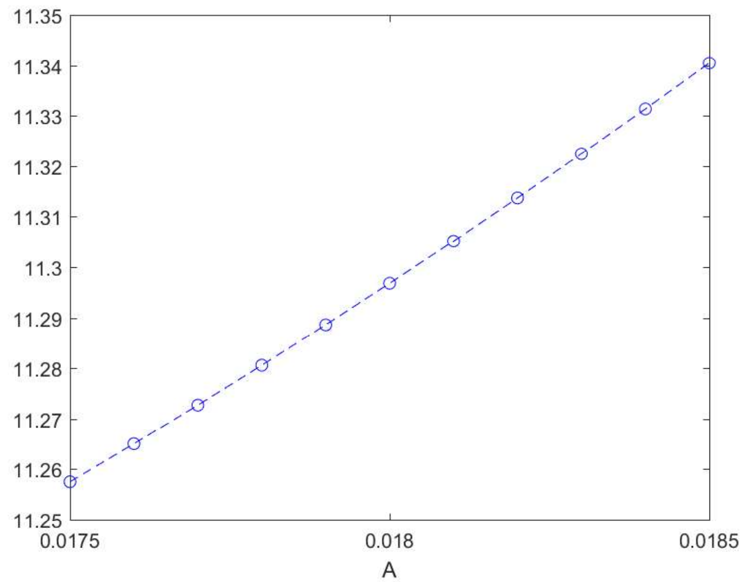
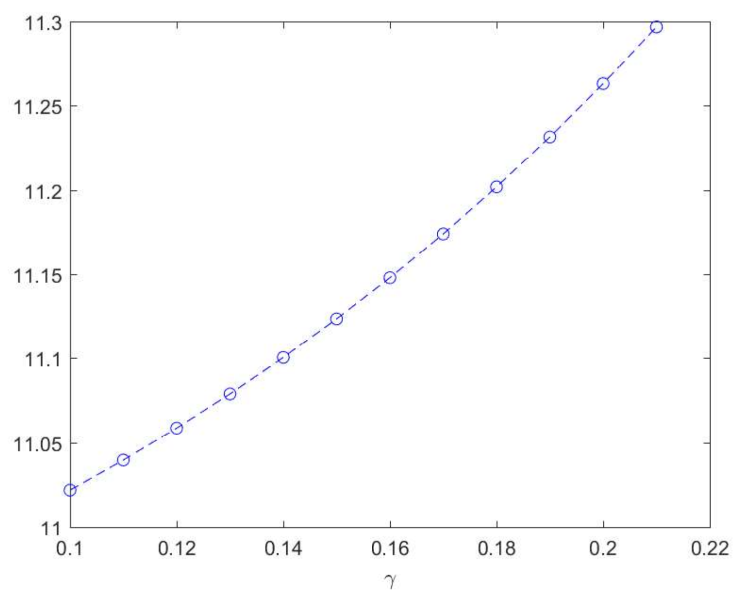


Figure 7: Consumer type ρ density

as in Equation 19. I find that the spread is increasing in both the efficiency of the matching function and the cost of default. This is interesting as bankruptcy policies and technological change could have different implications for consumers served by banks or by payday lenders.



(a) Spread for values of A



(b) Spread for values of γ

Figure 8: Interest rate spread

4 Conclusion and further work

I have documented new facts on households that take out payday loans and developed a model of the financial sector that delivers key facts from the unsecured credit market: interest rate and loan size spread between payday lenders and banks. Further work will consist of developing a quantitative model to understand why households use these loans and shed light on the welfare effect of payday lending and different regulations that affect this industry. Other interesting questions emerge from the model presented here: bankruptcy policy and technological change, which have been studied in relation to unsecured credit before, might have a differential effect on consumers depending on their types and the lender that they have access to. These aspects might be worth revisiting when considering alternative financial sectors like payday lending.

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A Appendix

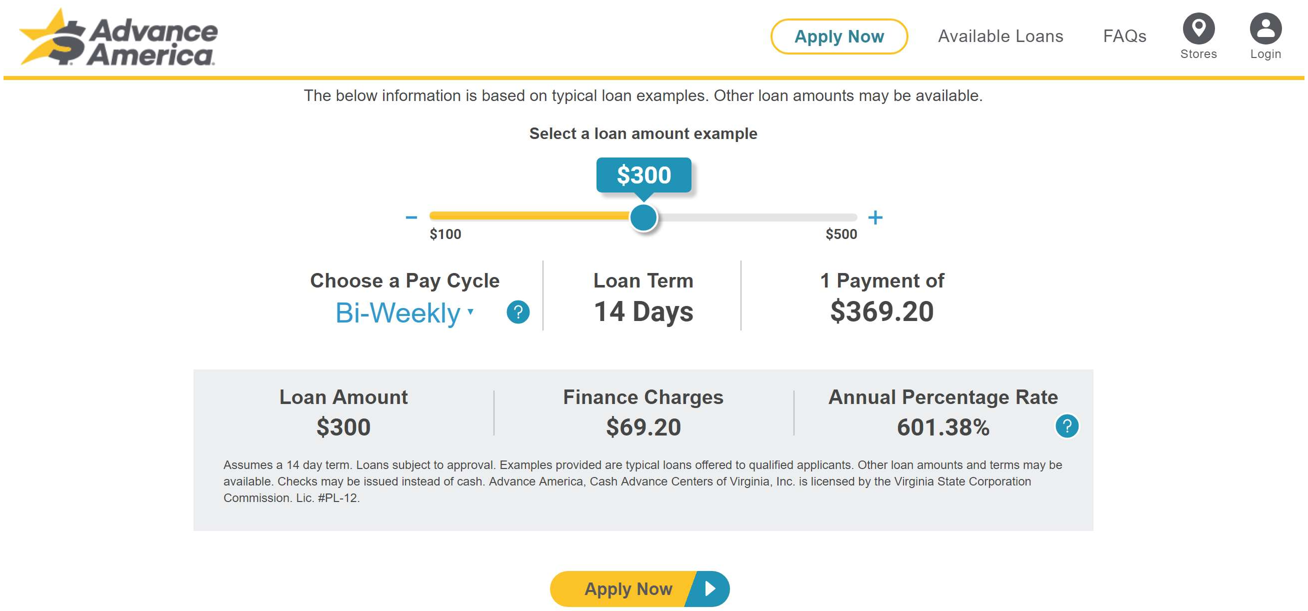


Figure 9: Example of a payday loan contract from Advance America for the Charlottesville area

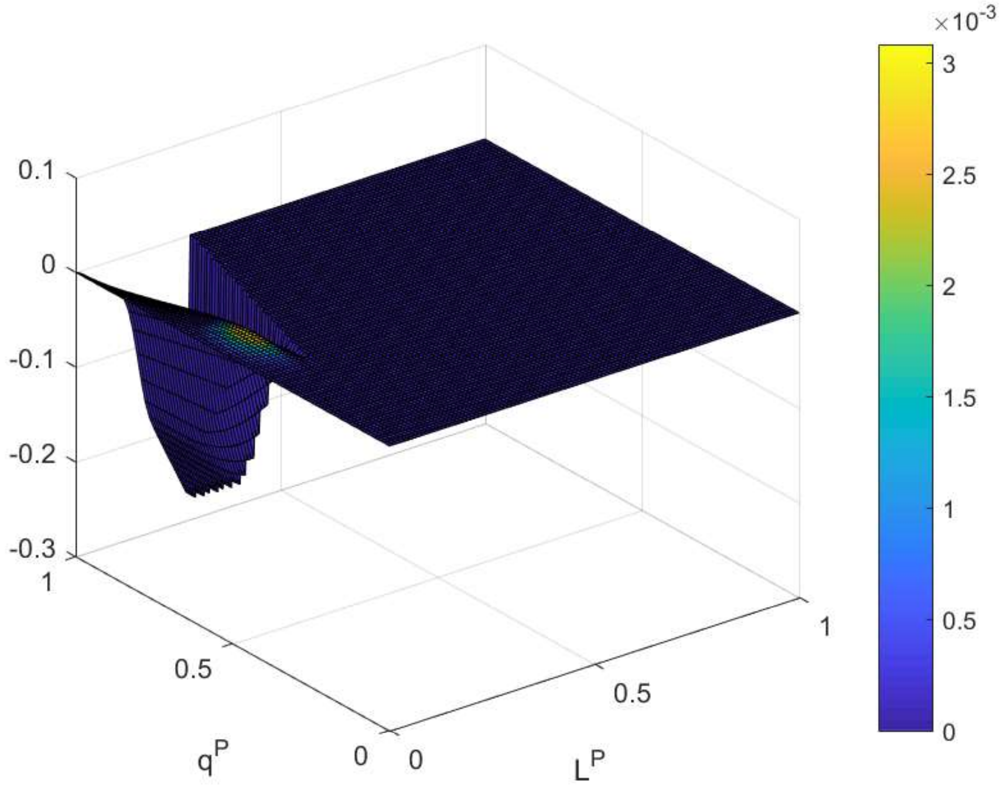


Figure 10: Payday lender profit function

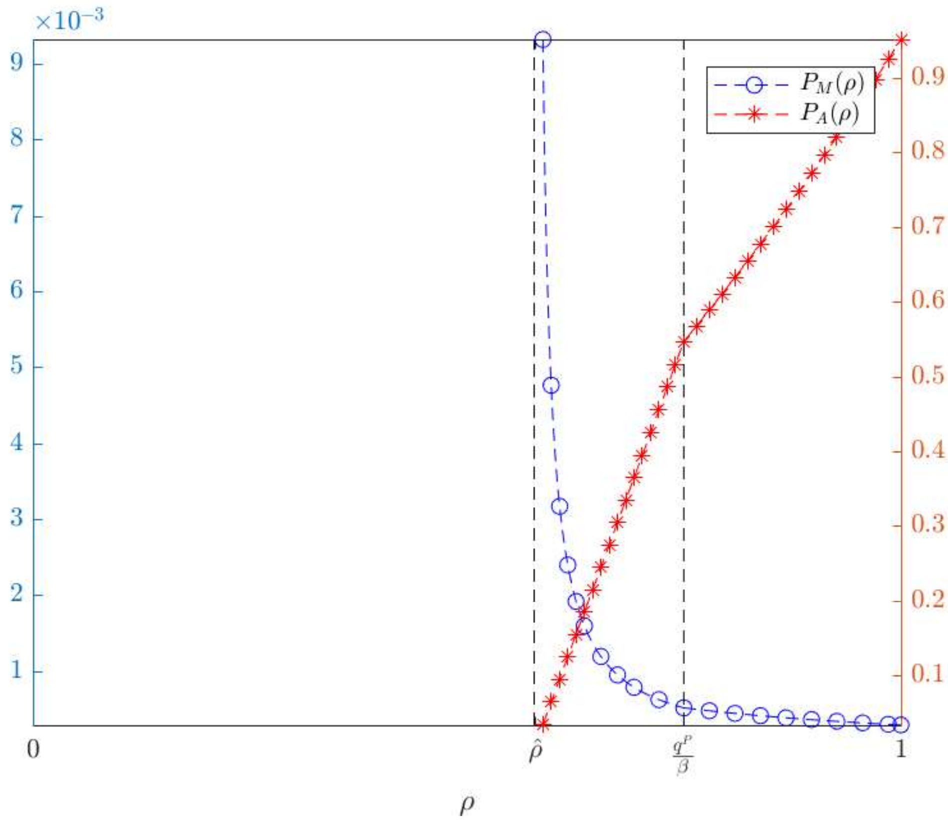


Figure 11: $P_M(\rho)$ and $P_A(\rho)$

Chapter 2

A Quantitative Model of High-Cost Consumer Credit

1 Introduction

High-cost consumer loans (e.g., payday loans, pawn loans, title loans) are used by 7% of US households, particularly by low-wealth and low-income households that lack access to the traditional financial system.[1] Most are payday loans which are small, short-term, high-cost unsecured loans. The activity is subject to tight regulations at the state level, from outright bans to interest rate caps, loan size limits, and rollover restrictions. For instance, a quarter of the US population lives in states where payday lending is banned. As shown in Figure 1, most regulatory borrowing limits are below $500.[2]

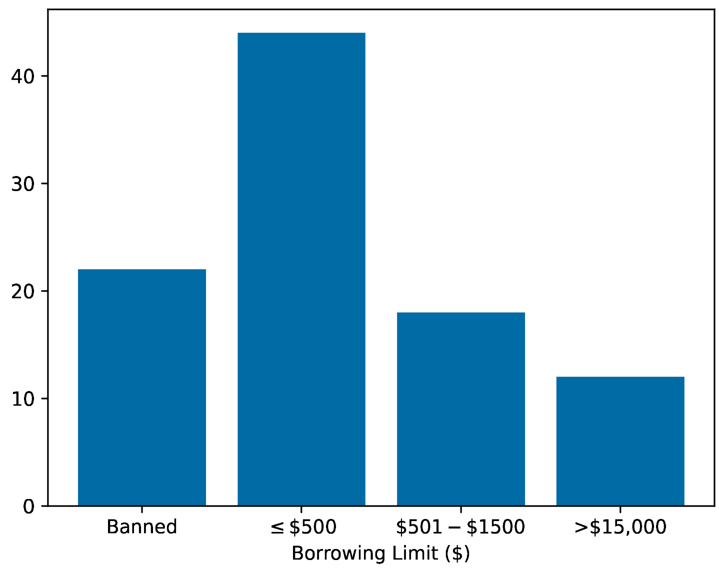


Figure 1: Distribution of borrowing limits in the US (Barth, Hilliard, Jahera, and Sun 2016)

This paper studies the welfare consequences of regulations of high-cost consumer credit markets in a dynamic general equilibrium model. Borrowers may be willing to borrow at high interest rates during bad times (e.g., health shocks), but they may also face a temptation to consume in the present more than what is desirable in the long run. In the first case, the optimal policy would seek to preserve access to credit, while in the second

[1]Current Population Survey 2015 and Survey of Consumer Finances 2016

[2]See Barth, Hilliard, Jahera, and Sun (2016) for details on payday lending regulations by state.

case, the optimal policy may seek to restrict borrowing by households that suffer from self-control problems. The main contribution of this paper is to study this trade-off under limited commitment on the part of borrowers. As a consequence, interest rates reflect the default risk at the individual level. Lenders' pricing can either exacerbate overborrowing or limit it, which affects the efficacy and optimality of regulations.

I find that regulations that restrict high-cost credit, such as those currently in place—noncontingent loan size limits and interest rate caps—reduce the welfare of households that suffer from temptation. The reason is that lenders offer borrowers tight individually-targeted pricing schedules, which already limit the extent to which borrowers can overborrow. Thus the case for regulation of high-cost credit due to self-control problems is not supported by the model.

