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Price Regulation in Credit Markets:
A Trade-off between Consumer Protection and Credit Access*

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Abstract. Interest rate caps are widespread in consumer credit markets, yet there is limited evidence on their effects on market outcomes and welfare. The effects of this policy are ambiguous and depend on a trade-off between consumer protection from bank market power and reductions in credit access. We exploit a policy change in Chile that lowered interest rate caps by 20 percentage points to understand its impacts. Using individual-level administrative data, we find that the policy decreased contract interest rates by 9%, but also reduced the number of loans by 19%. To assess welfare and counterfactuals, we develop and estimate a model of loan applications, pricing, and repayment. Consumer surplus decreases by an equivalent of 2.5% of average income, with larger losses for riskier borrowers. However, the same policy in a less competitive market increases welfare. Risk-based regulation reduces the adverse effects of interest rate caps, but does not eliminate them.

Keywords: credit, loans, interest rate caps, regulation, selection, competition

JEL Codes: D43, G2, L13, L51

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1 Introduction

Consumer credit penetration has increased steadily over recent decades and there is currently more that $41 trillion U.S dollars in household debt in the world, equivalent to around 40% of GDP across countries.[1] The growth of household debt has sparked a debate about whether consumer credit is under- or over-supplied. The former argue that households are credit constrained due to market power or adverse selection, whereas the latter argue that moral hazard or behavioral biases induce households to borrow too much (Zinman, 2015).[2] This disagreement motivates a varied array of policies that seek to increase or restrict credit access, and often coexist in the marketplace. While the regulation of consumer credit markets has been in the policy agenda for decades, its relevance increased substantially after the 2008 financial crisis (Campbell *et al.*, 2011).[3]

Interest rate regulation has historically been one of the main policy instruments in consumer credit markets (Temin and Voth, 2008). Several countries have interest rate regulation in place nowadays, often adopting interest rate caps (Maimbo and Henríquez, 2014). Regulators often argue that interest rate caps limit lender usury and market power, as well as their ability to exploit consumer behavioral biases. Detractors argue that this regulation makes risky borrowers unprofitable and may limit credit access. The welfare implications of stronger interest rate regulation are potentially heterogeneous along borrower risk, as it benefits protected borrowers and harms excluded ones. Despite the ambiguity of its welfare effects, research analyzing this regulation is somewhat limited, partly due to a lack of comprehensive data and compelling research designs.

In this paper, we study the equilibrium effects of interest rate caps on prices, credit access, loan performance, and consumer welfare. We study the Chilean market for consumer loans, which is attractive because it combines policy variation with extensive administrative data. Interest rate regulation in this setting takes the form of interest rate caps that vary across loan size, which were strengthened between 2013 and 2015. Throughout that period, interest rate caps decreased by between 17 p.p and 24 p.p for loans smaller than $8,000, leaving larger loans unaffected.[4]

For our analysis, we combine this policy variation with administrative data. The data cover contracts, repayment and credit histories for each consumer in the market, and loan applications for a large share of such contracts. We complement this data with a survey that we designed and collected from a sample of borrowers to describe their shopping process and aid our interpretation

[1]Calculations based on the IMF Global Debt Database (Mbaye *et al.*, 2018). See Figure A.1 for details.

[2]Research providing evidence of households being credit constrained includes Gross and Souleles (2002), Adams *et al.* (2009) and Jappelli and Pistaferri (2010); whereas examples of research that suggests households might be over-borrowing are Bertrand and Morse (2011), Bhutta and Keys (2016) and Beshears *et al.* (2018).

[3]For example, the U.S. government introduced the CARD Act in 2009 and then established the Consumer Finance Protection Bureau (CFPB) in 2010 to improve regulation and overall functioning of consumer credit markets, and European Commission has also taken steps in a similar direction (European Commission, 2015).

[4]Unless otherwise noted, all monetary units are measured in U.S. dollars of December 31st, 2016. For reference, the exchange rate at that point was of $667.29 Chilean pesos per U.S. dollar, according to the Central Bank of Chile.

of welfare effects. We focus on unsecured consumer loans, a simple product that 15% of households hold (EFH, 2014). The average contract is roughly for a three-year loan of $6,800 with an interest rate of 23 p.p., and there is substantial dispersion in interest rates.

We start by providing evidence for the effects of interest rate regulation on the distribution of contract rates. The policy change made the cap binding. As many as 31% of contracts in November 2013 were closed at rates higher than corresponding interest rate cap in December 2015. The policy shifted the distribution of interest rates downwards, and induced substantial bunching at the cap. One interpretation of this pattern is that banks hold market power, since under perfect competition banks would choose not to offer loans exposed to this regulation at rates below the cap.

To provide evidence of the market-level effects of interest rate caps, we exploit the variation across loan size and time in the intensity of regulation in a differences-in-differences framework. We find that the policy change had large effects on prices, quantities, and loan performance. Average contract rates decreased by 9% (2.6 p.p). The amount of credit also decreased, as the number of loans fell by 19%. Part of this effect stems from a decrease in loan applications driven by riskier borrowers. Both price and quantity effects are stronger for riskier borrowers, who were more exposed to interest rate caps due to risk pricing by banks. In particular, contract rates for risky borrowers decreased by 11% (3.3 p.p) and the number of loans for them decreased by 24%. As a result, the borrower pool became safer and default rates decreased by 18% (1.15 p.p).

Motivated by this evidence, we develop and estimate an equilibrium model, which allows for welfare and counterfactual analysis. Our model consists of three stages that cover application, pricing and repayment. First, consumers decide whether to apply for loans or not given their credit needs. Applications depend on approval probability, expected loan price, and application cost. Second, applicants draw a consideration set of banks shop across them. Banks offer homogeneous loans produced at heterogeneous costs. We model this process as an English auction, in which consumers shop for the best offer. In equilibrium, the bank with the lowest cost signs the contract with the consumer at an interest rate that leaves the second-lowest cost bank with zero profits.[5] By modeling the market in this way, we rationalize contract prices as a function of bank latent cost structure and borrower consideration sets. Third, repayment risk is realized. The model incorporates imperfect competition and adverse selection.

We estimate our model using administrative data on loan applications, approvals, prices and repayment, along with survey data on bank consideration. On the demand side, we estimate that consumers facing lower approval probabilities are less likely to apply for loans; and that riskier borrowers have a higher willingness to pay for credit and are less price-sensitive than safe borrowers. In terms of repayment, borrower risk score is the main correlate of repayment. While there is selection on observable risk, we find no compelling evidence of adverse selection

[5]This modeling choice provides a sensible characterization of the setting, and has also been adopted in recent work on markets with bargained prices (Allen *et al.*, 2019; Salz, 2020). It overcomes a usual problem with contract-level data, which is that the econometrician only observes chosen contracts, but not the full consumer choice set.

along the extensive margin of loan applications. On the supply side, we estimate substantial cost heterogeneity that stems from differences across banks, banks' incumbency advantages over related borrowers, and idiosyncratic bank-borrower cost heterogeneity.

Adopting a revealed preferences approach, we use our model to estimate welfare effects. We find that expected consumer surplus decreased by an average and median of $52.4 and $34.7 per month, equivalent to 2.5% and 1.7% of average income, respectively. However, not all consumers in the market are worse off under stronger regulation. Rather, 14.7% of consumers benefit, although the gains of this group are substantially smaller than the losses of those that are worse off. Consumer welfare effects are heterogeneous across borrowers. In particular, the average decrease in expected consumer surplus of risky borrowers is 2.6 times that of safe borrowers, because they are more exposed to this regulation in the presence of risk pricing, and because they have higher willingness to pay and lower price sensitivity. Moreover, profits per consumer decrease by $2.65 per month, which adds up to 29.7% of profits in the market, such that overall welfare decreases.

Evidence from our survey complements this analysis. We study how the impacts of economic hardships vary with access to bank credit. We find that households that deal with hardships with bank credit are less likely to decrease consumption and fall in financial distress. These results are consistent with our estimates of negative consumer welfare effects of interest rate caps, and suggest that reduced credit access may limit consumption smoothing and increase financial distress.

An important motivation for interest rate regulation is to protect consumers bank market power. We use our model to study how the effects of this regulation depend on the competitive environment. We simulate equilibrium outcomes for a range of scenarios in which we let borrowers consider varying numbers of banks when shopping for loans. We find that welfare effects are less adverse in more concentrated markets and eventually become positive, which suggests that the consumer protection role of this regulation depends crucially on the market structure.

The design of interest rate regulation is often strikingly simple. Few countries use designs that go beyond having caps specific to a few loan size and type brackets.[6] The mismatch between unsophisticated regulation and sophisticated risk pricing by banks reinforces the trade-off between consumer protection and credit access by increasing the exposure of risky borrowers to interest rate caps. In this line, we use the model to study risk-based interest rate caps, which combine the benefits of risk-based pricing for dealing with borrower heterogeneity, with the potential of interest rate regulation for limiting bank market power. In a simple example, this design reduces the average welfare loss of interest rate regulation by 23%, without increasing bank profits.

Overall, these results show that while interest rate regulation is meant to protect consumers facing high interest rates, it mostly harmed credit access and overall welfare in this setting. How-

[6]Several states in the U.S. have a single cap on consumer loans, and there is a federal cap at 36% for payday loans. In Europe, many countries impose caps at a mark-up over the average interest rate, including Germany and Italy. Other countries, such as Belgium and France, allow the cap to vary by a few loan type and size brackets, similar to the Chilean regulation. See Maimbo and Henríquez (2014) for more examples of interest rate regulation across countries.

ever, our theoretical predictions regarding credit access and welfare effects are ambiguous and this policy might improve outcomes in other settings. This paper informs the design of interest rate regulation by providing a framework to study how its implications depend on particular attributes of a setting, such as market structure, adverse selection, and borrower heterogeneity.

This paper contributes to different branches of the literature. First, to a literature that studies interest rate caps (Bodenhorn, 2007; Temin and Voth, 2008; Benmelech and Moskowitz, 2010; Zinman, 2010; Rigbi, 2013; Fekrazad, 2016; Melzer and Schroeder, 2017). Most of these papers find negative effects on credit access when regulation is binding; and many of them study payday lending in the U.S., with a focus on a single lender or market. Moreover, most of this work adopts reduced form approaches and focuses on credit access as their main outcome. Instead, we use administrative data to study a national market, and use a model to develop welfare and counterfactual analysis. Our application is also studied by Hurtado (2015), Schmukler *et al.* (2019) and Madeira (2019), all of which adopt reduced form approaches to study effects on credit access.[7]

Second, this paper contributes to a literature on imperfect competition in selection markets, which emphasizes that the effects of regulation in these markets depend on the degree of competition (Mahoney and Weyl, 2017). We relate to this literature by studying the relationship between the effects of interest rate regulation and market structure. Recent research develops empirical models that allow for adverse selection, imperfect competition, and product differentiation (Einav *et al.*, 2012, 2013; Crawford *et al.*, 2018; Kawai *et al.*, 2018; Allen *et al.*, 2019; Agarwal *et al.*, 2020; Robles-García, 2020; Benetton, 2021; Galenianos and Gavazza, 2021). In our model, we allow for adverse selection along the extensive margin of consumer credit and embed imperfect competition in bank cost heterogeneity and borrower consideration sets.

Finally, this paper also contributes to other literatures in household finance. First, it builds on a recent literature that studies the effects of regulation on other margins of contract pricing, also using administrative data (Agarwal *et al.*, 2015; Nelson, 2020; Benetton, 2021). Second, we also contribute to a literature that focuses on the welfare implications of access to expensive credit, which finds mixed effects (Melzer 2011; Morse 2011; Bhutta *et al.* 2015; Gathergood *et al.* 2018; Skiba and Tobacman 2019). While most papers in this work focuses on payday lending, we study a market segment in which interest rates are lower and risk composition is safer. For this setting, we develop a welfare analysis of a common policy that affects credit access.

2 The Chilean Credit Market

Our empirical application focuses on the Chilean market for unsecured consumer loans. Consumer loan contracts can be characterized by their interest rate, term and amount. Banks require no

[7]This paper also contributes to a broader literature on price controls. Research on the welfare effects of price caps often predicts adverse effects on consumers in competitive markets (Glaeser and Luttmer, 2003; Bulow and Klemperer, 2012). In our model, consumer welfare effects are ambiguous, because we study an imperfectly competitive market.

collateral on these loans.[8] Every year, more than 1.1 million contracts are signed, adding up to more than 7 billion U.S. dollars. While the consumer loan market is large, it is not the only source of consumer credit in this market. The two main alternative sources of consumer credit are credit cards and credit lines (SBIF, 2017b), both of which have increased its market penetration throughout the period we study.[9] These products are covered by the same interest rate regulation described in Section 2.1 below. Payday loans, a relevant source of expensive credit in other countries, are not widely available in Chile. Moreover, informal lending is a relatively small segment of the market, and only 7% of households hold some form of informal debt (EFH, 2018).[10]

The market is concentrated, as the combined market share of the top-3 and top-5 banks is 56% and 76%, respectively. We focus on the 15 banks that offer consumer loans in the market, which covers 92% of consumer loan contracts (SBIF, 2017b).[11] The remaining 8% consists of credit unions that offer loans paid through employers, a somewhat different product that we do not consider.

Regarding risk assessment by banks, there are no market-wide risk scores such as FICO scores in the U.S. Instead, there are three sources of information that banks may use for risk assessment: (i) comprehensive information on consumer covariates and credit history across all banks, that the regulator collects and provides to banks; (ii) information banks may collect directly from loan applicants; and (iii) risk scoring services provided by private firms. We have access to the first of these sources, which provides substantial information on borrower risk. This is emphasized by Foley *et al.* (2019) in their study of the role of information for bank lending using this same data.

Consumer debt is common in Chile. The 2014 Survey of Household Finance (*Encuesta Financiera de Hogares*, EFH), describes the relevance of consumer loans for households around the policy change (EFH, 2014). As much as 63% of households have some form of consumer debt and 15.4% have consumer loans. Among households with consumer debt, the average debt to income ratio is around 5 and every month households allocate 20.5% of income to debt repayment (SBIF, 2017a).[12]

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[8]These contracts impose prepayment penalties. Prepayment amounts must be of at least 25% of the loan balance. Upon prepayment, the borrower must pay a penalty of one month of interest on the prepaid balance.

[9]Figure A.2 displays the evolution of household credit card and credit line debt. The penetration of both products increased through our sample period in terms of number of consumers and amounts, although without a noticeable pattern around the policy change. Moreover, their average balances across consumers—which according to industry sources combine both transactional and borrowing uses in similar shares—add up to less than a fourth of the average consumer loan size. This suggests these products are used more often to finance smaller expenses than consumer loans.

[10]This statistic covers several sources of informal credit, including family and friends, informal lenders, pawn shops, among others. Figure A.3 shows that the share of households with informal debt remained between 2% and 10% since 2007, with no noticeable pattern around the policy change. In fact, it remained almost constant between 2014 and 2017.

[11]For comparison, this market structure is more concentrated than that in the U.S, where the average number of banks in a local market is around 45 (Aguirregabiria *et al.*, 2020), but similar to those in Canada and the U.K, where 8 and 6 banks respectively dominate most of the credit the market (see Allen *et al.* 2019 and Benetton 2021, respectively).

[12]In terms of utilization of loans, the share of households having consumer loans for different self-reported objectives varies as follows: 54% for household durables, 30% for clothing, 22% for debt consolidation, 11% for vehicles, 9% for medical treatment, 9% for home improvement and 5% for vacations (EFH, 2014).

2.1 Interest Rate Regulation

Interest rate regulation in the Chilean credit market has been in place in different forms since 1929. We focus on a policy change enacted by Law 20,715, which aimed at further providing credit access at lower interest rates (SBIF, 2017b). This law was approved on December 13th, 2013 and followed Law 18,010, which had been in place since 1981 and partially modified in 1999. This regulation covers virtually all credit market operations with a term of 90 days or higher. The main policy tool in these laws is a set of interest rates caps that vary with loan size. These caps are called Conventional Maximal Rate (TMC, *Tasa Máxima Convencional*). The policy change affected both the definition of loan size brackets for interest rate caps and the formulas for their calculation. Interest rate caps are measured in annualized interest rates. Loan size brackets are defined in UF (*Unidades de Fomento*), an inflation adjusted monetary unit used in Chile.[13]

Interest rate caps can be summarized by a linear function of a lagged reference rate, both before and after the policy change. The interest rate cap for loan-size bracket ℓ at period t is:

$$\bar{\iota}_{\ell t} = \psi_\ell \tilde{\iota}_{\ell t-1} + \alpha_{\ell t} \tag{1}$$

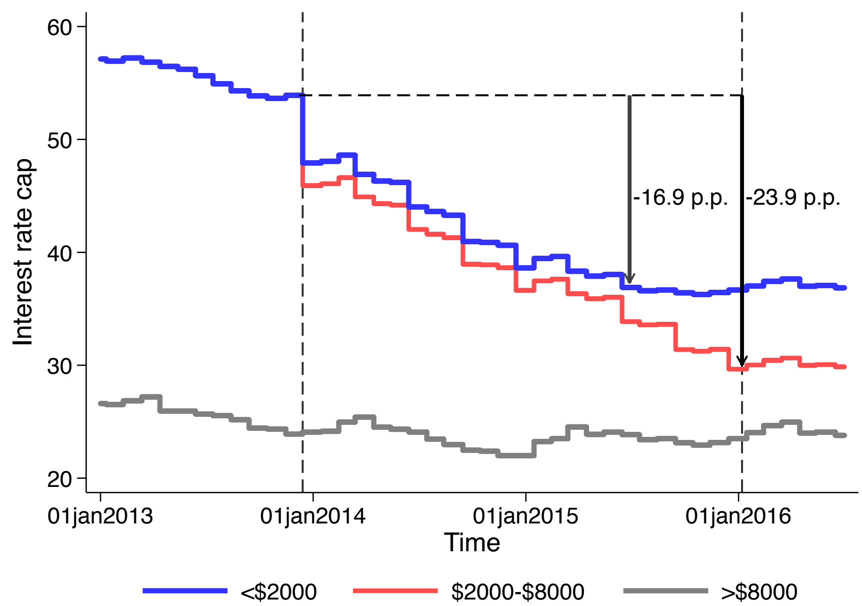
such that caps $\bar{\iota}_{\ell t}$ are set as a combination of proportional and constant mark-ups over a reference rate $\tilde{\iota}_{\ell t-1}$. Before the policy change, the regulation considered two loan size brackets, namely \$0-\$8,000 and \$8,000-\$200,000. For both brackets, the regulation considered $\psi_\ell = 1.5$ and $\alpha_{\ell t} = 0$. The reference rate $\tilde{\iota}_{\ell t-1}$ was calculated as a weighted average of interest rates for loans of size ℓ during the previous month. Figure 1 displays the monthly interest rate caps, and shows that before the reform these caps were beyond 50 p.p and 25 p.p for loans of \$0-\$8,000 and \$8,000-\$200,000.

The reform made four changes to the previous regulation. First, it split the \$0-\$8,000 bracket into two, namely \$0-\$2,000 and \$2,000-\$8,000. Second, it set $\psi_{0-8000} = 1$ while $\psi_{>8000} = 1.5$ remained unchanged. Third, it set constant mark-ups over the reference rate of $\alpha_{0-2000,t} = 21$ p.p and $\alpha_{2000-8000,t} = 14$ p.p. Fourth, the reference rate was set to be a weighted average of interest rates in the \$8,000-\$200,000 bracket for all loans. Therefore, only regulation for loans under \$8,000 was directly affected by the policy change. Moreover, the main qualitative change for such loans was to move from a regulation based on proportional mark-ups to one based on constant mark-ups.

Had the policy been fully enacted by December 2013, interest rate caps would have fallen at once by 16.9 p.p and 23.9 p.p for loans of \$0-\$2,000 and \$2,000-\$8,000 respectively. Instead, the policy was staggered to avoid such sharp decrease. This transition consisted of an immediate fall of 6 p.p and 8 p.p respectively, followed by quarterly decreases of 2 p.p in $\alpha_{\ell t}$. Under such schedule, the policy was fully in place by December 2015. Figure 1 displays the evolution of interest rate caps around the reform. The reduction in caps for loans of \$0-\$2,000 and \$2,000-\$8,000 is stark.

[13] According to the Central Bank of Chile, one UF was equivalent to 39.48 U.S. dollars on December 31st, 2016. Policy thresholds are set at 50UF and 200UF, which are equivalent to \$1,970 and \$7,880. We refer to these two thresholds as \$2,000 and \$8,000 respectively for expositional simplicity. All analyses are conducted without such approximation.

Figure 1: Evolution of interest rate caps



Notes: This figure displays the evolution of the interest rate caps by loan size. The first dashed black line indicates the implementation of Law 20,715, after which interest rate caps for all loans under $8,000 were reduced, in December 2013. The second dashed line indicates the date in which the policy was fully implemented, in December 2015.

However, the cap on larger loans remained roughly constant over the period of study. We exploit these features as identifying variation to study the effects of this regulation below.

2.2 Data

We use administrative data from the regulator, the Financial Market Commission (*Comisión para el Mercado Financiero*, CMF). The data cover from January 2013 to December 2015. Our population of interest is that of potential borrowers, defined as all consumers with access to any bank product, from checking accounts to mortgages. There were 2.5 million such consumers in January 2013, which is 25% of the working-age population. We observe demographics, income and credit history for each potential borrower. We exploit two main datasets: one that contains every loan, and one that provides a large sample of applications. We complement these data with a household survey.

2.2.1 Loan Contracts Data

The first dataset is a registry of all consumer loan originations in the market. This data have several features. First, borrower and bank identifiers are available for each contract, along with key contract attributes including interest rate, amount, and term. Second, the data track loan performance, which allows us to observe loan default. Third, the data provide borrower attributes including age, gender, income, and county of residence. Fourth, the data collect the full credit history of each borrower in the system, including amount of consumer and mortgage debt held and amount of debt in 90-day default. Importantly, this is the same data that the regulator provides to banks for borrower risk assessment, and cover the relationships between each borrower and all banks in the market. In the absence of market-wide risk scores in this setting, we exploit this information to construct risk scores for our analysis in Section 2.2.3. The fact that banks employ this same information when assessing borrower risk reinforces our approach. We measure all monetary variables in U.S. dollars, and all interest rates are annualized.

2.2.2 Applications Data

The second dataset is a large sample of loan applications. While the loan contracts dataset covers the entire market, the coverage of the applications dataset is only partial.[14] We link the applications and contracts datasets using borrower identifiers, and we are able to match application events for 64.5% of contracts in the data. Given we observe all loan contracts in the contracts dataset, the implication of this partial coverage is that we are unable to observe some rejected applications. For each application in the dataset, we observe the identity of the bank and the borrower, the application date, the loan size and term for which the borrower applies, and the outcome of the application. Whenever the application is approved by the bank, we also observe the interest rate.

We organize this data by constructing application events, and develop all our analysis using this definition of applications. We construct application clusters for a given borrower across possibly multiple banks in a short period of time. Concretely, we define an application event as a set of borrower applications such that no pair of applications are more than 30 days apart. We merge these application events with loan contracts using borrower and bank identifiers, and dates.

2.2.3 Measuring Credit Default Risk

We exploit data on loan performance, consumer covariates, and credit history to estimate default risk. In particular, we estimate a logit model of default using data for the period before the policy. The model uses an indicator for 90-day loan default over the term of a loan as dependent variable, and a rich vector of borrower covariates x_i determined before signing the contract as independent variables. This is a standard risk scoring model (Ohlson, 1980). We consider different sets of variables in x_i, starting with borrower income and leverage, then adding borrower credit history variables, and finally borrower demographics and macroeconomic controls.

The results point in the expected directions: borrowers with higher income and lower leverage default less.[15] Regarding credit history, borrowers with more consumer debt, without previous

[14] Bank reporting practices for this dataset were not as rigorous as those for the contracts dataset, as this was a new requirement for them. In particular, three banks did not report this data to CMF.

[15] Table A.2 displays results. For the rest of the paper, we refer to the income risk model and the history risk model

loans, and with more debt under default are more likely to default; while those with more mortgage debt are less likely to do so. In terms of demographics, both older and female borrowers are less likely to default. The model predicts 69% of loan defaults correctly out of sample. We construct risk scores as fitted default probabilities, such that borrowers with higher scores are riskier.[16]

2.2.4 Survey Data

We collect survey data from 1,003 consumers who applied for loans at least twice between 2013 and 2015, and were rejected by at least one bank in that period. The goal of this sampling strategy was to target a population that was active in the market. The survey collects information about financial literacy, familiarity with credit market, search and application behavior in the credit market. It also documents the evolution of household finances, credit access and financial distress over the period of interest, using questions based on the U.S. Survey of Consumer Finances.[17] We exploit this data to support our model assumptions, to estimate applicant consideration sets, and to interpret the consumer welfare effects we estimate using our model.

2.3 Descriptive Statistics

The contracts dataset contains more than 3.3 million loans for 2013-2015. Table 1 displays summary statistics. Average annualized interest rates are around 23 p.p, but more than 10% of the loans have rates higher than 35 p.p.[18] The average loan in the sample is about $6,700 and 33 months long, and has a monthly payment of $266. Regarding the distribution of loan size across size brackets defined by the regulation in place, the share of loan contracts in the year before the policy change was 30.8%, 41.5% and 27.7% respectively for loans in $0-$2,000, $2,000-$8,000 and over $8,000. In terms of loan performance, 5% of borrowers default during the first year and 11% through the loan term. The average predicted default risk is 0.11, and most of the borrowers are under 0.2.

There is substantial heterogeneity among borrowers. The average borrower has an annual income of $18,685 and is almost 44 years old. Moreover, 40% of borrowers are female. Most loan contracts are signed by consumers that had previously dealt with banks, and 76% of them are signed with a bank that the borrower has previously dealt with. In terms of credit history, the average consumer holds $7,022 in consumer loans and $12,447 in mortgage debt. The median borrower in

as those in columns (1) and (5) of Table A.2, where the latter includes the full vector x_i. For the analysis, we use a model that splits all covariates in twenty bins, to accommodate potential non-linearities in their relationship with default.