To study this trade-off, I develop a quantitative model of unsecured credit that features (i) households that face idiosyncratic risk in their income and expenditures; (ii) heterogeneity in preferences, with patient and impatient exponential discounters, and a third group that faces temptation and self-control issues; and iii) risk-based pricing by lenders. The model borrows extensively from the quantitative unsecured credit literature: Livshits, MacGee, and Tertilt (2007), Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Athreya, Tam, and Young (2012). In particular, it is closest to the model in Nakajima (2017) used to study technological changes in the unsecured credit market.

The risk in income and expenditures captures plausible sources of uncertainty for households, potentially driving the demand for high-cost borrowing. In Table 7, I document that households that take payday loans are more likely to have experienced unusually high expenditures or unemployment of the head of household than households that did not take payday loans, after controlling for income, wealth, and age of the head of household. In modeling expenditure shocks, I depart from the unsecured credit literature and use consumption thresholds from Miranda-Pinto, Murphy, Walsh, and Young (2020). Consumption thresholds are discretionary—households choose how much to adjust their consumption, and eventually their borrowing, in response to the expenditure shock. Consumption thresholds are also persistent and thus more appropriate for high-frequency borrowing than the traditional i.i.d. expenditure shock in the unsecured credit literature.

The different preferences allow the model to have households that potentially benefit from regulations such as those that have temptation and self-control issues, and others that will surely experience welfare reductions because of them—for instance, exponential discounters with high or low discount factors. Previous papers on high-cost lending (Skiba and Tobacman (2008) and Allcott, Kim, Taubinsky, and Zinman (2020)) have considered quasi-hyperbolic discounting as a driver for the demand for payday loans.[3] Also, heterogeneity in preferences is supported by previous papers. For instance, liquidity shocks, impatience, and time inconsistency coexist in driving demand for high-cost loans in Iceland (Carvalho, Olafsson, and Silverman 2019). In Allcott, Kim, Taubinsky, and Zinman (2020), the valuations of a no-borrowing incentive of $100 range from $0 to $160. The broad range of valuations suggests that some borrowers may benefit from not being able to borrow (high valuations)—e.g., households with temptation— but others suffer significantly (low valuations).

Finally, there is limited commitment, and households can default on their loans, so the prices posted by lenders will reflect that risk at the individual level. Here I am departing from the literature on models of high-cost credit, namely Skiba and Tobacman (2008) and Allcott, Kim, Taubinsky, and Zinman (2020), which considered exogenous interest rates for loans and limited risk-based pricing. The importance of modeling the price of credit is that price schedules can either limit overborrowing or exacerbate it, thus affecting the efficacy and optimality of regulations.

I estimate the model using a unique dataset of the universe of payday loan transactions in Florida between 2003 and 2018, totaling 100 million payday loan transactions. In addition, I use the valuations of a no-borrowing incentive from Allcott, Kim, Taubinsky,

[3] Self-control and temptation preferences, in particular the application by Krusell, Kuruşçu, and Smith (2009), generalize quasi-hyperbolic preferences. The latter is as an agent that fully succumbs to temptation.

and Zinman (2020). Households with temptation preferences value not being able to borrow in the future, so they have high valuations for the incentive program; exponential discounters have lower valuations since they weakly suffer from not borrowing. I use the valuations of the no-borrowing incentive to identify the fraction of households that have temptation and self-control issues. I estimate that two-thirds of households that use high-cost loans are exponential discounters (patient or impatient), and the remaining one-third are households with temptation.

I validate the estimation of the model in two ways. First, the identification of exponential discounters and temptation households is consistent with qualitative survey data on self-control from the National Financial Well-Being Survey, in particular, for high-cost borrowers.[4] The model and survey agree that more than one-third of high-cost borrowers are "not good at resisting temptation" and that 70% "can work diligently toward long-term goals."

Second, the estimated model is also consistent with the effect of real-world regulations on payday lending.[5] Zinman (2010) measures the effect of an interest-rate cap on the probability of re-borrowing in Oregon in 2007. The quantitative model can reproduce the drop of 28 percentage points in the likelihood of re-borrowing found in Zinman (2010) for the Oregon interest-rate cap.

In this model, high-cost borrowing is driven mostly by impatient and temptation households, but there are also loans to patient households. Patient households borrow when income is low, expenditure shocks are binding, and they have run out of savings. The price schedules they face quickly go to zero with the level of debt, so they take small loans at a high interest rate. Impatient and temptation households borrow at all

[4]See Consumer Financial Protection Bureau (2017).

[5]There is a large literature on payday lending that focuses on estimating the causal link between taking a payday loan and the financial well-being of borrowers (e.g., payday loan use, being late with loans or bills, demand for other sources of credit and bankruptcy), as well as the effect of regulations. See Agarwal, Skiba, and Tobacman (2009); Zinman (2010); Morse (2011);Melzer (2011); Bhutta (2014); Bhutta, Skiba, and Tobacman (2015); Bhutta, Goldin, and Homonoff (2016); Gathergood, Guttman-Kenney, and Hunt (2018); Skiba and Tobacman (2019).

income levels, which is consistent with data from the Survey of Consumer Finances (SCF, 2016), in which households from all income deciles borrow from payday lenders; however, the model exaggerates high-income borrowing. Depending on their income, they borrow small amounts at high interest rates when they have bad realizations of income or expenditure shocks or large amounts of debt at low rates when they have high-income and low-expenditure shocks. This negative correlation between loan size and interest rate is consistent with the microdata: larger loans are associated with lower interest rates in payday lending.[6]

I evaluate two types of noncontingent regulations: regulatory borrowing limits—cannot borrow more than the regulatory limit—and interest-rate caps—cannot borrow at interest rates higher than the cap. Results show that these regulations weakly reduce the welfare of all types of households, including those that suffer from temptation and self-control. Tight regulatory borrowing limits reduce welfare the most as it affects small and expensive loans because these are taken in bad states of the world—low-income, and high-expenditures—by households of all types.

There are significant distributional effects of noncontingent regulatory borrowing limits within temptation households across the income distribution. Low-income households are hurt by borrowing limits, but high-income households benefit from them. The latter occurs because high-income households face borrowing constraints that are not tight—in other words, they can afford the temptation. On the other hand, low-income households are, to a large extent, constrained by the pricing schedules of lenders and would benefit from more access to credit during bad times. Regulatory borrowing limits contingent on income, expenditures, and preferences can generate welfare gains but are unfeasible to implement.

Noncontingent interest-rate caps are also welfare-reducing. Relatively loose interest-rate caps are welfare-reducing since expensive and small loans correspond to borrowing

[6]See Bhutta, Skiba, and Tobacman (2015).

in states of the world where borrowers need them the most for consumption smoothing.

The rest of the paper is organized as follows. Section 2 presents a simple two-period model to show the optimality of regulatory borrowing limits when households suffer from temptation and how it depends on default costs. Section 3 presents a quantitative version of the two-period model. In section 4, I discuss the calibration of the parameters of the quantitative model, and section 5 presents the main results. Finally, section 6 concludes.

2 Two-period Model

The goal of this section is twofold. First, I present temptation and self-control preferences. Second, I show that regulatory borrowing limits can improve the welfare of households with temptation and self-control issues and that the optimal regulatory borrowing limit depends on the financial frictions in the credit market.

2.1 No Uncertainty

I start with a two-period model with a deterministic endowment economy and a fixed risk-free interest rate r, which I normalize to 1. Households can choose how much to save or borrow and consume.

The utility representation of preferences with temptation and self-control is taken from Gul and Pesendorfer 2001 and presented in (1). Actual household choices are a compromise between a commitment utility, which represents the long-run preferences of the household, and a temptation utility. There is also a utility cost, the maximal temptation, which is the temptation utility evaluated at the choices under the temptation utility exclusively.

Alternatively, one can think of these agents' choices as trading off commitment utility with the cost of self-control, which is the maximal temptation minus the temptation utility. If the household follows his commitment utility, the cost of self-control is positive since maximal temptation is greater than temptation utility. On the other hand, if the household's choices are driven by temptation, the cost of self-control is zero, and the household's welfare is simply the commitment utility. In both cases, the household can benefit from a reduced set of choices. In the first case, if there were no temptation options, he would benefit through a lower cost of self-control, even though his actual choices would be unchanged. In the second case, the household would benefit from not facing a temptation since his utility is just the commitment utility, which is maximized at choices made under the commitment utility.

I use the application to consumption-savings problem by Krusell, Kuruşçu, and Smith 2009. Commitment and temptation utility differ in the discount rates with the former having a discount rate β, and the latter a lower discount factor $\delta\beta$, since $\delta < 1$, so the agent is present-biased. Whether the agent follows its commitment or temptation utility depends on the parameter γ, the strength of the temptation. Allocations $\{c_1, c_2, a_2\}$ maximize $u(c_1) + \beta u(c_2) + \gamma [u(c_1) + \delta\beta u(c_2)]$ subject to the corresponding budget constraints. Temptation allocations $\{\widetilde{c_1}, \widetilde{c_2}, \widetilde{a_2}\}$ maximize $u(\widetilde{c_1}) + \delta\beta u(\widetilde{c_2})$ subject to the budget constraints. Since $\delta < 1$, the actual saving allocation will be higher than the one under full temptation.

$$
\begin{aligned}
\max_{c_1, c_2, a_2} \quad & \underbrace{u(c_1) + \beta u(c_2)}_{\text{Commitment utility}} + \underbrace{\gamma [u(c_1) + \delta\beta u(c_2)]}_{\text{Temptation utility}} - \underbrace{\gamma \max_{\widetilde{c_1}, \widetilde{c_2}, \widetilde{a_2}} u(\widetilde{c_1}) + \delta\beta u(\widetilde{c_2})}_{\text{Maximal temptation}} \\
\text{s.t.} \quad & c_1 = y - \frac{1}{R} a_2 \\
& c_2 = y + a_2 \\
& \widetilde{c_1} = y - \frac{1}{R} \widetilde{a_2} \\
& \widetilde{c_2} = y + \widetilde{a_2} \\
& \bar{a} \leq a_2, \widetilde{a_2}
\end{aligned} \tag{1}
$$

Suppose a regulator can impose a savings floor $\bar{a}$. Then, the regulator can increase the household's welfare with temptation by limiting how much he can save, as stated in the following proposition.

Proposition 1 *Consider, a savings floor $\bar{a}$. There is a unique welfare-maximizing $\bar{a}$ and it implements the allocations that maximize commitment utility.*

The proof is straightforward and given in subsection D.1. The idea is the following and illustrated in Figure 2: low levels of $\bar{a}$ are binding only for the temptation allocation, so welfare increases as the maximal temptation is lower. At greater levels of $\bar{a}$, when both allocations are constrained, utility is simply the commitment allocation, so there is an optimal $\bar{a}$ at the allocation that maximizes the commitment utility.

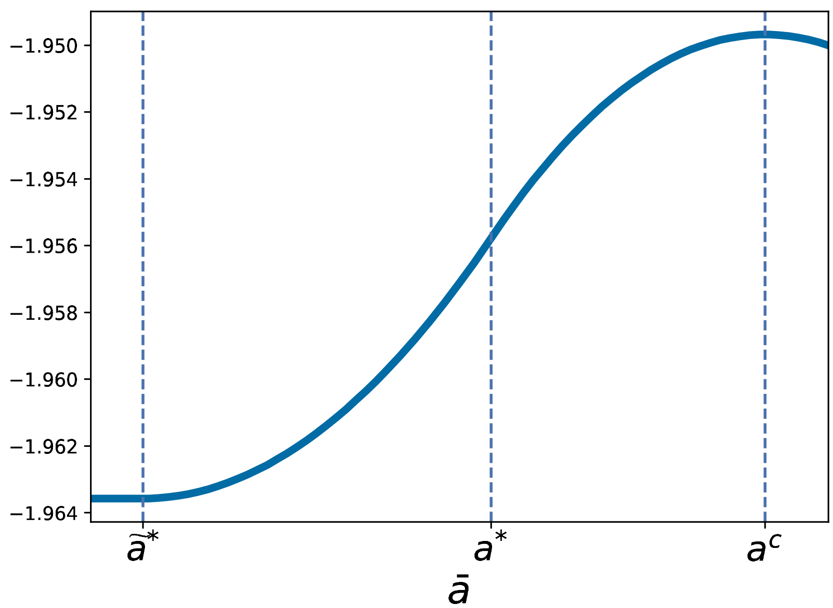


Figure 2: Welfare and regulatory borrowing limit $\bar{a}$

2.2 Uncertainty and Default

In this section, I introduce limited commitment in credit markets (when $a_2 < 0$) to show how the optimal $\bar{a}$ changes. Now, assume that the endowment in period 2 is stochastic and can take two values as in Equation 2. And, households can default on their debt in period 2 ($a_2 < 0$).

$$y_2 = \begin{cases} y_h, & \text{w/ prob. } \pi \\ y_l, & \text{w/ prob. } 1-\pi \end{cases} \tag{2}$$

Households now have to decide how much to consume and save in period one and in period two, if they will either repay their debt or default as in Equation 3. If they repay, they consume their endowment plus savings. If they default, which only happens when assets are negative, they do not have to pay back their debt, so they consume their endowment, but they face a disutility cost for defaulting λ. In Equation 4, identical decisions are made but under full temptation. Finally, lenders operate in perfect competition and make zero expected profits (Equation 5).