[16]Risk scores display positive correlations with rejections, interest rates and realized default. Figures A.4-a and A.4-b show a negative relationship with approvals; Figures A.4-c and A.4-d show a positive relationships with interest rates; and Figures A.4-e and A.4-f do so with realized default.

[17]We provide summary statistics of our survey in Table A.1. Survey respondents are on average similar to borrowers in the administrative data in terms of income and demographics, although somewhat riskier. Households are quite experienced in the credit market and most of them hold checking accounts, credit cards and have held consumer loans.

[18]Most of the price dispersion is cross-sectional. While there is time variation in bank funding cost, month dummies only explain 1.2% of the variation in interest rates. See Figure A.5 for the evolution of funding cost. On the other hand, there is substantial heterogeneity across banks: bank and month dummies jointly explain 25.4% of the variation.

the contracts dataset takes out only one consumer loan throughout the sample, although there is a group that take several loans and the average borrower takes 1.8 loans. Finally, borrowers in the system hold relationships with multiple banks, with a median of three banks.

Our applications dataset collects more than 3 million application events, and every month we observe 2% of potential borrowers in the market applying for a loan. Both loan amount and term are somewhat larger on average in the applications dataset than those in the contracts dataset. In terms of outcomes, as much as 90% of application events end with an approval.

Finally, we describe local market structure. We define local markets as the 54 provinces in the country. The average market has 8 banks and 43 branches. Most markets are dominated by a few banks. In particular, in the average market the top three banks hold 66% of market share in terms of loan contracts, and the top five banks hold 83% of it.

2.4 Descriptive Facts

In this section, we study the relationship of borrower behavior and contract outcomes with two key borrower attributes, namely borrower risk and previous bank relationships. We focus on the period before the policy change. First, we study loan application behavior. Column (1) in Table 2 shows results from a regression of an indicator for application on risk score, an indicator for previous relationships with any bank, and county-month fixed effects. We find that observably riskier individuals and those with previous relationships are more likely to apply for loans.

Second, we study the drivers of bank approval decisions. Column (2) in Table 2 displays results from a regression of an indicator for application approval on borrower covariates. The results show that banks are less likely to approve applications from observably riskier borrowers; and more likely to approve applicants with whom they hold a previous relationship.

Third, we show that previous relationships affect bank choice. Figure A.6-a shows there is substantial variation in the number of bank-borrower previous relationships, and few contracts are signed by borrowers new to the system. Figure A.6-b shows that the likelihood of signing a loan contract with a previously related bank is high, and that it increases with the number of previous relationships and decreases with borrower risk. This pattern may relate to the fact that applications from previously related borrowers are approved more often, perhaps because relationships make applications less costly for borrowers and banks.

Additionally, we study the determinants of interest rates. Banks engage in risk pricing and offer higher rates to riskier borrowers. Column (3) in Table 2 shows results of a regression of interest rate margins on borrower and contract covariates. Interest rates are increasing in borrower default risk. Moreover, borrowers with previous relationships receive lower rates, even after conditioning on contract attributes, borrower risk, and other covariates. Additionally, there is substantial price dispersion: 26% of the variation in interest rate margins remains unexplained after accounting for interacted month, bank, location, loan size, term and borrower risk fixed effects, as displayed

Table 1: Summary statistics

	N	Mean	SD	p10	p50	p90
Panel A - Loan attributes						
Interest rate	3,362,384	23.17	10.16	10.99	21.24	38.40
Amount	3,362,384	6,705.25	7,007.14	952.14	4,350.17	16,241.59
Term	3,362,384	33.02	16.19	12.17	36.17	50.87
Monthly payment	3,362,384	266.37	323.77	65.95	189.52	522.21
Panel B - Loan performance						
Default during loan first year	3,362,384	0.05	0.21	0.00	0.00	0.00
Default during loan term	3,362,384	0.11	0.31	0.00	0.00	1.00
Amount of charge-off	3,362,384	291.71	1,793.79	0.00	0.00	0.00
Predicted default probability - Income	3,362,384	0.11	0.06	0.04	0.11	0.18
Predicted default probability - History	3,358,842	0.11	0.10	0.02	0.09	0.24
Panel C - Borrower attributes						
Annual income	3,362,384	18,684.65	17,059.19	5,639.61	13,081.43	37,215.05
Age	3,358,842	43.80	13.30	28.00	42.00	63.00
Female	3,362,384	0.40	0.49	0.00	0.00	1.00
Consumer debt	3,362,384	7,021.96	10,514.91	70.72	3,149.40	18,285.16
Consumer debt to income ratio	3,362,384	4.58	5.29	0.07	2.92	10.97
Consumer debt under default	3,362,384	41.00	592.30	0.00	0.00	0.00
Mortgage debt	3,362,384	12,447.09	31,309.96	0.00	0.00	48,179.93
Mortgage debt to income ratio	3,362,384	5.87	13.59	0.00	0.00	24.20
Mortgage debt under default	3,362,384	11.67	664.78	0.00	0.00	0.00
Previously related to bank	3,362,384	0.76	0.43	0.00	1.00	1.00
Previously related to any bank	3,362,384	0.94	0.24	1.00	1.00	1.00
Panel D - Borrowers through the dataset						
Number of loans	1,909,393	1.76	1.22	1.00	1.00	3.00
Previously related banks	1,909,393	3.04	1.55	1.00	3.00	5.00
Panel E - Application events						
Loan amount	3,073,101	9,221.74	8,257.07	1,592.21	6,754.95	21,114.17
Loan term	2,729,861	34.59	16.87	12.13	36.47	60.47
Approved application	3,073,216	0.90	0.31	0.00	1.00	1.00
Panel F - Local Market Structure						
Number of banks	1,944	8.00	4.03	2.00	8.00	13.00
Number of branches	1,944	43.11	133.06	1.00	19.00	58.00
Top-1 market share	1,944	0.31	0.13	0.22	0.27	0.46
Top-3 market share	1,944	0.66	0.13	0.52	0.62	0.84
Top-5 market share	1,944	0.83	0.09	0.72	0.81	0.96

Notes: This table displays summary statistics for our datasets. All monetary variables are expressed in U.S. dollars for June 2016. Credit history variables are computed as averages over the year previous to each loan.

by Figure A.7. The standard deviation of residualized interest rate margins remains high at 3.9 p.p, around a third of its unconditional standard deviation.[19] The existence of substantial price dispersion even within narrow market segments is consistent with evidence from U.S. markets

[19] Evidence from our survey complements this fact by showing consumers are aware of this price dispersion. Figure A.8-a shows that consumers in the market perceive substantial price dispersion conditional on loan terms. In particular, the average perceived range of monthly payments in the market as a share of the highest monthly payment is 26%.

Table 2: Borrower risk, behavior and outcomes

	(1)	(2)	(3)	(4)
	1(Application)	1(Approval)	log(Interest rate)	1(Default)
Risk score	0.0003***	-0.011***	0.037***	0.035***
	(0.0000)	(0.000)	(0.000)	(0.000)
log(Loan size)		0.050***	-0.361***	-0.007***
		(0.000)	(0.000)	(0.000)
log(Loan term)		-0.098***	0.173***	0.071***
		(0.000))	(0.001)	(0.000)
Related to bank		0.099***	-0.008***	-0.042***
		(0.000)	(0.001)	(0.000)
Related to any bank	0.0144***	-0.042***	0.019***	0.022***
	(0.0001)	(0.001)	(0.001)	(0.001)
Mean of dep. var.	0.02	0.82	19.92	0.08
County-Month FE	Y	N	N	N
Bank-County-Month FE	N	Y	Y	Y
Observations	10,696,213	845,046	611,273	611,273
R-squared	0.002	0.138	0.609	0.080
Sample	Population	Applications	Contracts	Contracts

Notes: Results from regressions of individual behaviors and outcomes on risk scores, contract covariates, and previous relationships, for the period between January 2013 and November 2013, before the policy change. Column (1) displays results from a regression of an indicator for loan application on loan and borrower covariates. The sample includes a random sample of 10% of potential borrowers. Column (2) does so for an indicator for approval conditional on application, for all applications. Column (3) does so using interest rates as outcomes, for a sample of all loan contracts for which we observe approved applications. Finally, column (4) does so using an indicator for loan default as an outcome, using the same sample an in column (3). Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(Woodward and Hall, 2012; Stango and Zinman, 2016). Potential sources of price dispersion among similar contracts are loan officer discretion, bargaining over prices and search frictions.

Finally, we show that riskier borrowers are more likely to default. Column (4) in Table 2 shows the results from a regression of an indicator of loan default on borrower and contract covariates. Observably riskier borrowers are indeed more likely to default on loan payments, conditional on contract amount and term.

3 The Effects of Interest Rate Regulation

In this section, we provide descriptive evidence for the effects of the reform to interest rate regulation on market outcomes. We focus on price, quantity, and risk composition effects, with an emphasis on heterogeneous effects across borrowers of different observable risk.

3.1 Evidence from the Evolution of Interest Rates

The policy change reduced interest rate caps between December 2013 and December 2015 for loans smaller than $8,000. As a first piece of evidence, we inspect the evolution of interest rates. The top row of Figure 2 displays the evolution of the cap and the distribution of interest rates by loan size bracket. Interest rate caps were mostly not binding within the treated size brackets before the policy change, but became increasingly binding after it. On the other hand, the extent to which interest rate caps for loans over $8,000 were binding did not change over the period.

We also compare the distribution of interest rates before and after the policy change. The bottom row of Figure 2 shows such distribution for the month before the policy change and for the same month exactly two years after, when the policy was fully in place. The policy shifted downwards a sizable share of the density for treated loan-size brackets, inducing bunching at the caps. As much as 42% and 23% of loans of $0-$2,000 and of $2,000-$8,000 were exposed to the policy, respectively. In contrast, only 8% of loans of $8,000-$20,000 were exposed to it, and only marginally so.[20] One interpretation for this pattern is as evidence of imperfect competition. Had there been perfect competition, exposed loans would be unprofitable after the policy change and banks would have not offered them. However, this interpretation is not conclusive, as the pool of applicants might have also changed in response to the policy. Overall, these patterns suggest that banks had market power, which allowed them to charge interest rates above expected costs.

This evidence suggests that as interest rate caps were strengthened, the distribution of interest rates responded by bunching below the cap, and that riskier borrowers were more exposed to the policy. This implies that the regulation was enforced. The magnitude of the effects is large and we aim at understanding its implications for other outcomes in the remainder of the paper.

3.2 Effects on Market Outcomes

The policy change provides two sources of variation for estimating the effects of interest rate caps. First, it provides variation over time. Before December 2013, regulation was not binding for loans in $0-$8,000, but became binding as the reform was phased in. Second, it provides variation across loan size. Regulation became more binding for loans of $0-$2,000 and $2,000-$8,000 than for those of $8,000-$20,000, which remained essentially untreated. To measure market-level effects, we define bins for loan size and term indexed by k, and aggregate the data to that level.[21]

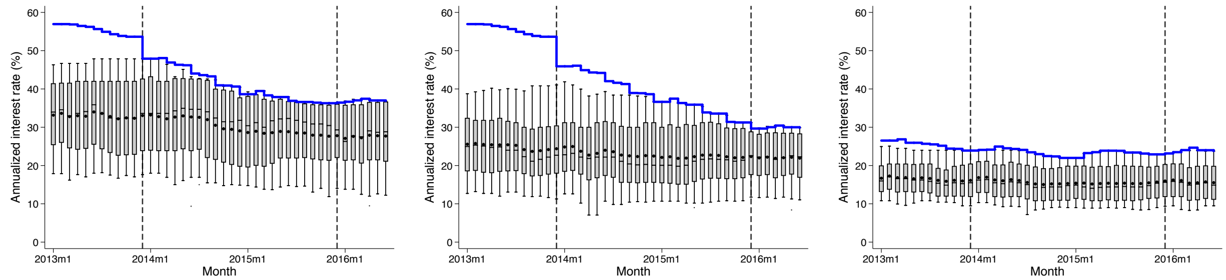
3.2.1 Evolution of Policy Effects

We study the evolution of market outcomes around the policy change. We estimate differences-in-differences models that decompose effects though time. The goal is to provide graphical evidence for the policy effects, while also addressing concerns related to trends in the outcomes leading to

[20]Exposure increases with borrower risk, which is as expected in the presence of risk pricing. As much as 49% and 31% of high-risk borrowers with loans of $0-$2,000 and $2,000-$8,000 were exposed to the policy, compared to 26% and 11% for low-risk borrowers. See Figure A.9 for details.

[21]We define loan size bins in intervals of 50 UF ($2,000) and use a clustering algorithm to classify loan term in 8 bins, adding up to 80 loan-type bins k. We then average or aggregate the outcomes of interest for each bin-month. To study heterogeneous effects, we implement the same procedure separately for low- and high-risk borrowers.

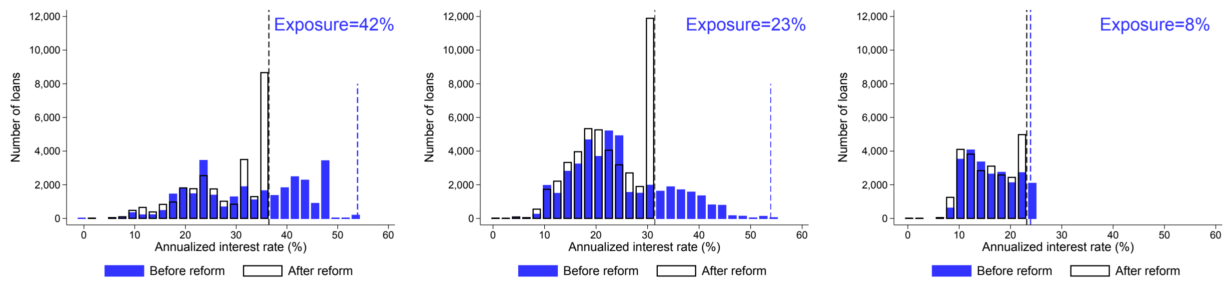
Figure 2: Evolution of the distribution of interest rates



(a) Under \$2,000

(b) Between \$2,000 and \$8,000

(c) Between \$8,000 and \$20,000



(d) Under \$2,000

(e) Between \$2,000 and \$8,000

(f) Between \$8,000 and \$20,000

Notes: Panels (a), (b) and (c) display the evolution of the distribution of interest rates by loan size. Each box displays the 25th, 50th and 75th percentiles. Whiskers display the 5th and 95th percentiles. Black dots indicate the mean. Blue lines indicate the interest rate cap. Panels (d), (e) and (f) display frequency histograms of interest rates for December 2013 (blue) and December 2015 (white). The dashed blue (black) line indicate the level of the interest rate cap before (after) the policy change. Exposure is calculated as the share of loans that were signed before the policy was implemented at interest rates higher than the cap once the policy was fully in place.

the policy change that could be correlated with the policy. We estimate the equation:

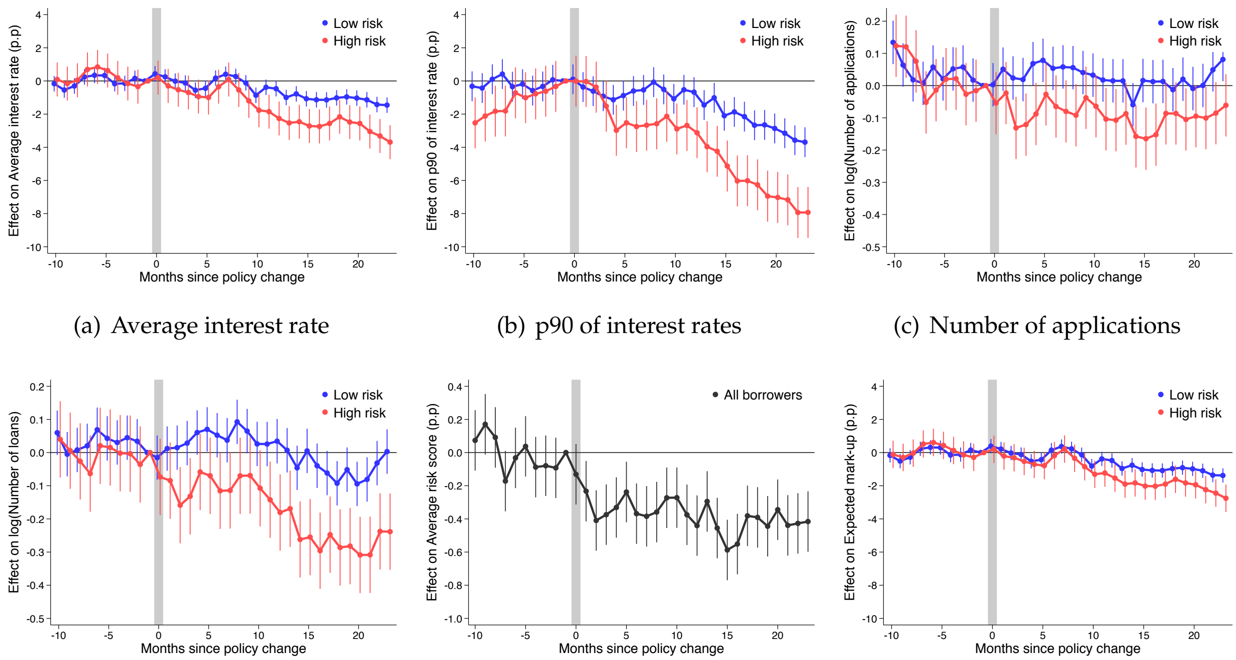
$$y_{krt} = \sum_{\tau} D_k \beta_{r\tau} + \alpha_{kr} + \delta_{rt} + \varepsilon_{krt} \tag{2}$$

where y_{krt} is an outcome for product bin k and risk group r in month t; D_k indicates loans k smaller than \$8,000 and thus affected by the policy change; α_{kr} are fixed effects that control for shocks specific to a loan size, term and risk group, but are constant through time; and δ_{rt} are fixed effects that control for shocks specific to a month and risk group, but are constant across loan size and term. The coefficients $\beta_{r\tau}$ measure the difference in the outcome y_{krt} between treated loans and the comparison group for borrowers of risk r, τ months after the policy change.[22]

Figure 3 displays results for low- and high-risk borrowers. Figure 3-a shows that the average interest rate in the market decreased after the policy change. Figure 3-b shows that the effect is

[22]We control for seasonal patterns specific to loan size for quantity outcomes by removing month-of-the-year fixed effects from the time series of each product type bin k, before estimating equation (2).

Figure 3: Differences-in-differences effects through time



(a) Average interest rate (b) p90 of interest rates (c) Number of applications

(d) Number of loans (e) Average risk score (f) Average expected mark-up

Notes: Results from equation (2). Within each plot, dots indicate estimated effects for a given month while dashed lines indicate standard errors. Effects for low- (high-) risk borrowers are displayed in blue (red). Regressions weighted by the number of loans in the product-risk bin before the policy was implemented.

concentrated on the upper part of the distribution of interest rates, as the effect on the 90th percentile is larger than on the average. Moreover, Figure 3-c shows that the number of applications by high-risk borrowers decreases, whereas Figure 3-d shows that the number of loans also decreased, and more so than applications. Figure 3-e shows that the average risk score in the market decreased, such that the borrower pool became safer. Finally, Figure 3-f shows that expected mark-ups also decreased after the policy change, but less than interest rates given the decrease in default risk.[23]

These results share two patterns. First, trends leading to the policy change are flat, which suggests that the comparison group evolved similarly to directly treated loans. We exploit that in our regression analysis below. Second, estimated effects are larger for high-risk borrowers, which suggests that they were more affected, consistent with their higher exposure. Overall, these results suggest that prices and quantities decreased under stronger regulation.

[23]We compute expected mark-up as $m_{krt} = \frac{1}{N_{krt}} \sum_{i \in \mathcal{I}_{krt}} [\iota_i(1 - d_i) - f_t]$, where m_{krt} is the average mark-up for loans in bin k for borrowers of risk r; ι_i is the interest rate charged to borrower i; d_i is the predicted default probability of i; f_t is the funding rate; and $\mathcal{I}_{krt}$ is the set of borrowers of risk r taking loans k in month t.

3.2.2 Regression Analysis

In this section, we exploit more granular variation in interest rate caps to estimate their effects on market outcomes. We define the following treatment intensity variable to exploit time variation in regulation within each size bracket, and to ease the interpretation of the results:

$$\Delta^{\bar{\iota}}_{\ell,t} \equiv (\bar{\iota}_{\ell,0} - \bar{\iota}_{\ell,t}) - (\bar{\iota}_{>8000,0} - \bar{\iota}_{>8000,t}) \tag{3}$$

for each treated size bracket $\ell \in$ {\$0-\$2,000, \$2,000-\$8,000}. The first term is the change in the interest rate cap for loan-size bracket l between month t and baseline month $t = 0$ at December 2013. The second term is the change in the interest rate cap for the comparison group of loans larger than \$8,000. Subtracting the second term removes variation in economic conditions that influences interest rate caps, and thus isolates the policy variation that we exploit.

Using these variables, we estimate the following specification:

$$y_{krt} = \sum_{\ell} \beta_{\ell(k),r} \Delta^{\bar{\iota}}_{\ell(k),t} + \delta_{kr} + \phi_{krm(t)} + \gamma_{rt} + \varepsilon_{krt} \tag{4}$$

where y_{krt} is an outcome for product bin k for borrower of risk r for month t; δ_{kr} is a set of fixed effects that controls for unobservable shocks specific to a loan size and term and borrower risk bin, but constant through time; $\phi_{krm(t)}$ are fixed effects that control for shocks specific to a product type, borrower risk bin and month-of-the-year $m(t)$; and γ_{rt} are fixed effects that control for shocks specific to a borrower risk bin and month but constant across loan size and term. The coefficients of interest are $\beta_{0-2000,r}$ and $\beta_{2000-8000,r}$, which measure the effect of *reducing* interest caps by 1 p.p. on the outcome of interest. We then compute full effects by scaling up these estimates by the full change in interest caps. Regressions are weighted by the number of loans in each product bin before the policy was implemented. Finally, standard errors are clustered at the product bin level.

We first study effects on interest rates, focusing on maximum and average rates. Then, we focus on quantity, including applications, number of loans and credit volume. Finally, we focus on risk selection, loan performance and expected profitability by estimating effects on borrower risk scores and on income, 90-day loan default in the first year, and expected mark-ups. In each case, we estimate regressions across all borrowers and separately for low- and high-risk borrowers.

Effects on interest rates. Stronger regulation reduced interest rates. Table 3 displays estimates of equation (4) interest rates. Pass-through of interest rate caps to maximum interest rates was high. The effects of a 1 p.p decrease in interest rate caps range from 0.96 p.p for low-risk borrowers to 1 p.p for high-risk borrowers for loans of \$0-\$2,000; and from 0.66 p.p for low-risk borrowers to 0.8 p.p for high-risk borrowers for loans of \$2,000-\$8,000. Full effects are large and close to the total change in the interest rate cap, particularly for riskier borrowers. These results verify that the policy was enforced, and that it was more binding for smaller loans and riskier borrowers.

Table 3: Effects on interest rates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A - Maximum interest rate			Panel B - Average interest rate		
	All	Low-risk	High-risk	All	Low-risk	High-risk
Loans in \$0-\$2000						
Marginal effect (β)	-1.001***	-0.961***	-0.996***	-0.231***	-0.126***	-0.262***
	(0.010)	(0.024)	(0.012)	(0.032)	(0.021)	(0.041)
Full effect ($\beta \times \Delta\bar{\imath}$)	-16.369***	-15.720***	-16.298***	-3.771***	-2.060***	-4.286***
	(0.157)	(0.390)	(0.200)	(0.526)	(0.345)	(0.666)
Baseline mean	55.145	54.675	55.384	33.023	28.630	35.256
Loans in \$2000-\$8000						
Marginal effect (β)	-0.785***	-0.660***	-0.803***	-0.073***	-0.033**	-0.107***
	(0.030)	(0.042)	(0.032)	(0.020)	(0.013)	(0.025)
Full effect ($\beta \times \Delta\bar{\imath}$)	-18.307***	-15.405***	-18.744***	-1.714***	-0.776**	-2.496***
	(0.701)	(0.972)	(0.745)	(0.478)	(0.295)	(0.590)
Baseline mean	50.401	48.920	51.634	24.912	21.426	27.813
Observations	2,880	2,880	2,829	2,880	2,880	2,829
R-squared	0.986	0.976	0.984	0.984	0.985	0.975
Product bin FE	Y	Y	Y	Y	Y	Y
Product bin-MofY FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Notes: Results from equation (4), estimated across borrower risk bins and by borrower risk bin. Marginal effects are effect of reducing caps by 1 p.p. Full effects are the product of the marginal effect and the full policy change. Regressions weighted by number of loans before the policy change. Clustered standard errors at the product bin-risk bin level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Average interest rates decreased as a result of stronger regulation, as displayed in Table 3-B. We estimate that reducing interest rate caps by 1 p.p decreases average interest rates by 0.23 p.p and 0.07 for loans of \$0-\$2,000 and \$2,000-\$8,000, respectively. These effects are heterogeneous across borrower risk. The effects on low-risk borrowers are smaller at 0.13 p.p and 0.03 p.p, while those on high-risk borrowers are much larger at 0.26 p.p and 0.11 p.p respectively. The full effects on average interest rates were 3.8 p.p and 1.7 p.p for loans of \$0-\$2,000 and \$2,000-\$8,000.

Effects on quantity outcomes. Interest rate regulation may affect application behavior. Regulation weakly reduces interest rates upon approval and thus induces marginal borrowers to take loans. However, banks may be less willing to approve applications if their pricing is constrained, which may deter applications if applying is costly. The latter should be more relevant for observably riskier borrowers. Table 4-A displays estimates of equation (4) for the number of applications. We find no statistically significant effects on average, nor for low-risk borrowers. However, we find suggestive evidence that risky borrowers apply less often for loans under stronger regulation. In particular, a 1 p.p decrease in interest rate caps reduced applications by 1% and 0.4% for loans of \$0-\$2,000 and \$2,000-\$8,000, although the latter is not statistically significant. These estimates imply that the full policy decreased applications by risky borrowers by 15% and 9% respectively.