The cost of default determines the regulatory borrowing limit that a regulator would want to impose if any at all. The cost of default affects the default decision by households for any given level of debt and the prices posted by lenders. Then, it affects how many households borrow and utility in states that lead to default in the future.

$$U = \max_{a_2} (1+\gamma)\, u\left(y_1 - q(a_2)a_2\right) + (1+\gamma\delta)\,\beta\,\mathbb{E}_{y_2} \max_{d\in\{0,1\}} \left\{u\left(y_2 - a_2\right), u\left(y_2\right) - \lambda\right\} - \widetilde{U} \tag{3}$$

$$\widetilde{U} = \gamma \max_{\widetilde{a}_2} u\left(y_1 - q(\widetilde{a}_2)\widetilde{a}_2\right) + \delta\beta\,\mathbb{E}_{y_2} \max_{d\in\{0,1\}} \left\{u\left(y_2 - \widetilde{a}_2\right), u\left(y_2\right) - \lambda\right\} \tag{4}$$

$$q(a_2) = 1 - \mathbb{E}[d(a_2)] \tag{5}$$

To illustrate how the cost of default affects the optimal borrowing limit, I use Figure 3 and Figure 4.[7] In the first one, for different levels of λ, I plot indifference curves for the household in (q, a_2), together with the price schedule posted by the lender that

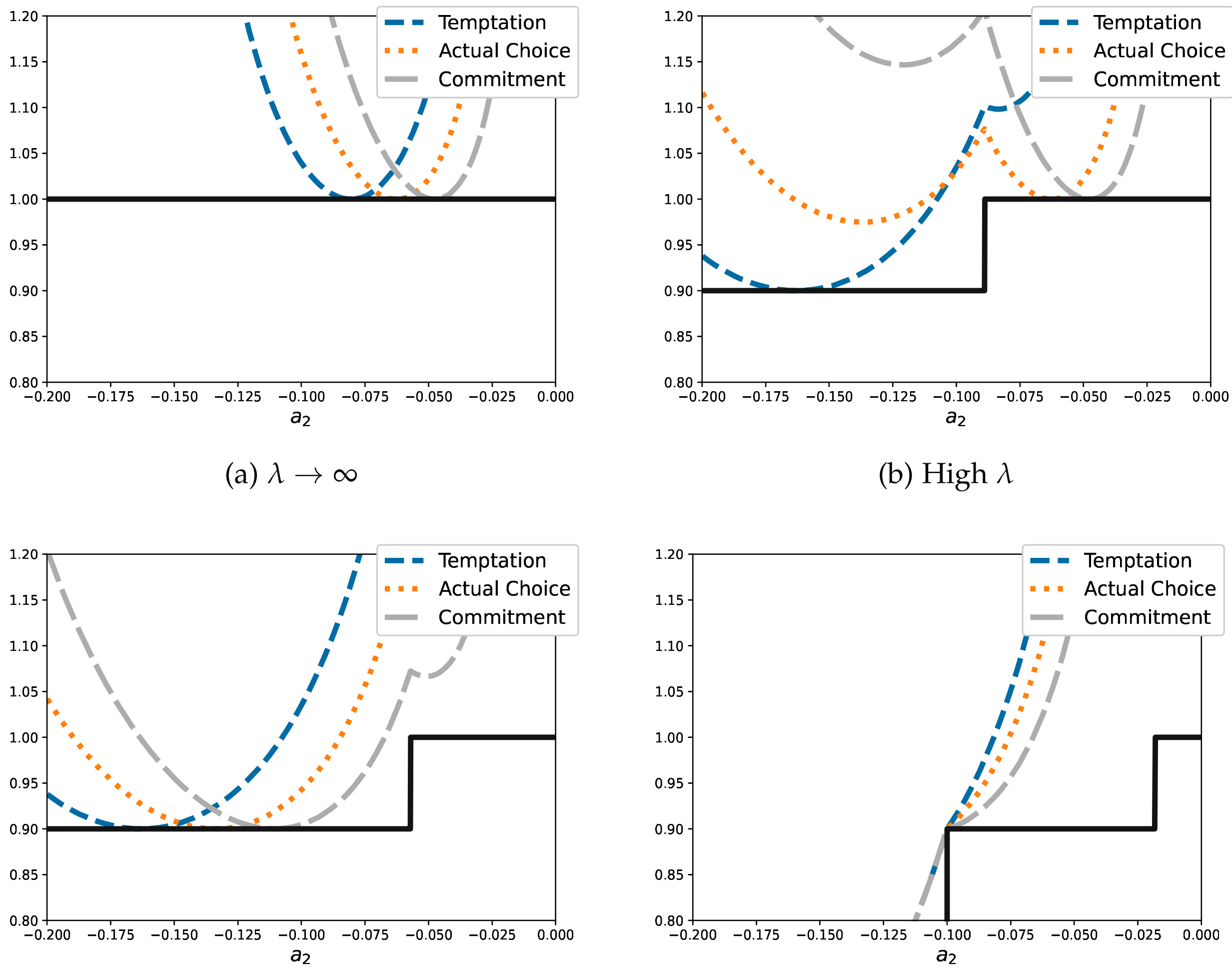
[7]Parameters used for these plots are: $\beta = 0.95$, $\delta = 0.60$, $\gamma = 1$, $y_1 = 0.30$, $y_h = 0.50$, $y_l = 0.20$, $\pi = 0.90$.

satisfies (5). There are three indifference curves: the one that governs the actual choice, which is a combination of commitment and temptation utility (orange dotted line); commitment utility (grey dash-dot line); and one for temptation utility (blue dashed line). The intersection of any of the indifference curves and the price schedule represents the choice under the utility underlying that indifference curve. The second plot shows lifetime utility as a function of borrowing limits.

In Figure 3a, the cost of default goes to infinity which is the case that households cannot default. Here prices are entirely horizontal, and allocations are all relatively low debt levels with the ordering expected for a present-biased temptation. As above, the optimal borrowing limit coincides with the commitment allocation.

Now, I look at cases where λ is low enough to default in some states of the world. In Figure 3b, λ is high such that commitment and the actual allocation remain the same as before. However, for the low discount factor of temptation, the temptation allocation has shifted towards higher debt levels. From Figure 4, we can see that the utility is now double-peaked with respect to the borrowing limit (orange dashed line). Now, the optimal one does not coincide with commitment allocation. Instead, the regulator wants to limit borrowing to the point where the price schedule jumps with the default probability. For lower levels of borrowing, utility goes down because now the loss from the maximal temptation increases due to the higher prices.

As λ continues to go down, eventually all allocations move to higher levels of debt because defaulting is not that costly, even though prices are lower as in Figure 3c. Now, the optimal borrowing limit coincides again with the commitment allocation but at a high level of debt. The optimal borrowing limit with extremely high costs of default is now too restrictive as the households want to borrow more. Finally, very low levels of the cost of default make debt prices go to zero very fast with the level of debt. In this case, all allocations are constrained by the pricing schedule. As we can see in the utility plot, welfare never improves with a borrowing limit since lenders are already constraining the maximal temptation and actual and commitment choices.



(a) $\lambda \to \infty$ (b) High λ

(c) Mid λ (d) Low λ

Figure 3: Indifference curves and prices

3 Quantitative Model

Time is discrete and goes on forever. There exists overlapping generations of J-period lived households. In each period, a measure one of households is born. Households face idiosyncratic endowment and expenditure risk, and make decisions about their savings/debt and default. Markets are incomplete as households only have access to a one-period bond. There is no aggregate uncertainty.

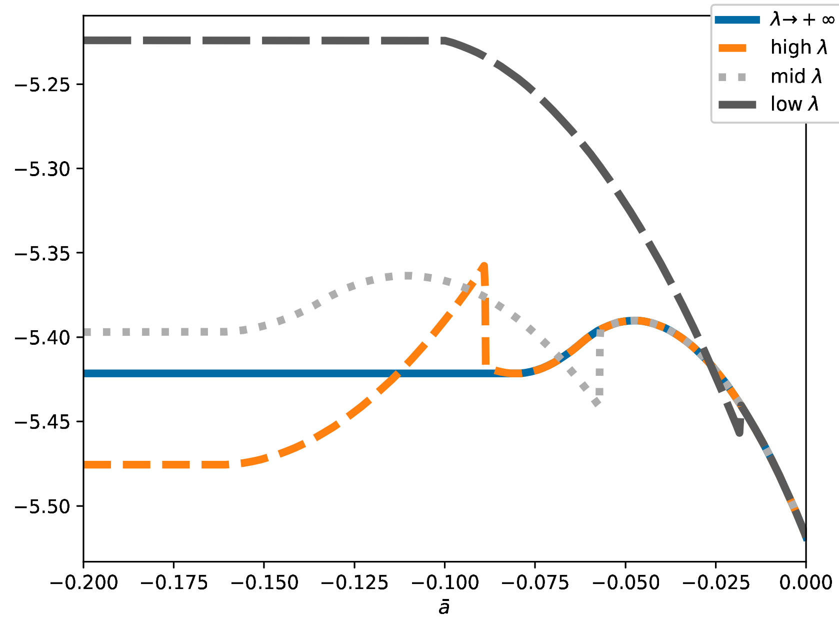


Figure 4: Welfare, default cost λ and regulatory borrowing limit $\bar{a}$

3.1 Households

Households live J periods. During ages $j \in [1, W]$, with $W < J$, households receive a stochastic endowment y given by (6); between ages $j \in [W+1, J]$, they receive a deterministic endowment equal to a fraction Θ of the last stochastic realization of their endowment in period W. The labor income process is standard in the unsecured credit literature and has two components, a permanent and a transitory one.

They face expenditure shocks during all ages. In the expenditure shocks I deviate from the unsecured credit literature which uses non-discretionary, i.i.d. expenditure shocks.[8] I use consumption thresholds $\underline{c}$ from Miranda-Pinto, Murphy, Walsh, and Young (2020). The consumption threshold evolves according to (9), and entails a utility cost $\eta \max(\underline{c} - c, 0)$. The household can decide how much to adjust its consumption to smooth out the expenditure shock, by lowering its asset holding—and eventually borrowing—or defaulting, trading off the marginal disutility of the expenditure shock and the marginal cost of increasing consumption. This mechanism is absent in the traditional

[8]See Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Livshits, MacGee, and Tertilt 2007.

non-discretionary expenditure shocks where households automatically reduce their assets or default when hit by an expenditure shock.[9] The presence of consumption thresholds allows consumption to vary as much as income but with a low correlation from it, both features that a standard model with incomplete-markets and idiosyncratic risk cannot deliver.[10]

$$y = x + z \tag{6}$$

$$x' = \rho_x x + \epsilon_x' \tag{7}$$

$$z' = \rho_z z + \epsilon_z' \tag{8}$$

$$\underline{c}' = (1 - \rho_c)\mu_c + \rho_c \underline{c} + \epsilon_c' \tag{9}$$

Households have access to a one-period asset a, with price q, that delivers one unit of consumption next period. Households can always save, $a > 0$, at the risk-free price $q = \frac{1}{1+r}$, which is exogenous. They can also borrow, $a < 0$, exclusively from a high-cost lender whose pricing is described below. I abstract from credit card borrowing for two reasons: i) approximately half of payday borrowers do not have credit cards (Survey of Consumer Finances (SCF), 2016); ii) as shown in Bhutta, Skiba, and Tobacman 2015 payday borrowers are searching unsuccessfully for credit before taking a payday loan, and taking one is associated with the exhaustion of credit limits in credit cards, on average. In Table 8 I provide additional evidence that household take high-cost loans like payday loans when traditional credit is unavailable to them. On average, households that took a payday loan are more likely to not have access to credit cards, or are searching for credit and being rejected by lenders during the same period they took a payday loan, with respect to households that did not take one, after controlling for wealth, income and age (SCF, 2016).

[9] In addition, the expenditure shock is persistent which is more realistic for high frequency borrowing like high-cost credit; i.i.d. shocks are used in annual or even triennial models.

[10] See Miranda-Pinto, Murphy, Walsh, and Young (2020) for further details.

Focusing exclusively in high-cost borrowing is also in line with previous papers in the literature.[11] An exception is Bethune, Saldain, and Young (2021), where households can borrow either from a low-cost or a high-cost lender.

Households can default on their debt. If they do default they are excluded from borrowing in the present, and with probability $1 - \chi$ they will be excluded in further periods. They can regain access to borrowing with probability χ in each period. State variable d takes value 1 if they are excluded from borrowing, and 0 otherwise.

There are three types of households: patient, impatient and a behavioral agent. Patient and impatient households differ in their discount factor β, such that the discount factor of the latter is lower than that of the former. The behavioral agent features self control and temptation problems as in Gul and Pesendorfer 2001. In particular, I use the specialization to consumption-savings problems by Krusell, Kuruşçu, and Smith 2010. I index households as P, I, T, respectively.

Below, I describe the optimization problem of an individual of type $i \in \{P, I, T\}$ with state vector $(a, y, \underline{c}, d)$. Sub-index j represents age and variables with $\prime$ represent next period values.

No default flag ($d = 0$) When the household is not excluded from borrowing, it has to decide whether to repay or default, as in (10). For patient and impatient households, $i \in \{P, I\}$, if the household decides to repay, the household chooses its optimal level of assets for next period and present consumption as in (11).

$$v_j^i\left(a, y, \underline{c}, 0\right) = \max\left\{v_j^{i,s}\left(a, y, \underline{c}\right), v_j^{i,d}\left(a, y, \underline{c}\right)\right\}, i = P, I, T \tag{10}$$

[11] See Skiba and Tobacman 2008 and Allcott, Kim, Taubinsky, and Zinman 2020.

$$v_j^{i,s}\left(a,y,\underline{c}\right) = \max_{c,a'}\left\{u\left(c\right) - \eta\max(\underline{c}-c,0) + \beta^i\,\mathbb{E}_{y',\underline{c}'|y,\underline{c}}\left[v_{j+1}^i\left(a',y',\underline{c}',0\right)\right]\right\},\, i=P,I$$
$$c = a + y - q_j\left(a',y,\underline{c}\right)a' \tag{11}$$

If it decides to default, represented in (12), the household consumes its endowment but faces three costs of defaulting: it cannot borrow or save in the period he defaulted; a utility cost λ, known as "stigma" in the literature; and stochastic exclusion from borrowing in the future.

$$v_j^{i,d}\left(a,y,\underline{c}\right) = u\left(y\right) - \eta\max(\underline{c}-y,0) - \lambda + \beta^i\,\mathbb{E}_{y',\underline{c}',d'|y,\underline{c}}\left[v_{j+1}^i\left(0,y',\underline{c}',d'\right)\right],\, i=P,I \tag{12}$$

Households with self control and temptation, $i=T$, are presented in equations (13) and (14). These households face identical choices as described above for the exponential discounters. Their default and consumption/saving choices will now be a compromise between their commitment and temptation utilities, each of them governed by discount factors β^T and $\delta\beta^T$, respectively. The extent to which choices are driven by one or the other is determined by parameter γ, the strength of temptation.

$$\begin{aligned} v_j^{T,s}\left(a,y,\underline{c}\right) = &\max_{c,a'}\left\{(1+\gamma)\left[u\left(c\right) - \eta\max(\underline{c}-c,0)\right] + (1+\delta\gamma)\beta^T\,\mathbb{E}_{y',\underline{c}'|y,\underline{c}}\left[v_{j+1}^T\left(a',y',\underline{c}',0\right)\right]\right\} \\ &- \widetilde{v}_j\left(a,y,\underline{c},0\right) \\ &c = a + y - q_j\left(a',y,\underline{c}\right)a' \end{aligned} \tag{13}$$

$$v_j^{T,d}(a,y,\underline{c}) = (1+\gamma)\left[u(y) - \eta \max(\underline{c}-y,0) - \lambda\right] + (1+\delta\gamma)\beta^T \mathbb{E}_{y',\underline{c}',d'|y,\underline{c}}\left[v_{j+1}^T(a',y',\underline{c}',d')\right] - \widetilde{v}_j(a,y,\underline{c},0) \tag{14}$$