Table 4: Effects on quantity outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A - log(Applications)			Panel B - log(Number of loans)			Panel C: log(Credit volume)		
	All	Low-risk	High-risk	All	Low-risk	High-risk	All	Low-risk	High-risk
Loans in \$0-\$2000									
Marginal effect (β)	-0.003	-0.002	-0.010**	-0.020***	-0.008***	-0.025***	-0.018***	-0.008***	-0.022***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Full effect ($\beta \times \Delta\bar{\imath}$)	-0.053	-0.030	-0.164**	-0.323***	-0.129***	-0.414***	-0.291***	-0.135***	-0.362***
	(0.058)	(0.046)	(0.082)	(0.053)	(0.044)	(0.058)	(0.060)	(0.048)	(0.065)
Baseline mean	20,402	5,594	14,807	28,793	9,702	19,091	35,108	12,377	22,733
Loans in \$2000-\$8000									
Marginal effect (β)	0.000	-0.001	-0.004	-0.005*	-0.002	-0.007**	-0.006*	-0.003	-0.007*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full effect ($\beta \times \Delta\bar{\imath}$)	0.004	-0.017	-0.094	-0.127*	-0.046	-0.171**	-0.133*	-0.066	-0.159*
	(0.071)	(0.068)	(0.099)	(0.073)	(0.061)	(0.082)	(0.073)	(0.063)	(0.080)
Baseline mean	33,312	13,582	19,730	38,823	17,633	21,190	170,026	81,855	88,170
Observations	2,800	2,800	2,713	2,880	2,880	2,880	2,880	2,880	2,880
R-squared	0.994	0.989	0.993	0.990	0.988	0.989	0.985	0.986	0.979
Product bin FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Product bin-MofY FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Results from equation (4), estimated across borrower risk bins and by borrower risk bin. Marginal effects are effect of reducing caps by 1 p.p. Full effects are the product of the marginal effect and the full policy change. Baseline mean for credit volume reported in thousands. Regressions weighted by number of loans before the policy change. Clustered standard errors at the product bin-risk bin level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Tables 4-B and 4-C display estimates of equation (4) for number of loans and credit volume. We find that reducing interest rate caps by 1 p.p reduced the number of loans by 2% and 0.5% for loans of \$0-\$2,000 and \$2,000-\$8,000. Again, our estimates are heterogeneous across borrower risk. For low-risk borrowers, we estimate decreases of 0.8% and 0.2% for loans of \$0-\$2,000 and \$2,000-\$8,000; whereas estimates are three times larger for high-risk borrowers, at 2.5% and 0.7% respectively. Results are similar for credit volume. Overall, the number of loans decreased by 27.6% and 11.9% for loans of \$0-\$2,000 and \$2,000-\$8,000. Effects are larger among high-risk borrowers at 33.9% and 15.8%, respectively. These effects on the number of loans are larger than those on applications, which implies that a large share of the quantity reduction comes from rejections.

Effects on risk selection, loan performance and profitability. Changes in applications and approvals due to regulation may affect the borrower pool. Table 5-A displays results from estimating equation (4) for ex-ante borrower risk measures. The policy change improved the borrower risk pool. A reduction of 1 p.p in the cap decreases average borrower predicted default rate by between 0.07 p.p and 0.04 p.p for loans of \$0-\$2,000 and by around 0.02 for loans of \$2,000-\$8,000, depending on the measure of predicted risk. The full policy decreased predicted default risk by between 1.14 p.p and 0.7 p.p for loans of \$0-\$2,000, and by between 0.49 and 0.35 p.p for loans of \$2,000-\$8,000.

Table 5: Effects on risk selection, loan performance and profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A - Risk selection			Panel B - Loan performance			Panel C - Profitability		
	Risk-I	Risk-H	log(Income)	Share of loans under 1Y default			Average expected mark-up		
	All	All	All	All	Low-risk	High-risk	All	Low-risk	High-risk
Loans in \$0-\$2000									
Marginal effect (β)	-0.067***	-0.043***	0.004***	-0.093***	-0.040***	-0.057**	-0.161***	-0.116***	-0.187***
	(0.003)	(0.007)	(0.001)	(0.018)	(0.010)	(0.027)	(0.027)	(0.020)	(0.032)
Full effect ($\beta \times \Delta\bar{\imath}$)	-1.136***	-0.700***	0.071***	-1.519***	-0.652***	-0.938**	-2.608***	-1.899***	-3.064***
	(0.052)	(0.115)	(0.014)	(0.287)	(0.161)	(0.450)	(0.447)	(0.320)	(0.530)
Baseline mean	6.925	6.616	13.013	6.747	3.353	8.472	22.491	20.773	23.364
Loans in \$2000-\$8000									
Marginal effect (β)	-0.021***	-0.015***	0.000	-0.038***	-0.004	-0.031*	-0.052***	-0.032***	-0.078***
	(0.004)	(0.005)	(0.001)	(0.011)	(0.006)	(0.018)	(0.016)	(0.012)	(0.020)
Full effect ($\beta \times \Delta\bar{\imath}$)	-0.486***	-0.348***	0.006	-0.879***	-0.101	-0.732*	-1.193***	-0.742***	-1.827***
	(0.101)	(0.113)	(0.014)	(0.259)	(0.143)	(0.411)	(0.380)	(0.271)	(0.471)
Baseline mean	5.782	6.011	16.641	6.026	2.873	8.649	16.013	14.285	17.452
Observations	2,880	2,880	2,880	2,880	2,880	2,829	2,880	2,880	2,829
R-squared	0.982	0.969	0.989	0.915	0.832	0.766	0.983	0.984	0.975
Product bin FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Product bin-MofY FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Results from equation (4), estimated across borrower risk bins and by borrower risk bin. Marginal effects are effect of reducing caps by 1 p.p. Full effects are the product of the marginal effect and the full policy change. Predicted risk is measured in a 0-100 scale. Share of loans under default in first year is computed in a 0-100 scale. See footnote 23 for details on the construction of average expected mark-ups. Regressions weighted by number of loans before the policy change. Clustered standard errors at the product bin-risk bin level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Relatedly, we find that average borrower income increases with stronger regulation.

A safer borrower pool may lead to improved aggregate loan performance. Table 5-B shows that the policy change improved loan performance. Reducing interest rate caps by 1 p.p decreased the share of loans under 90-day default in their first year by 0.09 p.p and 0.04 p.p respectively for loans of \$0-\$2,000 and \$2,000-\$8,000. This effect is higher among high-risk borrowers. The full policy reduced the average share of loans under 90-day default in their first year by 1.52 p.p and 0.88 p.p, equivalent to 22.5% and 14.6% of their baseline levels.

Finally, we study effects on expected mark-ups. We find that expected mark-ups decreased after the policy change, as displayed in Table 5-C. These effects are smaller than those on interest rates, because the composition of the borrower pool is safer and thus banks' expected costs decrease. These results suggest that interest rate caps constrain banks' exercise of market power.

3.3 Discussion

We have provided evidence for the effects of interest rate regulation on equilibrium market outcomes. The research design exploits policy variation across loan size and time. This strategy raises concerns, for instance due to potential substitution along the size margin. In Online Appendix A, we develop robustness checks to address these concerns, which support our main findings.

Overall, our estimates imply that 151,027 loans per year were deterred by stronger regulation, equivalent to 19% of the number of contracts signed during the year before the policy change and \$361.6 million in credit. Our price effects imply that interest rates decrease on average by 9%, which translates to an average decrease in monthly payments of \$3.26. The present value of reduced monthly payments during the year before the policy change is \$31.7 million.

This analysis is informative of the effect of interest rate caps on equilibrium outcomes, but several questions remain unanswered. First, the welfare implications of these estimates are unclear. To develop a welfare analysis, we need estimates of willingness to pay and bank costs. Second, market power partly determine these effects. However, it is hard to evaluate its role using observational data given the endogeneity of market structure. Third, we discussed that this regulation is often quite unsophisticated, and this analysis does not inform how alternative designs would perform. We develop and estimate an equilibrium model to address these aspects.

4 An Equilibrium Model of Applications, Pricing and Repayment

We develop a model of applications, pricing and repayment in the credit market. Several modeling choices aim at moving from a theoretical model to an empirical one that can be estimated using the data available for our setting. We discuss them and their implications in Appendix A.

4.1 Model

There are N consumers, denoted by i. There are J banks, denoted by $j \in \mathcal{J}$, where $\mathcal{J}$ is the set of banks in the market. The model is static. Consumers choose whether to apply for loans of a given amount and term (L_i, T_i), determined in a previous stage that we do not model. Applicants get quotes from a randomly drawn consideration set $\mathcal{J}_i$. For a given (L_i, T_i), contracts are homogeneous and only differ in their monthly payments, which vary across banks due to cost heterogeneity. Consumers thus shop across banks for the lowest monthly payment. Contracts are determined as the outcome of an English auction among banks in the consideration set $\mathcal{J}_i$, as in Allen *et al.* (2019). Finally, repayment is realized.[24]

Borrowers. A potential borrower is endowed with observable attributes x_i and unobservable attributes ε_i, such that (x_i, ε_i) summarizes her type. The vector x_i collects all public information, such as risk score, income and credit history, whereas $\varepsilon_i = (\varepsilon_{Ai}, \varepsilon_{Si})$ are potentially correlated application and repayment shocks that follow a distribution F_ε and are borrower private information.

The consumer decides whether to shop for loans. If she shops for loans, she incurs an application cost $\kappa(z_i)$ that depends on cost shifters z_i, draws a consideration set of banks $\mathcal{J}_i$ from a

[24]Figure A.17 summarizes the structure and timing of the model.

distribution Φ_i, and shops across them. If she does not shop for loans, she obtains her outside option. Let the indirect utility from a contract and the outside option be:

$$\begin{aligned} u_{Ci} &= v_C(x_i, L_i, T_i) - p_i \\ u_{Oi} &= v_{Oi} \end{aligned}$$

where $v_C(x_i, L_i, T_i)$ is the indirect utility of a contract, which depends on borrower and loan attributes; p_i is the monthly payment; and v_{Oi} is the indirect utility of the outside option. The borrower chooses to apply for loans by comparing the expected value of both options, given by:

$$\begin{aligned} u_{Ai} &= \underbrace{P_{Ci} \int u_{Ci} f_{p|C}(p) dp}_{\text{Value of approval}} + (1 - P_{Ci}) \underbrace{u_{Oi}}_{\text{Value of rejection}} - \kappa(z_i) + \varepsilon_{Ai} \\ u_{NAi} &= u_{Oi} \end{aligned}$$

where P_{Ci} is the probability that the application is approved by some bank, and where the borrower integrates the value of a loan contract over the density of loan prices conditional on approval, which we denote by $f_{p|C}(p)$. Both P_{Ci} and $f_{p|C}(p)$ are equilibrium objects known to borrowers. Finally, ε_{Ai} is a shock to the utility from applying for a loan relative to not applying.

Given this structure, a borrower applies for loans whenever her expected utility is higher than that of remaining out of the credit market. The application probability is:

$$P_{Ai} = \Pr\left(P_{Ci} \int (u_{Ci} - u_{Oi}) f_{p|C}(p) dp - \kappa(z_i) + \varepsilon_{Ai} \geq 0\right) \tag{5}$$

from where it is clear that application decisions are driven by the approval probability, the expected value of a loan relative to the outside option, the density of loan prices conditional on approval, an application cost, and a shock to the utility of application. Let a_i indicate that borrower i applies for a loan and $\mathcal{A}$ be the set of loan applicants. We set the utility of the outside option to $u_{Oi} = 0$ for the remainder of the paper, such that u_{Ci} is the utility of a loan relative to that outside option.

Conditional on applying for loans, the borrower solves a discrete choice problem to choose which bank to sign a loan contract with, which implies that utility from a loan contract is:

$$u_{Ci} = \max_{j \in \mathcal{J}_i} \quad v_C(x_i, L_i, T_i) - p_{ij} \iff p_i = \min_{j \in \mathcal{J}_i} p_{ij}$$

such that bank choice among banks in the choice set is driven by monthly payment, given there is no further product differentiation across banks.

After signing a loan contract, repayment is realized. Let $s_i \in [0, 1]$ be the share of payments made by borrower i relative to the total number of monthly payments in the contract:

$$s_i = s(x_i, L_i, T_i, \varepsilon_{Si}) \tag{6}$$

which is a function of borrower characteristics and non-price contract terms. Moreover, repayment is increasing in the repayment shock ε_{Si}. There is adverse selection if application and repayment display a negative correlation through unobservables to banks $(\varepsilon_{Ai}, \varepsilon_{Si})$.

Banks. We model bank competition as an English auction. Banks are heterogeneous in their costs. There are three components of cost: (i) funding cost f_i; (ii) bank-borrower match-value ω_{ij}, which is an i.i.d. shock from a distribution G_ω that is unobserved to borrowers and may make it less costly for a bank to serve some borrowers than others; and (iii) repayment risk. We combine the first two components in $m_{ij} = f_i - \omega_{ij}$. In terms of repayment risk, banks observe x_i and application choices a_i, which they employ to estimate repayment risk when pricing contracts.