In addition, each period they will suffer disutility from their maximal temptation, $\widetilde{v}_j(a,y,\underline{c},0)$. This is the value function when choices are consistent with discount factor $\delta\beta^T$. Their maximal temptation is described by (15), (16) and (17). This case is completely analogous to the choices described previously.

$$\widetilde{v}_j(a,y,\underline{c},0) = \max\left\{\widetilde{v}_j^s(a,y,\underline{c}), \widetilde{v}_j^d(a,y,\underline{c})\right\} \tag{15}$$

$$\begin{aligned}\widetilde{v}_j^s(a,y,\underline{c}) =& \gamma \max_{\widetilde{c},\widetilde{a}'}\left\{u(\widetilde{c}) - \eta \max(\underline{c}-\widetilde{c},0) + \delta\beta^T \mathbb{E}_{y',\underline{c}'|y,\underline{c}}\left[v_{j+1}^i(\widetilde{a}',y',\underline{c}',0)\right]\right\} \\ &\widetilde{c} = a + y - q_j(\widetilde{a}',y,\underline{c})\,\widetilde{a}'\end{aligned} \tag{16}$$

$$\widetilde{v}_j^d(a,y,\underline{c}) = \gamma\left\{u(y) - \eta \max(\underline{c}-y,0) - \lambda + \delta\beta^T \mathbb{E}_{y',\underline{c}',d'|y,\underline{c}}\left[v_{j+1}^i(0,y',\underline{c}',d')\right]\right\} \tag{17}$$

With default flag ($d = 1$) When the household is excluded from borrowing, they behave as described in (18) for patient and impatient, and (19) and (20) for self control and temptation. Now, households can only save but may regain access to credit exogeneously next period.

$$v_j^i\left(a, y, \underline{c}, 1\right) = \max_{c, a' \geq 0} \left\{ u\left(c\right) - \eta \max(\underline{c} - c, 0) + \beta^i \, \mathbb{E}_{y', \underline{c}', d' | y, \underline{c}} \left[v_{j+1}^i\left(a', y', \underline{c}', d'\right)\right]\right\}, i = P, I \tag{18}$$

$$c = a + y - \frac{1}{1+r} a'$$

$$\begin{aligned} v_j^T\left(a, y, \underline{c}, 1\right) = & \max_{c, a' \geq 0} \left\{ (1+\gamma)\left[u\left(\widetilde{c}\right) - \eta \max(\underline{c} - c, 0)\right] + (1+\gamma\delta)\beta^T \, \mathbb{E}_{y', \underline{c}', d' | y, \underline{c}} \left[v_{j+1}^T\left(a', y', \underline{c}', d'\right)\right]\right\} \\ & - \widetilde{v}_j\left(a, y, \underline{c}, 1\right) \\ & \widetilde{c} = a + y - \frac{1}{1+r} \widetilde{a}' \end{aligned} \tag{19}$$

$$\begin{aligned} \widetilde{v}_j\left(a, y, \underline{c}, 1\right) = & \gamma \max_{\widetilde{c}, \widetilde{a}' \geq 0} \left\{ u\left(\widetilde{c}\right) - \eta \max(\underline{c} - \widetilde{c}, 0) + \delta\beta^T \, \mathbb{E}_{y', \underline{c}', d' | y, \underline{c}} \left[v_{j+1}^T\left(\widetilde{a}', y', \underline{c}', d'\right)\right]\right\} \\ & \widetilde{c} = a + y - \frac{1}{1+r} \widetilde{a}' \end{aligned} \tag{20}$$

3.2 High-cost lender

Lenders have access to unlimited funds at an exogenous risk-free interest rate r. There is perfect information so they observe all relevant states and types of households when pricing their loans. It is common for payday lenders to use a subprime credit bureau like the Teletrack score—which tracks consumer being late with bills or other payady lenders—to make their lending decisions as described in Bhutta, Skiba, and Tobacman 2015. In addition, in payday lending, interest rates are positively correlated with the default probability even though loan amounts are mmostly less than \$ 500 because of regulatory limits. [12]

In addition, the lender has operational costs κ. As shown in the appendix and in Flannery and Samolyk 2005, a substantial part of payday loan interest rates can be explained by operational costs (wages, advertising and occupational costs). Operational costs generate a wedge between saving and borrowing rates. Households can save at the risk-free interest rate, but to borrow they have to pay substantially higher interest rates, independently of their default risk.

There is free entry. The break-even condition for payday lenders is shown in (21). The price of the loan reflects the expected default decision, d_j, and the operational costs.

$$q_j^i\left(a',y,\underline{c}\right)=\frac{1}{1+r}E\left[1-d_{j+1}^i\left(a',y',\underline{c}\right)-\kappa\right] \tag{21}$$

4 Calibration

To calibrate the parameters of the model I proceed in two steps. First, I calibrate a subgroup of parameters with values taken from the literature. A second group of 10 parameters, are jointly estimated with 11 moments.

4.1 External parameters

The parameters that are calibrated externally are shown in Table 1. The risk-free monthly interest rate is set to $r=\frac{0.03}{12}$ and the coefficient of risk aversion $\sigma=2$ as is common in the literature. With respect to the parameters that govern the income and expenditure process, I use the estimates from Miranda-Pinto, Murphy, Walsh, and Young 2020 for the mean, persistence and variance of both income and expenditure shocks. Their estimates are

[12] The perfect information assumption may be a strong assumption in high-cost markets. In a 2017 ruling on payday lending by the CFPB, which was later revoked, payday lenders were required to take actions to better determine the ability to repay of borrowers: verify consumer's debt obligations, housing cots, and forecast basic living expenses.

quarterly, so I find monthly approximations as explained in Appendix 3. The parameter that represents the disutility from the expenditure shock is calibrated in the second step since the model in Miranda-Pinto, Murphy, Walsh, and Young 2020 is a infinite horizon model, so the value they estimate cannot be used in this paper.

The parameter κ that represents the cost of operating the payday lending business is calibrated to match the lowest monthly interest rate observed in the data, which is 10%, yielding $\kappa = 0.09$.

Table 1: External parameters

Parameter	Value
σ	2
r	0.0025
μ_x	-0.12
ρ_x	0.79
σ_x	0.66
ρ_z	0.99
σ_z	0.10
μ_c	0.003
ρ_c	0.81
σ_c	1.25
κ	0.09

In the estimation of the model I include the current regulation in Florida: there is an exogenous debt limit, $\bar{a} \geq -\$500$ and a maximum interest rate, $\bar{r} = \frac{0.1a+5}{a}$ that depends on the loan amount.

4.2 Jointly estimated parameters

A second group of parameters is jointly estimated: discount factors $(\beta_P, \beta_I, \beta_T)$, costs of default (λ, χ), cost of expenditure shocks (η), weights for households types (ω_P, ω_I) and parameters that govern temptation (γ, δ).

I use two types of moments in the estimation: payday lending borrowing behavior data—how much households borrow, during how long and how frequently they default—, and valuations of a no-borrowing incentive from Allcott, Kim, Taubinsky, and Zinman (2020). Below, I present the data and moments used in the estimation.

4.2.1 Borrowing behavior

I use a database that comprises more than 100 millions payday loan transactions from the universe of payday lenders in Florida between 2003 and 2018. The statewide database is administered by a private firm, Veritec LLC, and the data can be accessed through the Florida Office of Financial Regulation.

All payday lenders have access to the database. State regulation requires lenders to check that a loan to a client satisfies the financial regulations of the state before issuing a new one. For instance, in Florida, an individual cannot have more than one payday loan at a time; the amount of a loan has to be less than \$ 500; the financial fees have to be less than 10% of the principal amount plus a maximum verification fee of \$ 5; and, clients cannot renew a loan before 24 hours after repaying their loan. Once the lender confirms that the new loan satisfies the state regulations, they can issue the new loan. And, they report the loan information to the state database.

For each transaction the data includes the date the loan was originated, the principal of the loan, the fees charged, the due date, whether there was a payment from the client and when, and the zip code of the lender. At the client level the data includes the date of birth and the zip code in which they live.

One limitation of the data is that a specific client cannot be followed across time. To surpass this limitation, I approximate a consumer across time using combinations of date of birth and zip code. If for a zip code and date of birth, there are two or more loans overlapping in at least one day, the observation is dropped. This is because regulation prohibits having more than one payday loan at a time. After doing this, 70% of transactions remain in the database. I use this identification of a consumer to measure borrowing sequences. I define loan sequences as consecutive loans that are separated by less than 30 days to be consistent with the frequency of the quantitative model.

Table 2 summarizes the characteristics of of payday loan transactions. On average, a payday loan is for $404, with a maturity of 17 days and a monthly interest rate of 22.4 % (equivalent to an APR of 268%). Thus, they are small, expensive and short term. The average borrowing sequence lasts 4 months, and approximately 2% of transactions are paid back late, with is my measure of default.

Table 2: Summary Statistics and Regulation

Summary statistics		
	Mean	SD
Loan size ($)	404.1	129.0
Monthly rate	22.4	9.1
Term (days)	17.3	7.0
Default (late $>$ 30 days, %)	1.9	13.7
Sequence length (months)	4.1	8.5
Regulation		
Loan size limit ($)	500	
Interest rate ceiling	10% of principal + $5	
Cooling-off period (days)	1	

A model of payday lending should be able to reproduce at least the borrowing behavior that is directly regulated through loan size limits, interest rate caps and rollover restrictions. That is, how much is borrowed, the length of their borrowing sequences and the cost of loans—reflected here in how frequently they default and operational costs. With respect to the amount borrowed, I approximate the loan distribution from Figure 5 by targeting the proportion of loans at the maximum loan size, the proportion of loans between $100 and $450 and, the average loan.

With respect to default rates, I consider a loan to be defaulted when the loan was late for more than 30 days. I target the default rate of short and long sequences, as shown in Figure 6. Longer sequences are defaulted more than twice as much with respect to shorter ones.

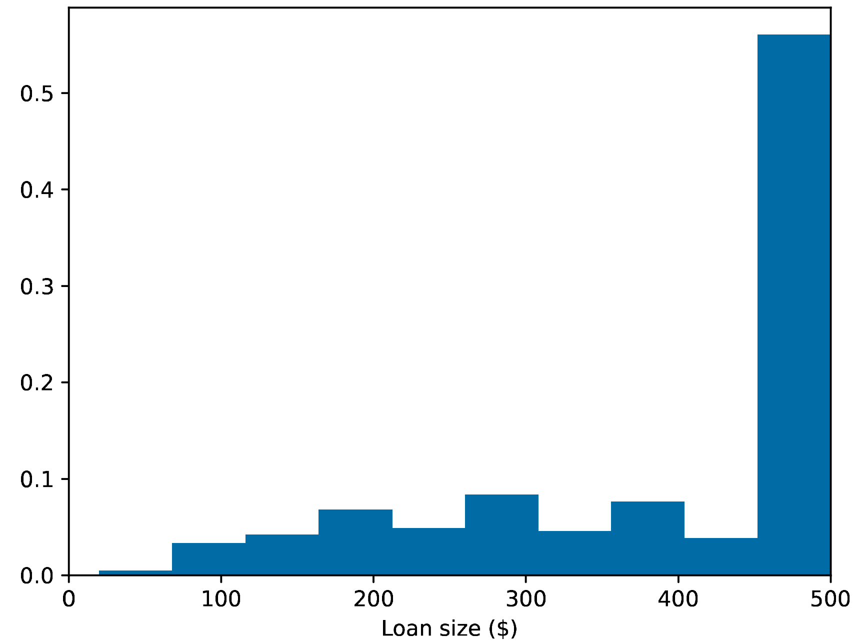


Figure 5: Fraction of loans by loan size (in dollars)

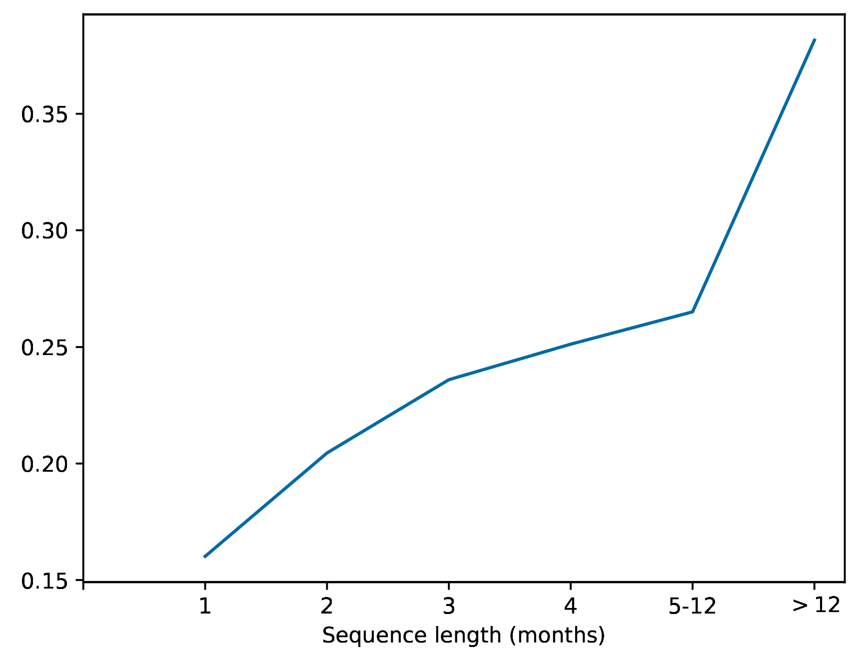


Figure 6: Fraction of sequences defaulted by sequence length (in months)

The distribution of sequences by length is presented in Figure 7. I approximate the distribution of the length of sequences with the fraction of sequences that last less than 1 month, the fraction that is more than 12 months and, the average sequence length. The loan sequences that I observe for Florida are quantitatively comparable to the ones in CFPB 2013 for a large payday lender. For instance, 41% of loan sequences last up to one month in Florida, while in the CFPB data they account for 54%. Similarly, longer sequences that last more than 5 months account for up to 22% and 17% respectively. The differences are due to the time between consecutive loans in each case. The CFPB defines sequences as loans separated by less than 14 days. In the Florida data I define sequences as consecutive loans separated by less than 30 days. That explains why there are more short sequences in the CFPB data, and more long sequences in the Florida microdata.