Bank profits depend on a risky stream of payments and a known stream of bank costs. Let $\varphi(T_i) \equiv \frac{1}{r}(1 - \exp(-rT_i))$ be a present value operator that discounts a stream of payments for T_i months at a discount rate r; and let $S_i = s_i T_i$ be expected repayment repayment length by borrower i. The expected profit from a loan at price p_{ij} is then:

$$E_\varepsilon[\pi_{ij}] = E_\varepsilon[\varphi(S_i)]p_{ij} - \varphi(T_i)(f_i - \omega_{ij})$$

where repayment risk and funding cost depend only on borrower-specific attributes, while match-value ω_{ij} depends on bank-borrower attributes. Thus, ω_{ij} introduces cost heterogeneity across banks that can be thought of as the match-value of a contract. For example, ω_{ij} could capture bank-borrower relationships and bank convenience in local markets. Conditional on x_i, banks with higher ω_{ij} have a cost advantage in offering a loan to borrower i.

A bank offers a contract if $E_\varepsilon[\pi_{ij}] \geq 0$, and otherwise rejects the borrower. Expected profits are decreasing in borrower repayment risk at a given price, and thus observably riskier applicants are less likely to be approved. Borrower application and bank approval decisions are related. Given banks observe x_i and know F_ε, they make inference about borrower unobservable repayment shock ε_{Si} from application choices. Banks incorporate that information for approval and pricing.[25]

Regulation. Interest rate regulation takes the form of an interest rate cap, which induces caps on monthly payments. In particular, banks cannot charge monthly payments higher than $\bar{p}_i$.

[25]In particular, banks compute $E_\varepsilon[\pi_{ij}] = E_\varepsilon[\pi_{ij}|a_i = 1, x_i]$. This implies that, conditional on x_i, application choices reveal information about ε_{Ai}. Given banks know F_ε, a signal about ε_{Ai} is informative about repayment risk ε_{Si}.

4.2 Equilibrium

Equilibrium is characterized by the pool of applicants, loan approvals and prices. In absence of interest rate regulation, the lowest cost bank wins the auction with a bid $b_{i(1)}$, such that the second lowest cost bank is indifferent between getting the loan contract or not at that price.[26] The equilibrium unconstrained price solves:

$$E_\varepsilon[\pi_{i(2)}] = E_\varepsilon[\varphi(S_i)]p_i^u - \varphi(T_i)m_{i(2)} = 0$$

which can be written as:

$$p_i^u = \frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}(f_i - \omega_{i(2)}) \tag{7}$$

which increases with borrower risk and funding cost, and decreases with match-value of the closest rival bank.[27]

Under interest rate regulation, there are three potential outcomes for an applicant. If regulation is not binding, the bank offers the contract at the unconstrained price. If regulation is binding, the unconstrained price is higher than the price cap, $\bar{p} < p_i^u$. In this case, the lowest cost bank offers the contract at price $p_i = \bar{p}$ as long as $E_\varepsilon[\pi_{i(1)}] = \bar{p} - \frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}m_{i(1)} \geq 0$. Finally, if the cost of the lowest cost bank is high enough to make lending at the cap unprofitable, then $E_\varepsilon[\pi_{i(1)}] = \bar{p} - \frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}m_{i(1)} < 0$ and all banks reject the applicant. Therefore, equilibrium prices under regulation are:

$$p_i^* = \begin{cases} p_i^u & \text{if } p_i^u \leq \bar{p} \\ \bar{p} & \text{if } \frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}m_{i(1)} \leq \bar{p} < p_i^u \\ \cdot & \text{if } \bar{p} < \frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}m_{i(1)} \end{cases} \tag{8}$$

The distribution of equilibrium prices determines application decisions by borrowers, which in turn determines the equilibrium set of applicants, $\mathcal{A}^*$. In equilibrium, (i) borrowers optimally make application choices given both the application approval probability and the distribution of prices they face in the market, and their application costs, while (ii) banks optimally make price offers in a competitive environment given both their costs and the pool of loan applicants.

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[26]The notation $x_{(m)}$ indicates the mth order statistic of x, calculated among banks in the consideration set $\mathcal{J}_i$.

[27]This expression for the unconstrained equilibrium price can be rewritten as:

$$p_i^u = \underbrace{\frac{\varphi(T_i)}{E_\varepsilon[\varphi(S_i)]}}_{\text{Risk adjustment}} (\underbrace{f_i - \omega_{i(1)}}_{\text{Mg. Cost}} + \underbrace{\omega_{i(1)} - \omega^f_{i(2)}}_{\text{Cost heterogeneity}} + \underbrace{\omega^f_{i(2)} - \omega_{i(2)}}_{\text{Search frictions}})$$

where we denote the match-value of the closest rival under full consideration as $\omega^f_{i(2)}$, such that unconstrained prices depend on risk-adjusted cost, and a mark-up $\omega_{i(1)} - \omega_{i(2)}$ that combines bank cost advantages and search frictions.

4.3 Effects of Interest Rate Regulation

Application behavior and consumer welfare. Stronger regulation affects borrower application behavior by (i) reducing the approval probability, and by (ii) weakly reducing prices conditional on approval. These incentives jointly determine the effect of regulation on application behavior:

$$\frac{du_{Ai}}{d\bar{p}_i} = \underbrace{\frac{\partial P_{Ci}}{\partial \bar{p}_i} \int u_{Ci} f_{p|C}(p) dp}_{\text{Credit access } (\geq 0)} + \underbrace{P_{Ci} \frac{\partial}{\partial \bar{p}} \int u_{Ci} f_{p|C}(p) dp}_{\text{Consumer protection } (\leq 0)} \tag{9}$$

which depends on which incentive dominates. If the effects of stronger regulation on approval probability are large (small) relative to those on expected prices conditional on approval, then borrowers will apply for loans less (more) often, and expected consumer surplus will decrease (increase). The relative strength of these effects depends on borrower preferences and attributes, and thus changes in regulation may yield a combination of winners and losers among borrowers.

Bank lending and profits. Stronger regulation affects bank expected profits through (i) affecting the pool of applicants, (ii) limiting incentives to approve applicants, and (iii) limiting the ability of banks to charge high prices on profitable loans. With some abuse of notation, let expected profits from a potential applicant be $E_\varepsilon[\Pi_{ij}] = P_{Ai}\phi_{ij}P_{Ci}E_\varepsilon[\pi_{ij}]$, which depends on the probabilities that the consumer shops for loans, considers bank j, and bank j approves her, and on the expected profits conditional on approval. Then the effect of regulation on expected profits is given by:

$$\frac{dE_\varepsilon[\Pi_{ij}]}{d\bar{p}_i} = \underbrace{\frac{\partial P_{Ai}}{\partial \bar{p}_i} \phi_{ij} P_{Ci} E_\varepsilon[\pi_{ij}]}_{\text{Application effect } (\lessgtr 0)} + \underbrace{P_{Ai}\phi_{ij} \frac{\partial P_{Ci}}{\partial \bar{p}_i} E_\varepsilon[\pi_{ij}]}_{\text{Approval effect } (\geq 0)} + \underbrace{P_{Ai}\phi_{ij}P_{Ci} \frac{\partial E_\varepsilon[\pi_{ij}]}{\partial \bar{p}_i}}_{\text{Price effect } (\geq 0)}$$

where the second and third terms capture how stronger regulation limits bank profitability by reducing its approval probability and its prices conditional on approval, whereas the first term is ambiguous, and depends on how regulation affects application incentives.

Market power and selection. The extent of bank market power determines the potential for consumer protection through interest regulation. In a setting without market power, no borrower is protected by the policy, as all marginal borrowers become unprofitable for banks under stronger interest rate regulation. In addition, if there is selection into the market on observable risk and if willingness to pay for loans is correlated with risk, then the direction of selection will matter for welfare implications, given (observably) riskier borrowers are more likely to be affected.

5 Econometric Model

The objects of interest on the demand side are the indirect utility function of consumers, $u_{Ci}(x_i, L_i, T_i, p_i)$; the the application cost, $\kappa(z_i)$; the repayment equation, $s(x_i, L_i, T_i, \varepsilon_{Si})$; the joint distribution of application and repayment shocks, F_ε; and the distribution of consideration sets Φ_i. On the supply side, we are interested in the distribution of bank costs, G_ω.

We estimate the model using four sets of observables. First, we observe borrower covariates x_i, application shifters z_i, funding cost f_i, relationships with banks r_{ij}, and application choices a_i for all borrowers. Second, we observe loan amount and term (L_i, T_i) for each applicant. Third, we observe loan monthly payment and repayment (p_i, s_i) for each approved applicant. Finally, we observe which banks were considered by borrowers in our survey when applying to banks, along with consideration shifters w_i. In this section, we specify the model and state relevant statistical assumptions, and then provide identification arguments before moving to estimation.

5.1 Model Specification

Application and repayment. We specify the indirect utility of a contract as a linear function of borrower attributes x_i, loan amount, term, and prices; and the application cost as a linear function of shifters z_i. In particular, we specify the application probability in equation (5) as:

$$P_{Ai} = \Pr\left(P_{Ci} \int (x_i'\delta_X + \delta_L L_i + \delta_T T_i - \delta_p p) f_{p|C}(p) dp - z_i'\kappa + \varepsilon_{Ai} \geq 0\right) \tag{10}$$

where x_i includes the borrower risk score, income, debt to income ratio, default to debt ratio, gender, and age along with market and month dummies. Additionally, z_i includes the total number of bank branches in the local market, and the number of related banks of the borrower in the previous year. We discuss the role of these application shifters for identification below. Finally, we allow for heterogeneity in the price sensitivity coefficient across low- and high-risk borrowers.

For loan repayment, we adopt the same specification as Einav *et al.* (2012). In particular, we specify the repayment share in equation (6) as a function of borrower covariates and contract terms:

$$s_i = \min\{\exp(x_i'\alpha_X + \alpha_L L_i + \alpha_T T_i + \varepsilon_{Si}), 1\} \tag{11}$$

which has the advantages that: (i) it is bounded in the unit interval, and that (ii) it accommodates the possibility of a mass point at full repayment, something we do observe in the data. The vector x_i in this specification is the same as that in the application equation above.

We specify the joint distribution of application and repayment shocks F_ε as a bivariate normal:

$$\begin{pmatrix} \varepsilon_A \\ \varepsilon_S \end{pmatrix} \sim N\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{matrix} \sigma_A^2 & \rho\sigma_A\sigma_S \\ \rho\sigma_A\sigma_S & \sigma_S^2 \end{matrix} \right) \tag{12}$$

where ρ determines selection. In particular, $\rho < 0$ implies adverse selection, as riskier borrowers are more likely to apply for loans. Moreover, σ_A^2 and σ_S^2 are the variances of application and repayment shocks, and we normalize σ_A^2 to 1. This assumption provides a closed form relationship between the conditional and unconditional distributions of shocks, something that previous work also exploits (Einav *et al.*, 2012; Crawford *et al.*, 2018). Under this specification, the demand side of the model is a selection model with a normality distributional assumption (Heckman, 1979).

Borrower choice set. We model borrower consideration sets following Goeree (2008). We define a consideration index $c_{ij} = w'_{ij}\lambda + \varepsilon_{Cij}$, which depends on consideration shifters w_{ij} that depend only on attributes of borrower i and bank j, and where ε_{Cij} follows an i.i.d. T1EV distribution. Moreover, we assume that borrowers always consider banks with which they have previous relationships. The probability that bank j is in the choice set of borrower i is:

$$\phi_{ij} = \begin{cases} \Lambda(w'_{ij}\lambda) & \text{if } j \notin \mathcal{R}_i \\ 1 & \text{if } j \in \mathcal{R}_i \end{cases} \tag{13}$$

where Λ is the logistic function, and $\mathcal{R}_i$ is the set of previously related banks of borrower i. The probability of any choice set $\mathcal{J}_i \subseteq \mathcal{J}$ is then:

$$P(\mathcal{J}_i) = \prod_{l \in \mathcal{J}_i} \phi_{il} \prod_{k \notin \mathcal{J}_i} (1 - \phi_{ik})$$

To take this component of the model to the data, we use survey data on which banks borrowers considered, combined with administrative data on borrower and bank covariates. In particular, w_{ij} includes the same borrower covariates in x_i above, along with the number and share of total of branches that bank j has in the local market where i lives, and bank fixed effects.

Bank costs. We specify the bank costs as $m_{ij} = f_i - L_i\omega_{ij}$ such the bank-borrower idiosyncratic component is measured per loan unit. We assume that the match-value component follows an i.i.d. T1EV distribution, with location and scale parameters δ_{ij} and σ_ω.[28] We parametrize the location parameter as $\delta_{ij} = \tau_j + \gamma r_{ij}$, where τ_j is a bank-specific intercept, and r_{ij} indicates a previous relationship with borrower i. Fixed effects τ_j capture cost differences across banks that are constant across borrowers. The parameter γ captures the potential incumbency advantage that banks previously related to an applicant hold. Finally, we denote the idiosyncratic component of ω_{ij} as $\varepsilon_{\omega ij}$, which captures variation in cost at the borrower-bank level, which could be driven by heterogeneity in bank services in local markets or relationships between borrowers and branch officers.[29] We allow for parameter heterogeneity across four bins of loan term.

[28]The distributions of order statistics of ω_{ij} have a closed form under this distributional assumption, which is useful for estimation. We summarize these properties in Online Appendix B.4. Proofs are available in Froeb *et al.* (1998).