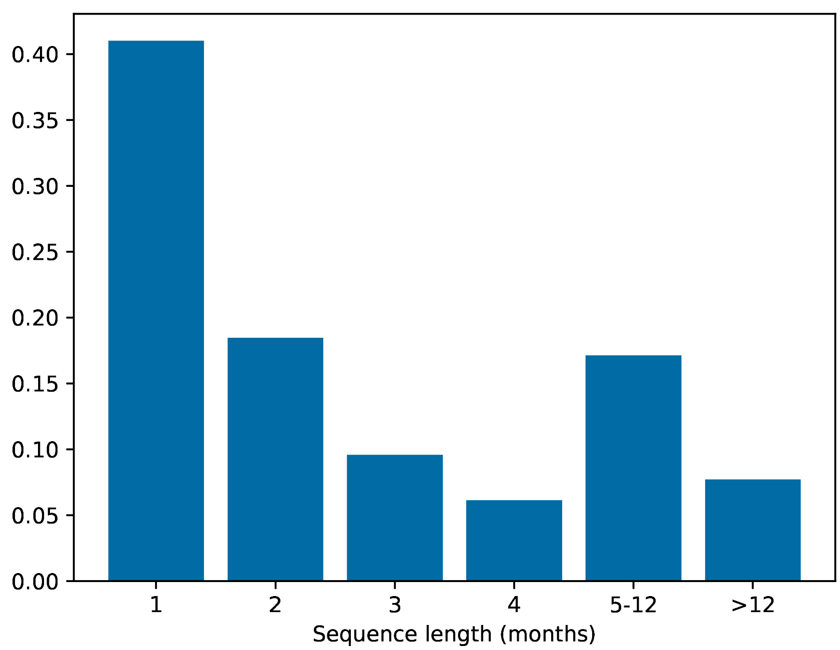


Figure 7: Fraction of sequences by sequence length (in months)

In addition, I also include the payday loan take up rate to discipline the model in the sense that only a small fraction of households actually take up payday loans. I use the Survey of Consumer Finances (SCF) to measure payday take-up rates. The SCF asks respondents whether they took a payday loan during the previous 12 months. In the Survey of Consumer Finances 2016, 3.6% of total households borrowed from a payday lender. I adjust this number to 4.8% of households to take in account the fact that 25% of the population lives in states that completely ban payday lending.

4.2.2 No-borrowing incentive

Finally, I use valuation data from a no-borrowing incentive (NBI) offered to payday customers in Indiana in Allcott, Kim, Taubinsky, and Zinman 2020. The NBI consists of offering $ 100 to payday customers in 3 months if they do not borrow from a payday lender within the next 2 months. As shown in Figure 15, there is a distribution of how valuable the incentive is—that is, the amount of money-for-sure in 3 months that would make borrowers indifferent with respect to the incentive. Two facts from this figure are interesting for the purpose of this paper: i) a quarter of the borrowers have valuations close to zero for the incentive, indicating that not being able to borrow is very painful for them; ii) there are valuations above $ 100, which is and indication that there are customers who benefit from not being able to borrow. The valuations data will be critical to identifying temptation households from exponential discounters. Exponential discounters with low discount factor—who are likely to borrow in the future— will be hurt by the NBI and have a low valuation. Households with temptation have a demand for commitment, they value not being able to borrow in the future as it limits their temptation, so they have high valuations.

To distinguish between exponential discounters (patient or impatient) and temptation households, I target the average valuation of the NBI and the fraction of valuations between $100-$160[13]. Zinman (2010) use this moment to identify the average borrower as time inconsistent in their model. Valuations above $100 can only be achieved by household with temptation, so that moment will be a lower bound to the weight of that

[13] Allcott, Kim, Taubinsky, and Zinman (2020) use the average valuation and argue that the average borrowers is time inconsistent.

type of households.[14] As showed below, this strategy identifies a mass of households with temptation consistent with independent survey data.

5 Results

5.1 Model fit

The model is able to capture the moments of payday lending borrowing. It captures a fraction of borrowers taking very short high-cost loan sequences but long sequences too. A fraction of borrowers bunching at the maximum loan size allowed by regulation, but also smaller loans too. The largest deviation is related to the loan size distribution. The model delivers too many small loans (less than $ 50) that in the data practically do not exist. This is due to two reasons. On the one hand, price schedules for households with binding consumption thresholds are very tight and go to zero very fast before a debt level of $ 100.[15] Thus, in states of the world where income is low and consumption thresholds are binding, loan are relatively low and explains the excessive fraction of small loans that the model delivers with respect to the data.

The parameters that yield this fit for the model are presented in Table 4. First, 94% of households have a relatively high discount factor; the remaining households are impatient or have temptation and self control preferences, almost in equal measure. The impatient agent has a very low discount factor of $\beta_2 = 0.15$. The temptation agents combines an intermediate discount factor of $\beta_3 = 0.55$ and even lower temptation discount factor given by $\delta\beta_3 = 0.17 * 0.55$. The borrowing is dominated by the impatient and temptation agents as 95% of the loans are demanded by them, and the remaining by patient households.

[14] In Allcott, Kim, Taubinsky, and Zinman (2020) they find that future borrowing beliefs are affected by the incentive as households report a lower probability of borrowing than the actual one. This is another reason for why using the valuatons above $100 is a lower bound to the mass of households with temptation: with a greater probability of borrowing in the future, temptation households would likely have a higher valuation.

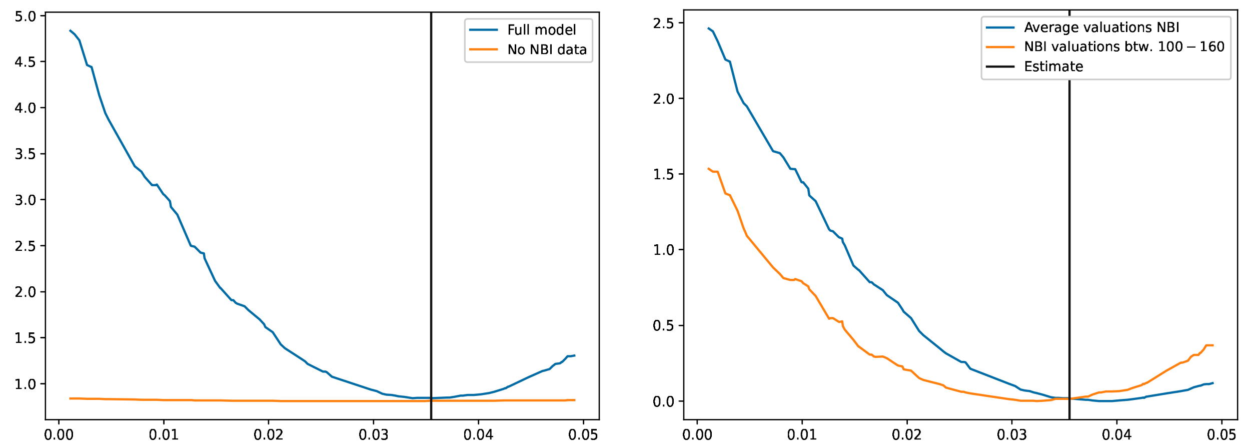
[15] This is a combination of high risk for these holds and binding interest rate ceilings from the current Florida regulation.

Table 3: Joint estimation: data vs model

	Data	Model	Source
Average Sequence (months)	4.2	5.1	Florida (2003-2018)
Sequences $>$ 12 months	7.7	8.0	Florida (2003-2018)
Sequences = 1 months	41.0	26.7	Florida (2003-2018)
Average Loan ($)	404	260	Florida (2016)
Fraction loans = $500	55.8	37.4	Florida (2016)
Fraction loans $100 - $450	43.68	21.5	Florida (2016)
Default rate long seq.	38.0	29.0	Florida (2003-2018)
Default rate short seq.	16.0	17.9	Florida (2003-2018)
Take-up rate	4.8	5.0	SCF (2016)
Average valuation NBI	52.0	58.8	Zinman et al (2020)
Fraction of valuations between $100-$160	16.0	13.1	Zinman et al (2020)

Table 4: Estimated parameters

	Parameters	Description
β_1	0.99	Discount Factor 1
β_2	0.15	Discount Factor 2
β_3	0.55	Discount Factor temptation
δ	0.17	Nature of temptation
γ	105.2	Strength of temptation
ω_1	0.94	Weight β_1
ω_2	0.034	Weight β_2
λ	0.15	Default utility cost
η	314	Exp shock utility cost
χ	0.05	Re-access probability



(a) Sum of Squared Errors

(b) Squared deviation from target moment

Figure 8: Identification of ω_2

5.2 Identification

Figure 16 shows the sum of squared errors between moments from the data and the model, evaluated at the calibrated parameters. Each of the boxes changes one parameter at a time. Most of the parameters are well identified, in the sense that the sum of squared errors is minimized at the calibrated value. There are a few exceptions. First, the identification of γ is not clear for values greater than approximately 30. For higher values of the parameter, the effective discount rate in the Euler equation of the agent with temptation and self control issues converges to $\delta\beta$.

The identification of ω_2 is only achieved with the NBI valuations data. Without it, any value of the parameter will yield the same borrowing observables as shown in Panel A of Figure 8. The sum of squared errors between the model and data is completely flat if moments from the NBI are ignored. However, once we incorporate the valuations data, we can pin down the measure of impatient households.

5.3 Validation

In this section I validate the model by checking how it performs relative to data that was not used in the calibration above.

5.3.1 Temptation

First, I use the National Financial Well-Being Survey, a nationally representative survey, in particular, its questions regarding self-control.[16] The survey asks respondents how well, in general, each statement presented in Table 5. Respondents can answer "Completely well", "Very well", "Not very well" or "Not at all". I bundle the first two and compare with model measurements of households that have temptation or not from the model.

Table 5: Fractions of answers "Completely well" or "Very well" to self-control statements in National Financial Well-Being Survey

	High-cost borrowers
Data	
I am able to work diligently toward long-term goals	69.9
I am good at resisting temptation	61.1
I often act without thinking through all the alternatives	38.2
Model	
$\omega_P + \omega_I \mid a' < 0$	64.3
$\omega_T \mid a' < 0$	35.7

Among households that have taken high-cost loans, the data and the model are very close: nearly 70% of survey respondents were well described by the statement they are able to work towards long-term goals, and more than 60% are good at resisting temptation; those values compare favorably to the fraction of households that do not have temptation issues in the model, 64.3%. Likewise, 35.7% of households that actually have temptation in the model, is closed to the households that are not good at resisting temptation, cannot work towards long-term goals or do not think through all the alternatives.

In the general population, model and data do not compare so favorably. They do in the sense that there is an enormous fraction of households that do not have temptation issues. The model is likely biased towards more exponential discounters than there should be, as reflected in the second column of Table 5. This is due to two reasons: first, there may be

[16] Consumer Financial Protection Bureau 2017

households that suffer from temptation but that exert self-control, and do not borrow at high rates; second, there could be households that have temptation and are effectively tempted, but the temptation discount factor is not as low as the households that actually borrow at high rates, This is a limitation of this paper and likely overestimating the welfare losses from regulations in the patient households, although the patient households are likely mostly high discount factor households.

5.3.2 Effect of regulations

There is a large empirical literature on high-cost lending that estimates the causal effect of regulations, or the causal effect of using these credit products. Here, I replicate in the model the findings of Zinman 2010. This paper evaluates the effect of an interest rate cap for payday lending in Oregon, using a difference-in-difference approach with the state of Washington, which did not place an interest rate cap. The new policy consisted of limiting the cost of payday loans to a maximum APR of 150% on loans under $ 50,000, while Washington state did not impose an interest rate cap on loans up to $ 500. The paper uses survey panel data of payday borrowers, before the policy change and 5-months after the policy change. They measure the effect of the interest rate cap on the likelihood that households that were borrowing before the change, continue to do so, 5 months after the policy change. I run the same exercise in my model.

Table 6: Effect of the Oregon interest rate cap on payday loan usage

	Zinman 2010			Model		
	Oregon	Washington	Effect	Oregon	Washington	Effect
Likelihood payday borrowing after cap	0.51	0.79	-0.28	0.18	0.49	-0.31

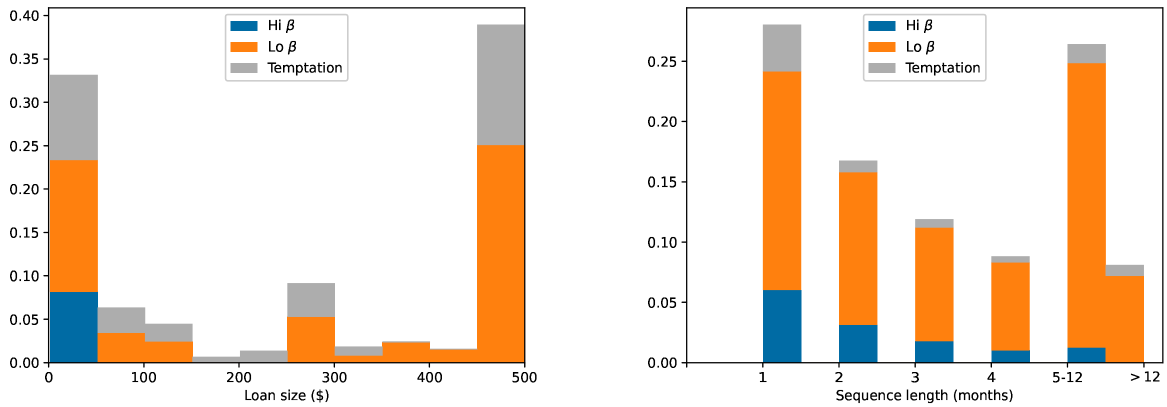
The results of the model and data are reported in Table 6. The effect of the interest rate cap on the use likelihood of payday borrowing after the cap in the model is very close to the one in Zinman 2010. There are level differences in the likelihood of continued borrowing, but that can be due to the fact that the sample they use is not representative of payday borrowers, for instance. Also, the policy is completely unanticipated in my model, but likely to be anticipated to some extent in the real world.

5.4 Drivers of high-cost borrowing

Patient households borrow small amounts and mostly short sequences of loans, as shown in Figure 9. This is due to the fact that patient households borrow when they have low income and binding expenditure shocks; otherwise, they are saving to insure against negative shocks. In these states, price schedules are particularly tight, as shown in Figure 10, due to a high probability of default, which leads to small loans for these households. Due to their saving behavior, they are able to insure against negative income shocks, and only need short borrowing sequences to pass the binding expenditure shocks.