[29]As an example of the cost heterogeneity captured by $\varepsilon_{\omega ij}$, Drexler and Schoar (2014) use data from a large Chilean bank to show that loan officer turnover has sizable effects on loan approval and borrower default behavior.

This specification of bank costs is consistent with the facts in Section 2.4. In particular, it allows for: (i) expected default cost to vary across borrowers according to borrower observables; (ii) bank costs for a given borrower to vary across banks; and (iii) bank costs to depend on previous relationships with borrowers, thus introducing the potential for incumbency advantages.

5.2 Identification

We now state our identification assumptions and discuss how variation in the data identifies the model. We assume that borrower covariates, loan amount and term, application cost shifters, and consideration set shifters $(x_i, L_i, T_i, z_i, w_i)$ are exogenous. The main identification assumption is conditional independence between application and repayment shocks $(\varepsilon_{Ai}, \varepsilon_{Si})$, shocks to consideration sets ε_{Cij}, and cost shocks ω_{ij}. This assumption implies that banks do not have any informational advantage relative to the econometrician in terms of the determinants of application and repayment behavior that affects bank costs and pricing. While restrictive, this assumption relies on our detailed dataset being the same that the regulator provides to banks for screening. Note that this assumption does not imply that bank costs are invariant to borrower attributes and application behavior. In fact, banks consider observable risk for pricing and also infer unobservable risk from applications. Under these assumptions, we can treat identification and estimation of the demand and supply sides of the model separately.

Application and repayment. The demand side of the model has the structure of a selection model, where application is the selection equation and repayment is the outcome equation. Parametric and non-parametric identification of this model is established in Heckman (1979) and Das *et al.* (2003). The latter emphasizes the role of exclusion restrictions. We exploit two application cost shifters in z_i as exclusion restrictions. First, the number of branches across all banks in the local market as a measure of bank density. This shifter is in line with research using distance as a shifter of school applications (Walters, 2018). Second, the number of previously related banks as a measure of market experience. Both shifters should decrease application cost and arguably shift application choices, but are unlikely to affect the utility from loans or repayment behavior.

Given the model specification and our identification assumption, the intuition for how variation in the data identifies the demand side of the model is as follows. Application responses to variation in (x_i, L_i, T_i, p_i) identify δ in the application equation. Moreover, repayment responses to variation in (x_i, L_i, T_i) identify α in the repayment equation. Regarding the joint distribution of application and repayment shocks F_ε, the intuition is that consumers observed applying for loans when the model predicts they should not, are likely to have a high ε_{Ai}. The conditional correlation between those shocks and observed repayment identifies ρ. In particular, if those borrowers are observed to repay less, then $\rho < 0$ and there is adverse selection.

Consideration sets. To identify the distribution of consideration sets Φ_i, we exploit our survey as an additional source of data. In particular, we have information for that sample about the set of banks that consumers considered in their last shopping attempt. These data coupled with the i.i.d. assumption on ε_{Cij} identify the distribution Φ_i.

Bank costs. The identification of bank costs follows from arguments in the auctions literature. Assuming independence in cost shocks ω_{ij} across banks and borrowers, the supply side of our model corresponds to an asymmetric independent private values auction with unobserved set of bidders. As shown in Komarova (2013) and Kong (2021), the distribution of values in this model is non-parametrically identified from transaction prices, the identity of the auction winner, the set of potential bidders and their entry probabilities. In our setting, we observe prices and the identity of the bank for all contracts, and our consideration set model informs us about entry probabilities for potential entrants, and therefore the distribution of bank costs is identified.

We relate this argument to our specification of bank costs. Given funding cost f_i and consideration probabilities ϕ_{ij}, identification of bank costs relies on variation in contract prices, bank choices, and application outcomes. First, identification of cost differences across banks τ_j relies on differences in prices across chosen banks. Second, identification of incumbency advantage γ relies on variation in prices within chosen banks across applicants with and without a previous relationship with the bank. Finally, any remaining variation in loan prices within banks and bank-borrower relationships identifies the scale of idiosyncratic cost shocks, σ_ω.[30]

5.3 Estimation

Estimation proceeds in three steps. First, we jointly estimate the parameters of the application and repayment equations. Second, we estimate the consideration set model. Third, we exploit the auction structure of the supply side of the model to estimate bank costs.

Application and repayment. The estimation of the application and repayment equations in (10) and (11) proceeds in three steps. The first step deals with the fact that loan terms (L_i, T_i) are not observed for non-applicants. We estimate the conditional distribution of loan amount and term using data from applicants and then draw from that distribution for non-applicants. To deal with concerns about selection into application, we adopt a control function approach based on Das *et al.* (2003), similar to Attanasio *et al.* (2008). In the first stage, we estimate a flexible probit model for applications on a rich vector of borrower covariates and application shifters in z_i. In the second stage, we compute the fitted propensity score of each potential applicant and include it as a control function in a regression of loan amount on the same set of borrower covariates. Finally, we estimate an ordered logit model for loan term on the same set of borrower covariates and loan amount. We then draw loan amount and term for non-applicants from these estimated distributions. Predicted

[30]The diagram in Figure A.18 connects data to supply side primitives, conditional on consideration. For unconstrained approvals, observed prices depend on the cost of the second lowest bank. For constrained approvals, observed prices are given by the cap and are bounded from below by the chosen bank cost and from above by the unconstrained price. For rejections, prices implied by the cap are bounded from above by the cost of the lowest cost bank.

loan amount differs for applicants and non-applicants: loan amount for applicants is $1,010 larger on average, equivalent to 0.16 standard deviations. See Online Appendix B.1 for details.

In the second step, we deal with the fact that the approval probability P_C and the density of prices conditional on approval $f_{p|C}$ are not directly observed for every borrower. First, we estimate P_C using a probit for approval on borrower covariates, previous relationship variables, and application amount and term from the first step. We compute fitted approval probabilities for each consumer and use them as inputs in the third step below. Second, we estimate $f_{p|C}$ using a kernel density estimator after conditioning on the same variables. We take draws from this estimated density in the third step of estimation. We let both P_C and $f_{p|C}$ vary over time, to capture the effects of changes in interest rate caps over time. See Online Appendix B.1 for details.

In the third step, we estimate the parameters in the application and repayment equations by maximum likelihood using inputs from the first and second steps to take 100 Halton draws from the density of prices conditional on approval to compute the expected indirect utility of applying. We then exploit the joint normality of $(\varepsilon_{Ai}, \varepsilon_{Si})$ in equation (12) to derive the likelihood function. See Online Appendix B.2 for details.

Consideration sets. To estimate the distribution of consideration sets, we exploit survey data to estimate equation (13). We estimate a logit model for an indicator of whether a borrower considered bank j when applying for a loan, on borrower and bank covariates in w_{ij} and bank fixed effects. Using estimates of ϕ_{ij}, we compute fitted consideration probabilities and use them as an input in the estimation of bank costs.

Bank costs. We exploit the auction model structure and the distributional assumption on ω_{ij} to estimate the distribution of bank costs by maximum likelihood. We start by computing fitted repayment risk $E_\varepsilon[\varphi(S_i)]$ using estimates from the application and repayment equations and 100 Halton draws for $(\varepsilon_{Ai}, \varepsilon_{Si})$.[31] Then, we work separately on the likelihood for each of the potential application outcomes in equation (8), for 100 Halton draws of consideration sets $\mathcal{J}_i$. We then integrate each likelihood over the applicant consideration set. See Online Appendix B.3 for details.

Estimating dataset. We estimate the model using a sample of potential applicants covering the full period of study. The sample includes 344,858 potential applicants, of which 64,558 apply for loans. Given application events are rare at a monthly frequency, we collapse the data to the yearly level. We define the set of banks that consumers potentially shop as the 12 largest banks, which account for 98% of market share. The sample covers all markets in which all 12 banks are active.

5.4 Results

Application behavior. Table 6-A displays our estimates of the application equation. Borrowers are more likely to apply for loans when facing a higher approval probability, and increasing the

[31] We employ an annual discount rate of $r = 5\%$ for all banks in the market for both estimation and counterfactuals.

approval probability by 5 p.p increases the application probability by 4.4 p.p. Riskier borrowers are more likely to apply, and a 5 p.p increase in risk score increases the application probability by 1.78 p.p. Moreover, female and older consumers are less likely to apply. Finally, higher expected prices reduce the application probability. High-risk borrowers are less price-sensitive than low-risk borrowers, for instance a $200 increase in expected monthly payment decreases the application probability of the former by 2.4 p.p, and of the latter by 3.8 p.p.[32]

Regarding application costs, both the number of branches in the local market and consumer previous experience with banks make applications less costly, as expected. In particular, increasing the total number of branches in a local market by 50% increases application probability by 0.6 p.p, whereas holding a previous relationship with an additional bank increases the application probability by 3.2 p.p.

Repayment behavior. Estimates for the repayment equation are displayed in Table 6-B. As expected, riskier borrowers repay less on their loan contracts, and a 5 p.p higher risk score decreases repayment share by by 0.8 p.p. Moreover, female and older borrowers display better repayment behavior. In terms of loan terms, borrowers taking larger loans and shorter term loans tend to repay more. Finally, our estimate of σ_S implies there is substantial unobservable borrower risk.

Adverse selection. We find no compelling evidence of adverse selection, conditional on borrower risk scores. Our point estimate for ρ is negative and close to 0, but imprecise and not statistically significant, so we cannot rule out some degree of adverse selection. This result implies that although there is substantial unobservable repayment risk σ_S, that risk does not drive application behavior, conditional on (x_i, L_i, T_i). This result does not imply that there is no selection on observables. In fact, we estimate that riskier borrowers are more likely to apply for loans and less likely to repay them. However, given that is captured in x_i it is not reflected in our estimate of ρ.[33]

Borrower consideration set. Our estimates of the consideration set model are displayed in Table 6-C. Riskier, female and older borrowers consider less banks. In particular, a 5 p.p higher risk score decreases bank consideration probabilities by 17.7 p.p. As expected, borrowers are more likely to consider banks with stronger presence in the local market. Increasing the share of the branches in a local market of a bank by 50% increases its consideration probability by 9.6 p.p.

[32] A concern for our strategy is the potential for unobservables that drive both application behavior and bank pricing, which would influence our estimates of price sensitivity δ_p. We evaluate this concern by adopting a control function approach (Petrin and Train, 2010). The results show that the coefficient on the control function is statistically significant. However, the estimates of price sensitivity remain almost unchanged, which suggests that the set of covariates in x_i might be able to deal with this concern. See Online Appendix B.5 for details.

[33] We address the role of observables in determining our selection estimate. Figure A.19 shows estimates of ρ for different sets of borrower covariates in x_i in *both* the application and repayment equations. Not accounting for borrower observables yields estimates that would provide strong evidence of adverse selection ($\hat{\rho} < 0$). However, once we include borrower risk score and income, estimates of ρ remain close to 0. These result suggest that observables in our data—which are the *same* provided by the regulator to banks for risk assessment—account for most of risk selection.

Table 6: Model estimates

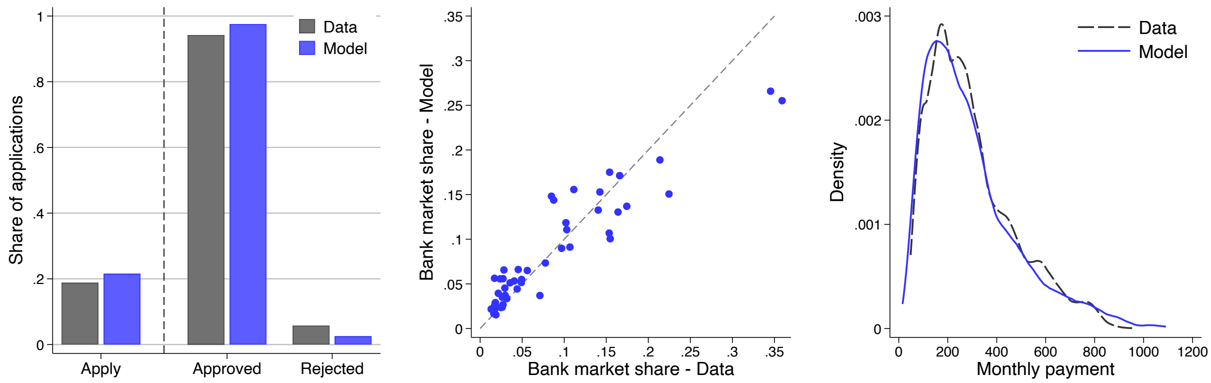
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A - Application		Panel B - Repayment		Panel C - Consideration	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Borrower and contract covariates						
Risk score	1.353***	(0.063)	-1.968***	(0.084)	-1.572***	(0.457)
Female	-0.114***	(0.005)	0.067***	(0.009)	-0.27***	(0.055)
Age ∈ [33,55)	-0.064***	(0.006)	0.027***	(0.009)	-0.142**	(0.057)
Age ∈ [55,+)	-0.372***	(0.007)	0.129***	(0.014)	-0.485***	(0.116)
log(Annual income)	0.041***	(0.002)	0.099***	(0.009)	-0.313***	(0.015)
Debt to income ratio	0.354***	(0.023)	-0.034	(0.054)	-0.727*	(0.380)
Loan term	0.009**	(0.004)	-0.080 ***	(0.004)		
Loan amount	0.021***	(0.001)	0.005***	(0.001)		
Monthly payment, low risk	0.719***	(0.036)				
Monthly payment, high risk	0.465***	(0.038)				
Application cost (κ)						
Previously related banks	-0.120***	(0.002)				
Number of branches of all banks	-0.043***	(0.003)				
Application and repayment shocks						
Standard deviation (σ_A, σ_S)	1.000	—	0.538***	(0.007)		
Correlation (ρ)	-0.047	(0.052)				
Consideration set shifters						
Share of bank branches in local market					0.785**	(0.346)
Number of bank branches in local market					0.090***	(0.031)
Month FEs	Y		Y			
Market FEs	Y		Y			
Bank FE					Y	