An average 1-month sequence for patient households looks like the one presented in Figure 19: before borrowing at time 0, they are facing binding expenditure shocks, thus, reducing their assets to keep consumption high. When they run out of assets they borrow with the high-cost lenders to reduce the utility loss from the expenditure shock. Borrowing sequences that end with repayment (left panel) lasts as long as the consumption threshold binds; they end up in default when the consumption thresholds binds even further. In the latter case, the level of assets takes longer to accumulate again because households are saving constrained as in Miranda-Pinto, Murphy, Walsh, and Young 2020.

Temptation households, on the other hand, borrow small and large loans, as well as short and long borrowing sequences. This is because households of different income levels and expenditure shocks are facing different price schedules. An interesting feature is that price schedules are tighter than the ones for the patient agents. This is because default costs are lower, since the default cost associated to future exclusion from borrowing is heavily discounted in comparison to patient agents. This can be seen by comparing the price schedule for low income, non-binding expenditure shock (blue line) in Figure 10,



(a) Fraction of loans

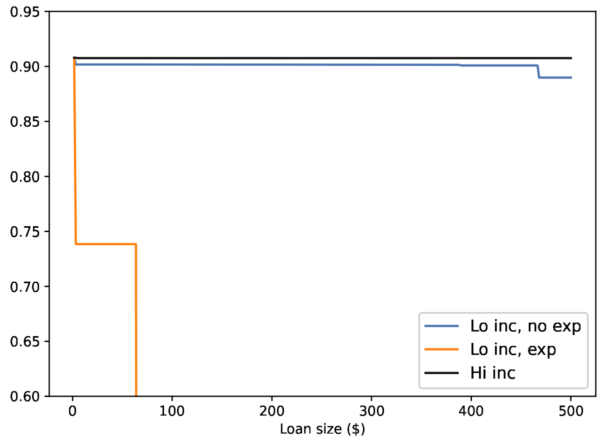
(b) Fraction of sequences

Figure 9: Distribution of loans and sequences, model and data

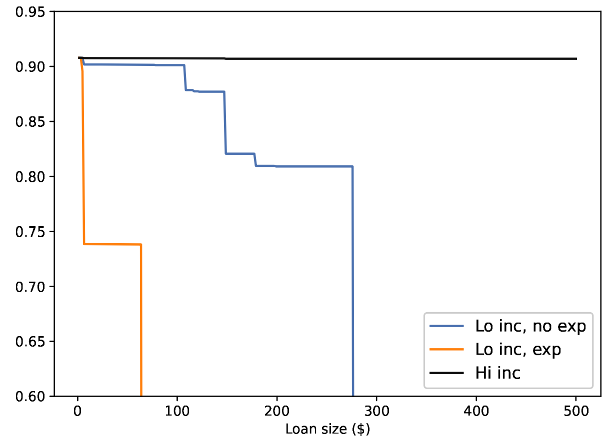
between patient and temptation households.

In Figure 24 and Figure 25, I show average 4-month sequences for temptation households. Low discount factors prevent households from accumulating savings to insure against negative expenditure shocks, so their level of assets is low. Borrowing sequences for temptation households starts with good news, as opposed to patient households: now, sequences on average start with low expenditure shocks, which increases the price of debt through a decrease in the probability of default. The borrowing sequence finishes when consumption thresholds go back to its relatively high value for these households, decreasing the price of debt.

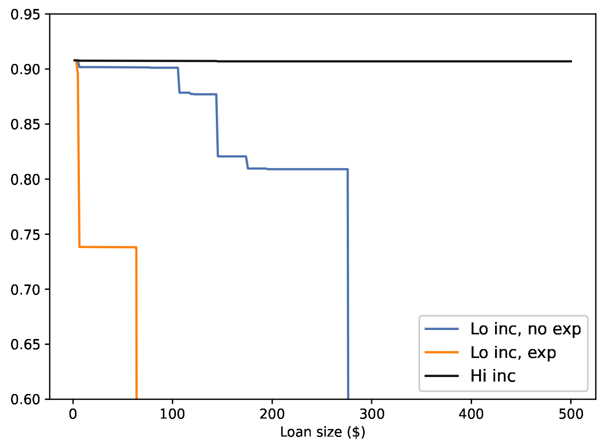
Thus, here, high-cost borrowing happens when households obtain access to credit or a better access to it in terms of pricing to satisfy their desire for present consumption; as opposed to patient households, who borrow when they get binding expenditure shocks, and they borrow even at very high interest rates due to their high marginal utility from consumption.



(a) Patient household



(b) Impatient household



(c) Temptation household

Figure 10: Price schedules by agent type

5.5 Policy experiments

I perform two types of experiments that replicate current payday regulations: regulatory borrowing limits and interest-rate caps. Both of the policies are noncontingent, meaning they are the same across the board. The regulatory borrowing limit, $\bar{a}$, imposes a constraint on debt holdings such that $a'(a, y, \underline{c}) \geq \bar{a}$. The interest-rate cap, $\bar{q}$ limits how much lenders can charge for any given level of debt such that $q_j^i(a', y, \underline{c}) \geq \bar{q}$.

5.5.1 Regulatory borrowing limits

The current calibration yields noncontingent regulatory borrowing limits undesirable from a welfare perspective, as shown in Figure 11. All household types have a lower welfare from tighter borrowing limits. This was expected for patient and impatient households, but also occurs for temptation households, although to a smaller extent. The welfare costs from banning high-cost lending are large for the fraction of impatient households (2.5% of consumption).

Temptation households could potentially benefit from borrowing limits, although these turn out to be costly in terms of welfare in the present model calibration, as shown in Figure 12. However, by income levels, there is significant disagreement towards this policy. Low income households face higher welfare costs, but higher income levels benefit from the borrowing limits to the extent of completely banning high-cost loans. The welfare gains in the latter case are quantitatively small though.

In Figure 13 I present alternative parameter values for default, temptation and expenditure shocks. Turning the temptation household into an exponential discounter—$\gamma \to \infty$—increases the losses from the regulatory borrowing limits, indicating there is overborrowing but not enough to justify the noncontingent limit. Increasing the default cost $\lambda \to \infty$ also increases the welfare costs of borrowing limits, as household now face horizontal prices of debt and are not constrained, in particular, those that face bad income and expenditure shocks. Finally, removing the expenditure shocks barely increases the welfare losses.

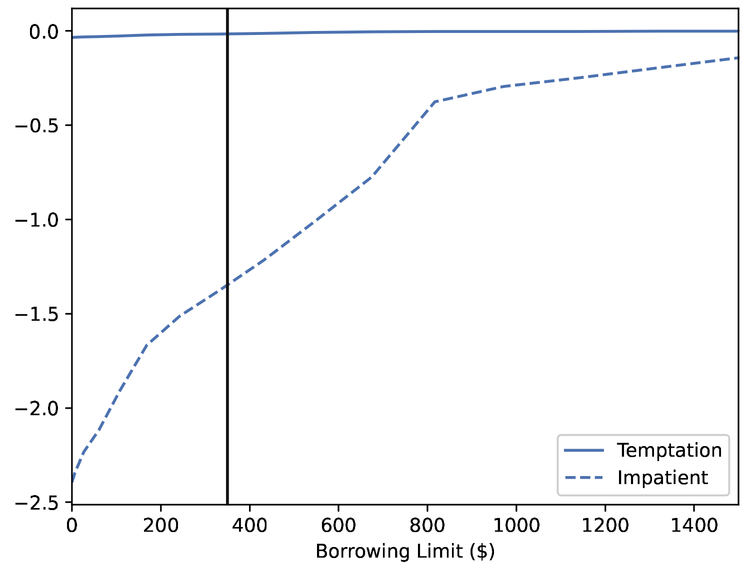


Figure 11: Welfare gains (%, consumption equivalent), patient and impatient

5.5.2 Interest rate ceilings

The case for interest rate ceiling as a tool for improving the welfare of temptation households is also not supported by the model. In Figure 14, I plot the welfare gains from varying interest rate ceilings. These turn out to decrease the welfare of households that suffer from temptation. What is interesting is that as you impose tighter interest rate ceilings, the welfare costs occur at interest rate ceilings that are not tight at all. This is a result of the selection in this market by loan size and interest rates. Households that face low in income shocks and binding consumption thresholds are riskier so the price schedules that they face drop very quickly as debt increases. As a result they borrow small loans at high interest rates. So, even high interest rate ceilings reduce the welfare of households that suffer from temptation. Very tight ceilings actually increase the welfare to the extent that they limit overborrowing by high-income households at low interest rates, but not enough to revert the initial losses.

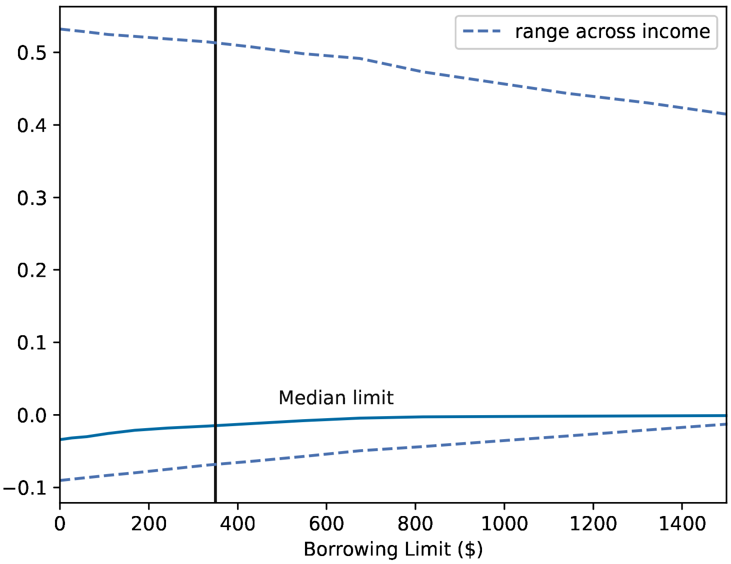


Figure 12: Welfare gains (%, consumption equivalent), temptation households

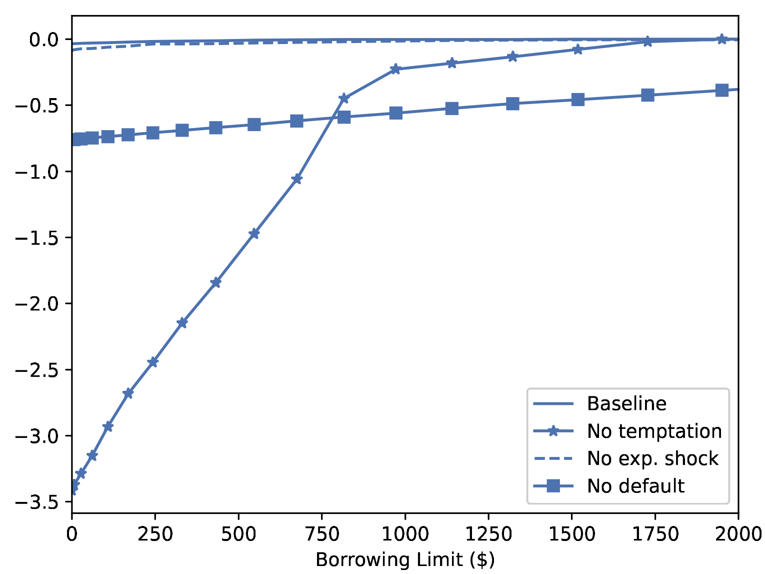


Figure 13: Welfare gains (%, consumption equivalent), temptation households

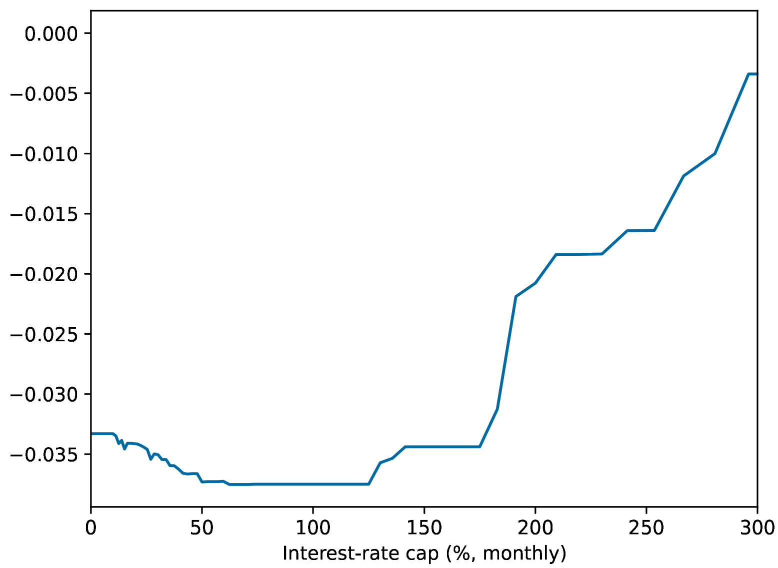


Figure 14: Welfare gains (%, consumption equivalent), temptation household

6 Conclusion

This paper studies the welfare consequences of regulations in high-cost credit markets such as payday lending. I develop and estimate a quantitative unsecured credit model that can reproduce the key features of borrowing in these markets. Also, I can separate the role of households that are exponential discounters and those that suffer from self-control and temptation, which is critical for the welfare evaluation of policies. I find that borrowing limits and interest rate caps reduce the welfare of all households, even those with temptation which are the ones that could potentially benefit from them.

Two directions for future research on regulating high-cost consumer credit emerge from this paper. Both are related to frictions not explored here. First, the case of asymmetric information between lenders and borrowers. The assumption that payday lenders know all the relevant information to predict the default rate of borrowers might not be realistic. Allowing lenders to observe the income of borrowers, for instance, could lead to pooling equilibrium between types of households across preferences or expenditure shocks. The welfare consequences of the regulations studied in this paper could be different in the asymmetric information case. Second, the role of market power in these markets. Accounting in a model how costs, market power, and default rates explain the spread in interest rates between credit cards and payday lenders could yield lessons on interest rate caps, for instance.

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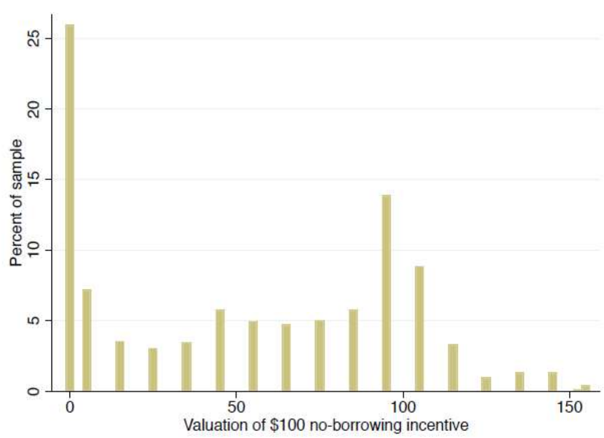
A Figures

Figure A2: **Distribution of Valuations of the No-Borrowing Incentive**



Notes: This figure presents the distribution of valuations of the $100 no-borrowing incentive, as revealed on a multiple price list.

Figure 15: Histogram valuations No-Borrowing Incentive (Allcott, Kim, Taubinsky, and Zinman 2020)

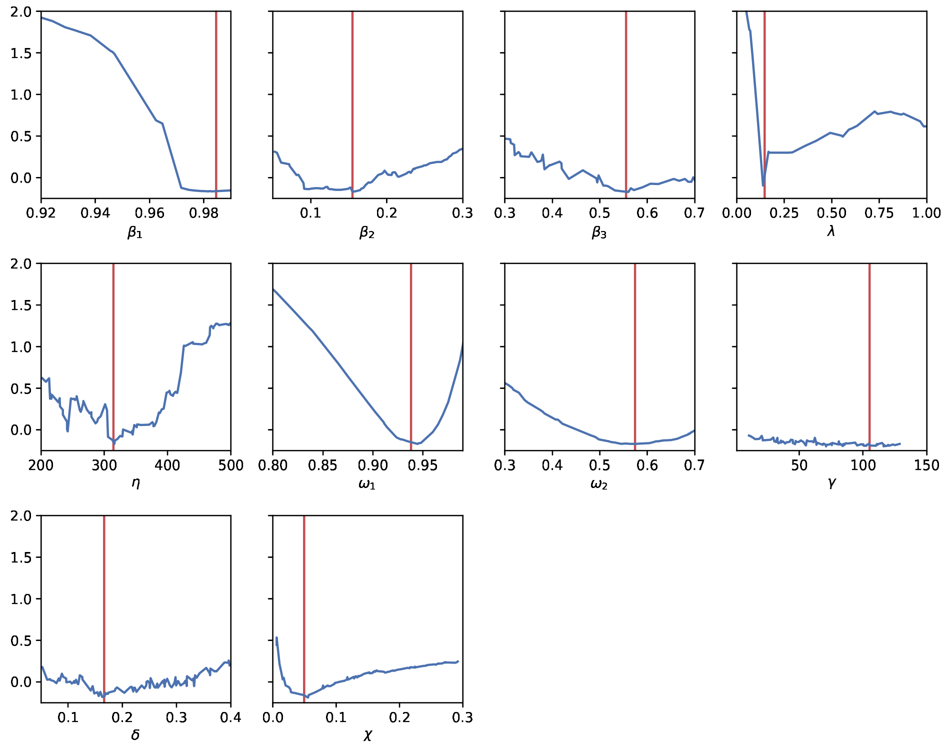
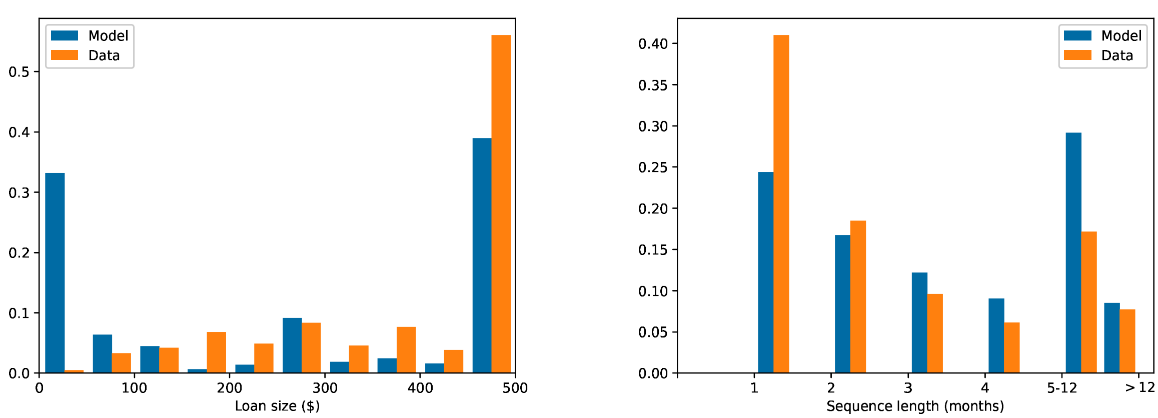


Figure 16: Sum of squared errors between target and model moments (in logs)



(a) Fraction of loans

(b) Fraction of sequences

Figure 17: Distribution of loans and sequences, model and data

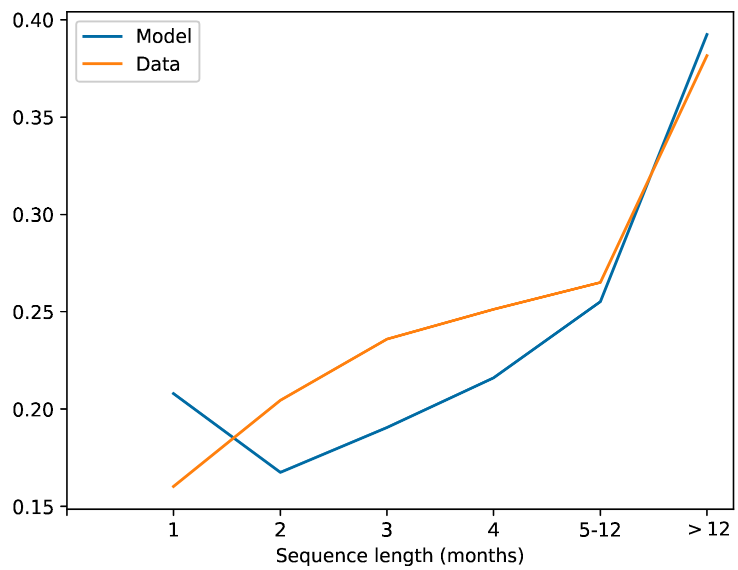


Figure 18: Default rate: model and data

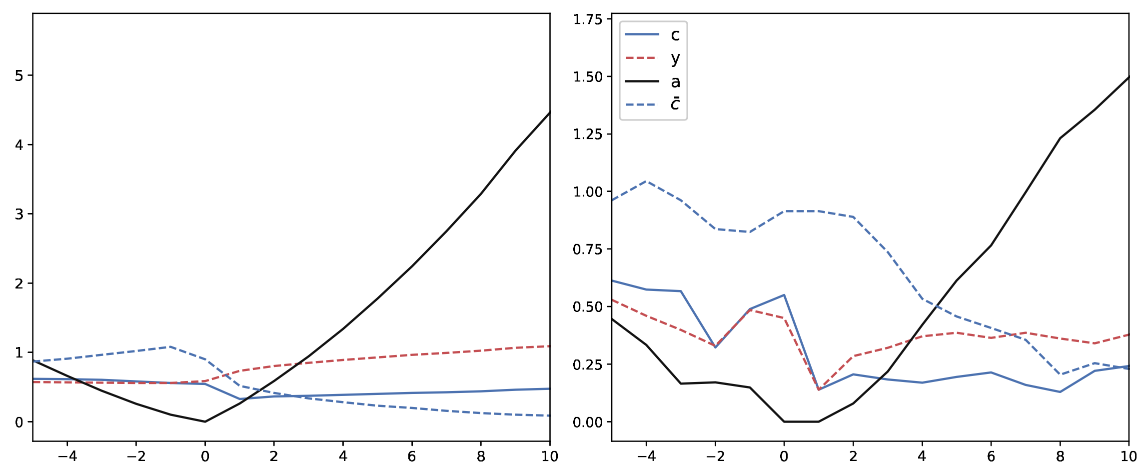


Figure 19: Average patient household's 1-month borrowing sequence

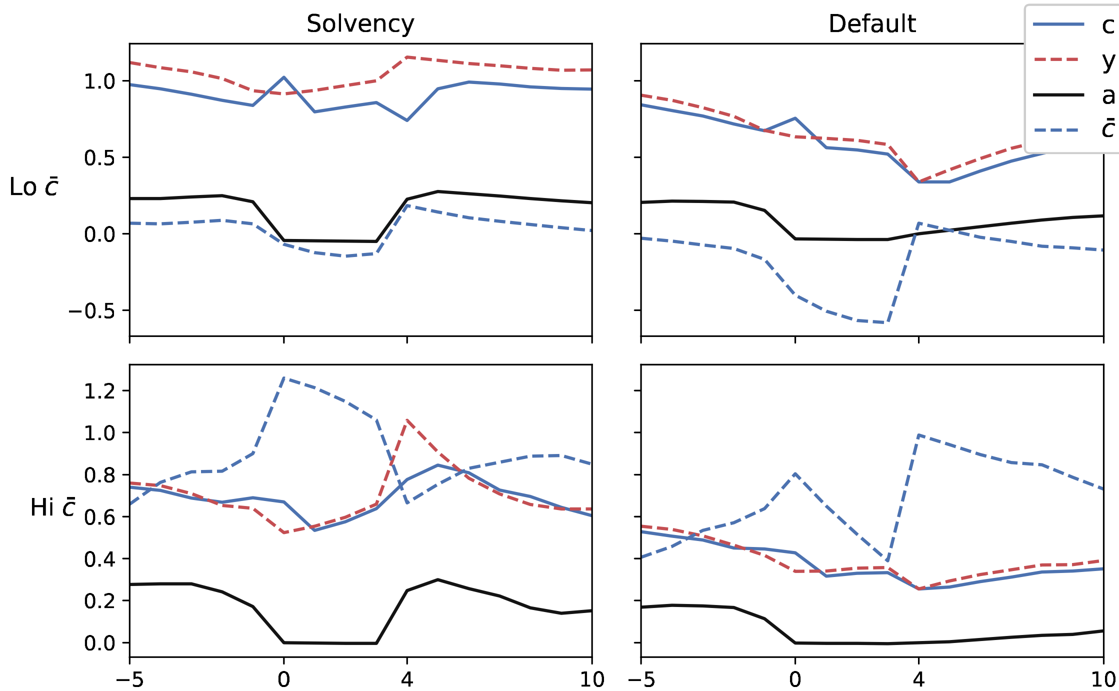


Figure 20: Average 4-month borrowing sequence for low income, impatient households

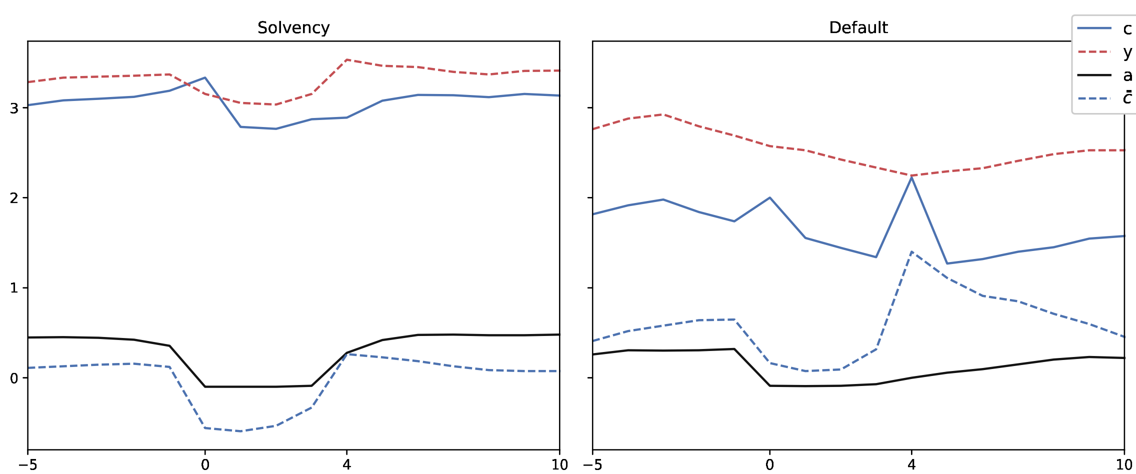


Figure 21: Average 4-month borrowing sequence for high income, impatient households

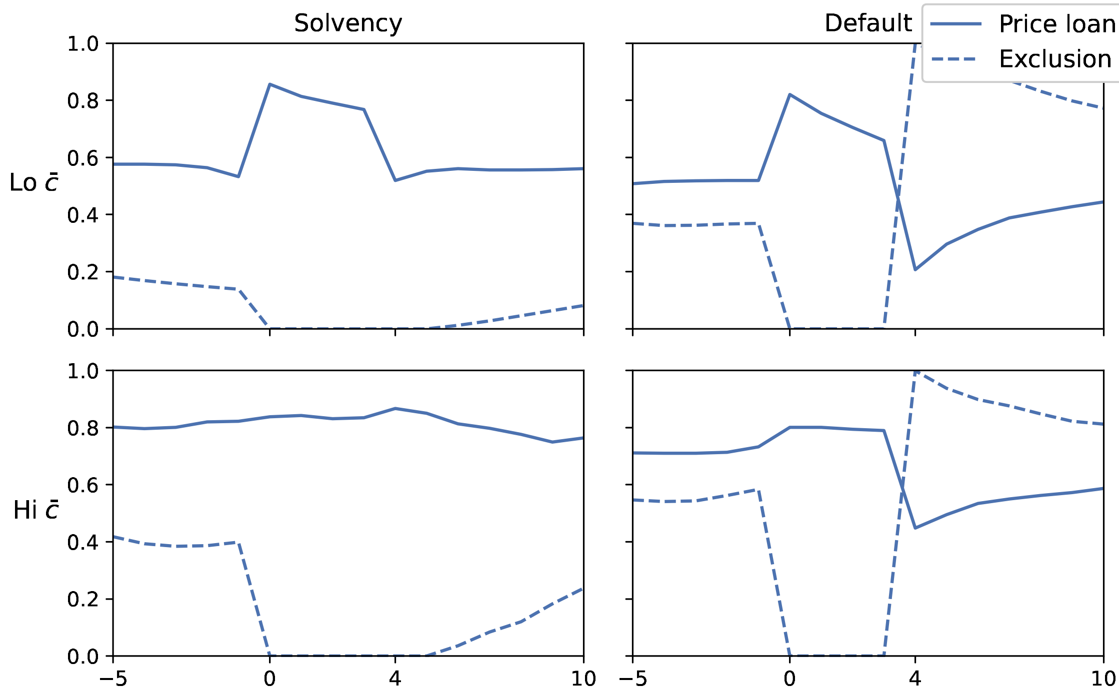


Figure 22: Average price of loans in a 4-month sequence, low income impatient household

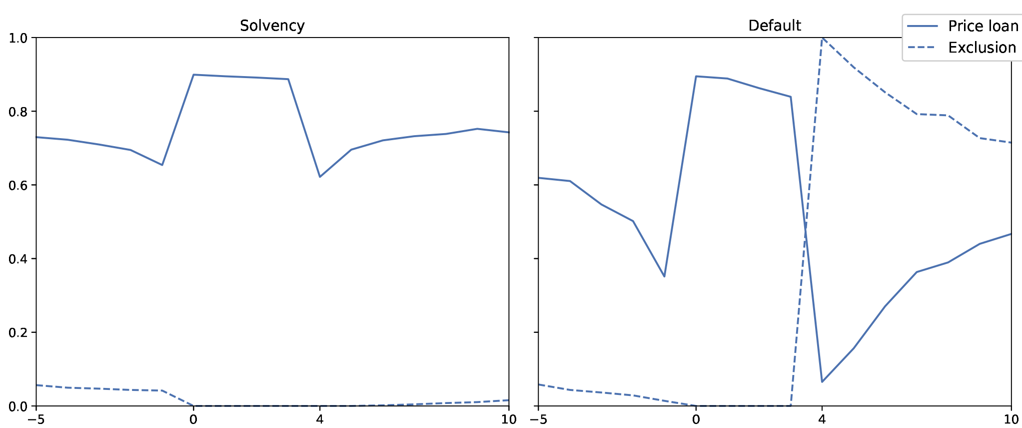


Figure 23: Average price of loans in a 4-month sequence, high income impatient household

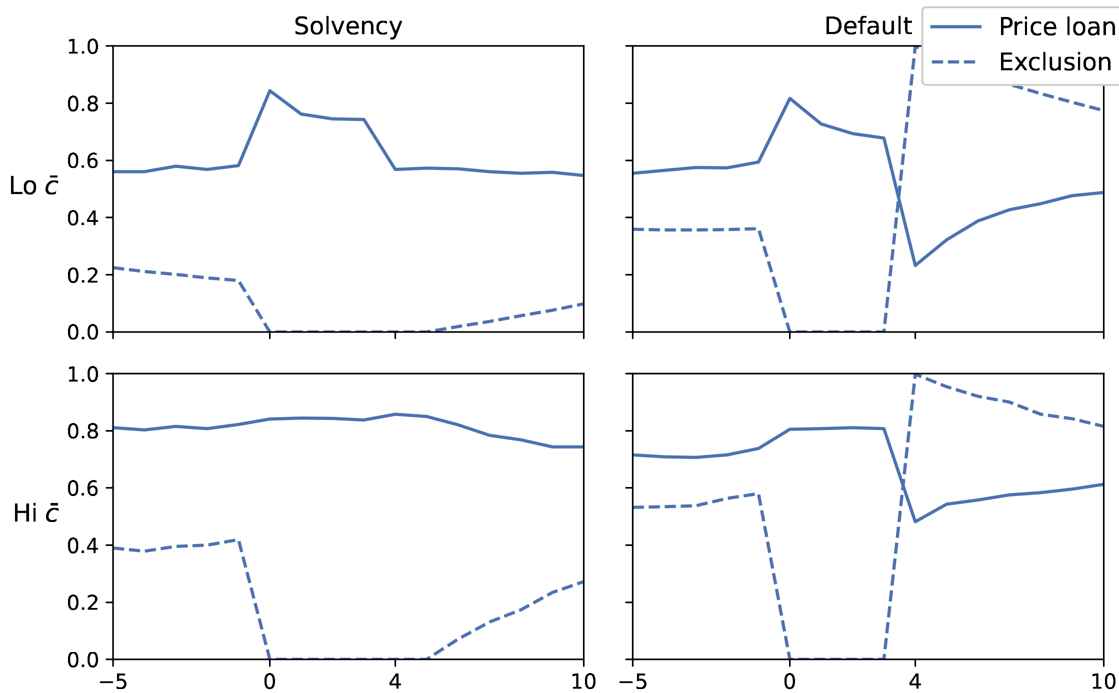


Figure 24: Average price of loans in a 4-month sequence, low income temptation household

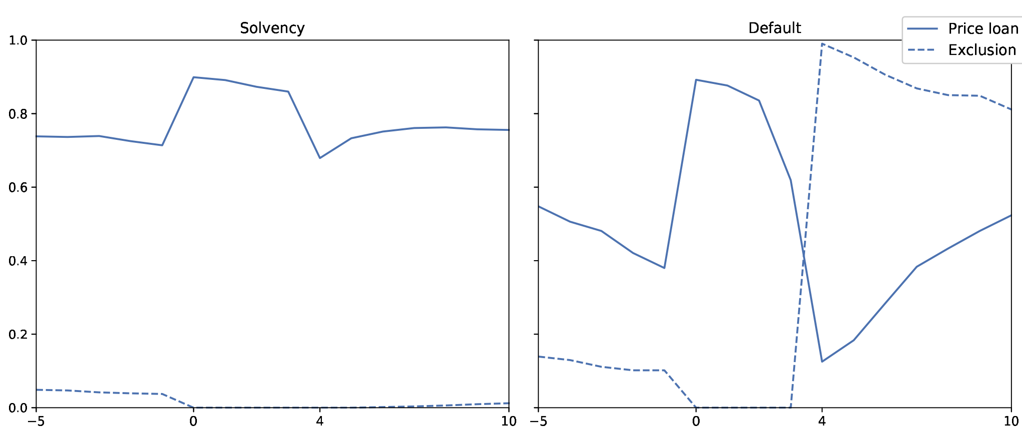


Figure 25: Average price of loans in a 4-month sequence, high income temptation household

B Tables

Table 7: Income, expenses and savings

	Coefficient	SE	p-value
Saving habits: spending>income	0.097	0.023	0.000
Saving habits: spending=income	0.118	0.026	0.000
Saving habits: some saving	-0.213	0.026	0.000
Spending>income (prev. 12m)	0.190	0.036	0.000
Spending=income (prev. 12m)	-0.003	0.034	0.926
Spending<income (prev. 12m)	-0.186	0.020	0.000
Expenses unusually high (prev. 12m)	0.076	0.025	0.002
Income unusually low (previous year)	0.000	0.019	0.982
Head: unemployed prev. 12m?	0.067	0.027	0.012
Spouse: unemployed prev. 12m?	0.044	0.035	0.209

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF.

Table 8: Credit attitudes

	Coefficient	SE	p-value
Apply credit card (prev. 12m)	0.111	0.026	0.000
Request increase limit in card (prev. 12m)	0.064	0.015	0.000
Apply auto loan (prev. 12m)	0.101	0.024	0.000
Apply other consumer credit (prev. 12m)	0.127	0.020	0.000
Request increase limit other loans (prev. 12m)	0.076	0.018	0.000
Turned down/less credit wrt applied, prev. 12m	0.288	0.025	0.000

Notes: Coefficient is β from the regression $y_i = \alpha + \beta Payday_i + Controls_i + \epsilon_i$. $Controls_i$ include networth deciles, normal income per capita (square root scale) deciles and age groups. SE is standard error of β. Standard errors are calculated taking into consideration the imputation uncertainty of the SCF.

C Why are interest rates so high?

Finally, as part of the empirical analysis of this paper, I look at data on payday lenders to explain the high interest rates we observe. Specifically, how much of the observed interest rates are explained by operating costs and default?

In Equation 22 I write an expression for the zero profit interest rate for payday lenders, $\bar{R^P}$:

$$\begin{aligned} \Pi &= \rho \bar{R^P} L - \kappa - RL = 0 \\ \Rightarrow \bar{R^P} &= \frac{1}{\rho}\left[R + \frac{\kappa}{L}\right] \end{aligned} \tag{22}$$

where, ρ is the probability of repayment; κ are fixed costs of the payday lender (wages, occupancy costs , advertising, corporate expenses), L is the total amount loaned; and, R is the rate at which the lender borrows the funds that it lends. I use the store level data from Flannery and Samolyk 2005 and K-10 forms for two public payday lenders, between 2009 and 2011, Advance America Cash Advance Centers Inc. and QC Holdings, Inc[17], to calibrate these parameters.

Results are shown in Table 9. Comparing the zero profit interest rate and the effective interest rate that these lenders charge, surprisingly, the former explains most of the fees charged by lenders which indicates that payday lending is a very costly activity.

[17]Explain why these and period

Table 9: Calibration of zero-profit payday lending interest rate

	Flannery and Samolyk	AEA	QCCO
$\frac{\kappa}{L}$	0.12	0.10	0.093
R	1.015	1.002	1.002
ρ	0.98	0.97	0.96
$\bar{R}^P$	1.156	0.140	0.145
R^P	1.176	$\leq$ 1.22	1.15-1.20

Notes: Flannery and Samolyk uses data from Flannery and Samolyk 2005; the remaining columns uses data from K-10 forms for Advance America Cash Advance Centers Inc. and QC Holdings, Inc., between 2009 and 2011.

D Analytical Appendix

D.1 Proof Proposition 1

First, consider $\bar{a} < \widetilde{a_2^*}$. $\bar{a}$ is not binding in the temptation or actual allocation. Welfare is given by

$$V^* = (1+\gamma)u\left(c_1^*\right) + \beta(1+\gamma\delta)u\left(c_2^*\right) - \left[u\left(\widetilde{c_1^*}\right) + \delta\beta u\left(\widetilde{c_2^*}\right)\right] \tag{23}$$

Now, consider $\bar{a} \in [\widetilde{a_2^*}, a_2^*)$. Welfare is now:

$$V(\bar{a}) = V^* + \gamma\left[u\left(\widetilde{c_1^*}\right) + \delta\beta u\left(\widetilde{c_2^*}\right) - u\left(\widetilde{c_1}\left(\bar{a}\right)\right) - \delta\beta u\left(\widetilde{c_2}\left(\bar{a}\right)\right)\right] \tag{24}$$

The second term in the RHS is positive since restricted allocations $\{\widetilde{c_1}\left(\bar{a}\right), \left(\widetilde{c_2}\left(\bar{a}\right)\right)\}$ yield a lower temptation utility than the optimal ones, $\{\widetilde{c_1^*}, \widetilde{c_2^*}\}$. Welfare is increasing with $\bar{a}$:

$$\frac{\partial V(\bar{a})}{\partial \bar{a}} = -\gamma\left[-u'(\widetilde{c_1}\left(\bar{a}\right)) + R\delta\beta u'(\widetilde{c_2}\left(\bar{a}\right))\right] > 0 \tag{25}$$

The derivative is positive because the term in parenthesis is the temptation Euler equation, which is negative when the agent is saving more than it would want to.

Finally, consider $\bar{a} > a_2^*$. Now, welfare is:

$$V(\bar{a}) = u\left(c_1\left(\bar{a}\right)\right) + \beta u\left(c_2\left(\bar{a}\right)\right) \tag{26}$$

In this case, welfare will be increasing with $\bar{a}$ up to the level of assets that maximizes commitment utility, Θ_2, as you take the actual choice of assets closer to the optimal under commitment utility. Welfare drops at $\bar{a} > a_2^c$, since now even the agent's commitment utility is constrained.

D.2 Valuations no-borrowing incentive

Among payday borrowers, I randomly choose N borrowers. For each borrower of type $i \in \{P, I, T\}$, states $(a, y, \underline{c}, d)$ and age j, I:

- compute the expected value of the no-borrowing Incentive (NBI) of \$100 in 3 months, $v_j^{i,*}(a, y, \underline{c})$;
- find the money-for-sure (MFR) value, p in $j+2$ that makes the borrower indifferent between the NBI and the MFR, $v_j^i(a, y, \underline{c}, 1, p) = v_j^{i,*}(a, y, \underline{c})$;

D.2.1 No-borrowing incentive

Households get a_0 in 3 months if they do not borrow the next 2 months. The value of the incentive to a household of type i and state $(a, y, \underline{c}, d)$ in period j is:

$$v_{j+2}^{i,*}(a, y, \underline{c}) = v_{j+2}^{i,s}(a + a_0, y, \underline{c}) \tag{27}$$

$$\begin{aligned} v_{j+1}^{i,*}(a, y, \underline{c}) = \max_{c, a' \geq 0} & \left\{ u(c) - \eta \max(\underline{c} - c, 0) + \beta \mathbb{E}_{y', \underline{c}' | y, \underline{c}} \left[v_{j+2}^{i,*}(a', y', \underline{c}') \right] \right\}, \; i = P, I \\ c = a + y - & \frac{1}{1+r} a' \end{aligned} \tag{28}$$

$$\begin{aligned} v_{j}^{i,*}(a, y, \underline{c}) = \max_{c, a' \geq 0} & \left\{ u(c) - \eta \max(\underline{c} - c, 0) + \beta \mathbb{E}_{y', \underline{c}' | y, \underline{c}} \left[v_{j+1}^{i,*}(a', y', \underline{c}') \right] \right\}, \; i = P, I \\ c = a + y - & \frac{1}{1+r} a' \end{aligned} \tag{29}$$

D.3 Income and Expenditure Shocks

I use quarterly income and expenditure shocks estimated in Miranda-Pinto, Murphy, Walsh, and Young (2020) to obtain monthly processes.

I find $x_{i,t}, z_{i,t}$ such that $y_t = \log \sum_{i=1}^{3} \exp\left(\mu + x_{i,t} + z_{i,t}\right)$, with $t =$ quarter, $i =$ month. y_t is the quarterly income (in logs) process from Miranda-Pinto, Young, Murphy and Walsh (2020).

$$x_{i,t} = \rho_x x_{i,t-1} + \sigma_x \epsilon^x_{i,t-1} \tag{30}$$

$$z_{i,t} = \rho_z z_{i,t-1} + \sigma_z \epsilon^z_{i,t-1} \tag{31}$$

For expenditures, I find $\bar{c}_{i,t}$ such that $\bar{c}_t = \frac{1}{3}\sum_{i=1}^{3} \bar{c}_{i,t}$, with $t =$ quarter, $i =$ month. $\bar{c}_t$ is the quarterly consumption threshold process from Miranda-Pinto, Young, Murphy and Walsh (2020).

$$\bar{c}_{i,t} = \rho_c \bar{c}_{i,t-1} + \sigma_{\bar{c}} \epsilon^{\bar{c}}_{i,t-1} \tag{32}$$