	Panel D - Bank costs				
	Bank fixed effects (τ)	Previously related to bank (γ)		Borrower-bank shock (σ_ω)	
	Range of estimates	Estimate	S.E.	Estimate	S.E.
Term quartile 1	[-0.020***,-0.011***]	0.005***	(0.000)	0.007***	(0.000)
Term quartile 2	[-0.020***,-0.010***]	0.004***	(0.000)	0.007***	(0.000)
Term quartile 3	[-0.016***,-0.010***]	0.003***	(0.000)	0.007***	(0.000)
Term quartile 4	[-0.018***,-0.009***]	0.003***	(0.000)	0.007***	(0.000)

Notes: Panel A displays estimates from the application equation, and Panel B displays estimates from the repayment equation. Panel C show estimates of the consideration set model. Panel D displays estimates from the supply side of the model by quartile of loan term. Standard errors based on the inverse of the hessian of the log-likelihood function in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Bank costs. Table 6-D displays estimates of bank costs. We describe these estimates relative to the monthly payment on a loan of $2,000, which have median and standard deviation (σ_p) of $114 and $72.9. Bank fixed effects in ω_{ij} imply sizable cost differences: the average difference between the most and least efficient bank is $17.4 ($0.24\sigma_p$) per month. Moreover, having a previous relationship with a borrower provides an incumbency advantage. In particular, a previous relationship reduces

Figure 4: Model fit



(a) Application outcomes

(b) Market shares

(c) Loan monthly payments

Notes: Results for model fit. Panel (a) displays observed and predicted shares of approved and rejected applications. Panel (b) displays observed and predicted market shares for each cost bin used in estimation. Panel (c) displays the observed and predicted distribution of monthly payments.

the monthly cost of providing a \$2,000 loan by \$7.7 ($0.11\sigma_p$) per month. Finally, our estimates of the standard deviation of bank-borrower idiosyncratic shocks imply that a 1 s.d increase in this shock decreases cost by \$14.3 ($0.20\sigma_p$) per month. This suggests that unobserved cost heterogeneity is a relevant determinant of price dispersion. There is some heterogeneity in estimates across cost bins, although without a clear pattern associated with loan term.[34]

5.5 Model Fit

We examine model fit by using the estimated parameters to simulate equilibrium outcomes and compare simulated to observed outcomes. We describe the simulation procedure in Appendix B. Figure 4-a shows that simulated application and approval shares are close to what observed in the data. Figure 4-b shows that predicted market shares track observed market shares closely. Moreover, Figure 4-c shows that the model fits the distribution of loan prices well, with a correlation between predicted and observed monthly payments of 0.95. Finally, the estimated model provides a good fit of repayment outcomes. In particular, the model predicts that 7.8% of contracts ever default, as compared to 7.5% in the data. These estimates imply average expected profit margins of 23%, with substantial dispersion across loans.

[34]It is useful to understand how these estimates relate to the data. Figure A.20-a shows that bank fixed effects $\hat{\tau}_j$ align with observed market shares. This is, the model rationalizes high market shares as cost advantages in ω_{ij}. Figure A.20-b shows that market shares and the share of previously related borrowers are correlated. The model rationalizes this correlation as that banks with a previous relationship with a borrower hold an incumbency advantage relative to rivals without it, hence $\hat{\gamma} > 0$. Both arguments condition on heterogeneity in borrower consideration across banks.

Table 7: Simulated effects of interest rate regulation

	(1)	(2)	(3)
	Baseline Nov/2013	Effect by Nov/2014	Effect by Nov/2015
Panel A - Borrower behavior and outcomes			
Apply for loans (p.p)	22.79	-1.14	-3.64
Approved|apply (p.p)	99.94	-1.21	-3.67
Number of loans (%)	100.00	-6.20	-19.08
Monthly payment on all approved loans ($)	203.29	-6.14	-13.62
Monthly payment on loans approved under full policy ($)	195.38	-3.09	-5.72
Default probability (p.p)	7.39	-0.02	-0.04
Monthly profit all approved loans ($)	39.23	-3.07	-5.14
Monthly profit on loans approved under full policy ($)	39.72	-3.04	-5.63
Mark-up on all approved loans (p.p)	20.35	-0.57	-0.77
Mark-up on loans approved under full policy (p.p)	21.25	-0.82	-1.67
Panel B - Welfare effects			
Average monthly profit ($)	8.93	-1.21	-2.65
Consumer surplus ($)	-	-16.76	-52.38
Average welfare ($)	-	-17.97	-55.03

Notes: Simulated policy effects of regulation in November 2014 and November 2015 relative to baseline. Column (1) displays simulated equilibrium outcomes for regulation by November 2013. Columns (2) and (3) display simulated changes in equilibrium outcomes from baseline regulation to regulation in November 2014 and November 2015. Variables reported for loans approved under full policy show effects on a fixed borrower pool.

6 Equilibrium Effects of Interest Rate Regulation

6.1 Effects on Market Outcomes

We simulate equilibrium outcomes for different levels regulation, corresponding to its level at the moment of the policy change, and those one and two years after the policy change, which is November 2013, November 2014 and November 2015. Table 7 summarizes these results.

The model predicts that stronger interest rate regulation decreases the number of loans by 19.1%, which combines a decrease in applications and an increase in rejections by banks. As highlighted in Section 4.1, the effect of interest rate regulation on application choices depends upon its relative effects on decreased approval probability and decreased expected loan prices. In this case, we find a decrease in applications that in turn implies that the former effect dominates the latter. Moreover, loan monthly payments on loans approved under stronger regulation decrease by $5.72 and the mark-up on such loans decreases by 1.7 p.p, reflecting that stronger interest rate regulation is in fact protecting consumers who remain in the market. These simulated effects are quantitatively similar to the results of our analysis in Section 3.

6.2 Welfare Analysis

We estimate the welfare effects of interest rate regulation, based on a revealed preferences approach that relies on our estimated model. Expected consumer surplus for consumer i under an interest rate cap $\bar{p}_i$ is given by:

$$E[CS_i(\bar{p}_i)] = \frac{1}{\hat{\delta}_p} \int \max\{P_{Ci}(\bar{p}_i) \int u_L(x_i, L_i, T_i, p; \hat{\delta}) f_{p|C}(p; \bar{p}_i) dp - z_i' \kappa + \varepsilon_A, 0\} f_{\varepsilon_A}(\varepsilon_A) d\varepsilon_A$$

where regulation enters through the approval probability and the density of prices conditional on approval. We calculate the effect of a change in the interest rate cap from $\bar{p}_i^0$ to $\bar{p}_i^1$ on expected consumer surplus as $\Delta E[CS_i] = E[CS_i(\bar{p}_i^1)] - E[CS_i(\bar{p}_i^0)]$. This change in expected consumer surplus is measured from an expected utility perspective, and thus reflects how credit market conditions change for potential applicants in terms of approval probability and expected prices, regardless of whether those applicants are ex-post approved at lower prices or are rejected.

We find that expected consumer surplus decreases by an average and median of \$52.4 and \$34.7 per month, which is equivalent to 2.5% and 1.7% of average monthly income. On the other hand, bank monthly profits decrease by \$2.65 per potential borrower under stronger regulation, which adds up to 29.7% of total profits. The combination of decreases in consumer surplus and profits implies that average welfare per potential borrower decreases.

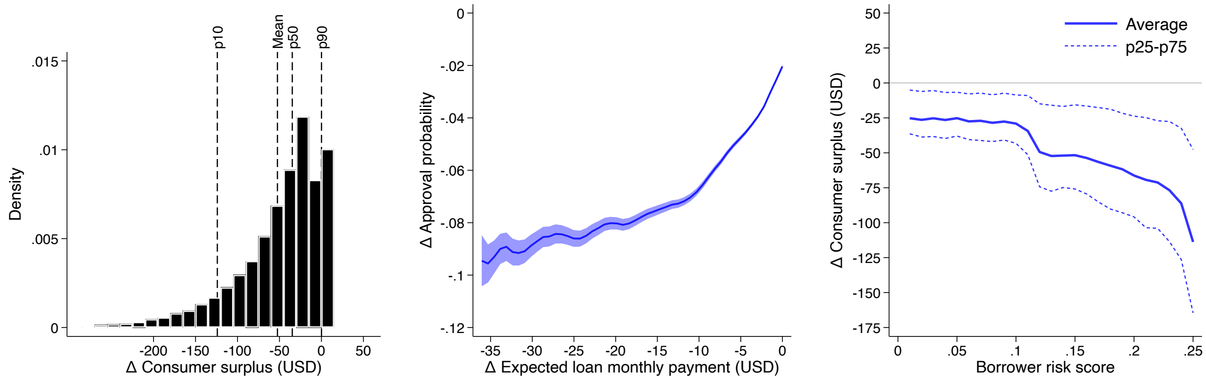
Interest rate regulation has heterogeneous effects across consumers, as shown by Figure 5-a. Expected consumer surplus decreases for 84.2% of consumers, remains unchanged for 1%, and increases for 14.7%. However, the average loss for the former is \$62.3, whereas the average gain for the latter is only \$0.51. Therefore, the effect of a decreased approval probability dominates that of a decreased expected monthly payment in terms of expected surplus. These effects are positively correlated, as displayed in Figure 5-b, where the lack of borrowers in the upper-left region explains the small share of borrowers who benefit from stronger regulation—few borrowers receive large decreases in expected prices without large decreases in approval probability.

Risky borrowers are the most affected by in terms of expected consumer surplus, as displayed in Figure 5-c. The average decrease in expected consumer surplus for low- and high-risk borrowers is \$27 and \$71 per month. This heterogeneity is driven by three forces: risky borrowers were charged higher prices at baseline and therefore more exposed to stronger regulation; display a stronger preference for loans; and are less sensitive to expected monthly payments.

We decompose changes in expected consumer surplus to further quantify the trade-off between credit access and consumer protection as follows:

$$\Delta E[CS_i] = \underbrace{(E[CS_i(P_{Ci}^1, p_i^1)] - E[CS_i(P_{Ci}^0, p_i^1)])}_{\text{Credit access}} - \underbrace{(E[CS_i(P_{Ci}^0, p_i^1)] - E[CS_i(P_{Ci}^0, p_i^0)])}_{\text{Consumer protection}}$$

Figure 5: Heterogeneity in welfare effects of interest rate regulation



(a) Effects on consumer surplus (b) Effects on drivers of applications (c) Consumer surplus and risk

Notes: All figures compare outcomes under full regulation by November 2015 to baseline regulation by November 2013. Panel (a) displays changes in consumer surplus. Panel (b) displays the correlation between effects on expected approval probability and expected monthly payment. Panel (c) displays the average, and 25th and 75th percentiles of changes in consumer surplus across borrower risk.

where the first term isolates the effect of lower approval probabilities, and the second term isolates the effect of lower prices. We estimate that the average effects of decreased credit access and increased consumer protection on expected consumer surplus are -$54.1 and $1.7. This pattern reflects that the value borrowers place on reduced credit access under stronger regulation is substantially higher than that on the expected price decrease they would obtain.

6.3 Survey Evidence on the Effects of Reduced Credit Access

Our descriptive evidence shows that stronger regulation decreased the number of loans. In the previous section, we adopted a revealed preferences approach and found that stronger regulation also decreased average consumer surplus. In this section, we exploit our survey to study potential channels for how reduced credit access could decrease consumer surplus.

We study how the effects of economic hardships depend on household access to bank credit. We exploit information on whether households experienced economic hardships over the last five years, how they dealt with them, and how it affected their consumption and financial outcomes.[35] We compare outcomes of households that did not experience any shocks with those that experienced shocks and financed them by (i) obtaining bank credit, (ii) liquidating savings or assets, or

[35] We define economic hardship in the survey as a sustained period of time over which household expenses were higher than its income. In practice, 58.6% of survey participants answered they were under such situation over the previous five years. The questions related to how this shock was dealt are expressively linked to the shock in particular, rather than general questions about credit access.

(iii) another source, including informal credit or increased labor supply. We then estimate:

$$y_i = \alpha + \beta_c \text{credit}_i + \beta_s \text{savings}_i + \beta_o \text{other}_i + x_i' \gamma + \varepsilon_i \tag{14}$$

where y_i is the outcome of interest, x_i is a vector of control variables that includes household income, vulnerability and age of survey respondent, as well as loan approval probability, estimated using administrative data. The coefficients of interest are β_c, β_s and β_o, which measure the difference between outcomes for households that did not experience an adverse shock relative to those that did experience an adverse shock and financed it with either credit, savings or other sources.

First, we study whether credit access upon shocks is associated with consumption. Our survey measures whether households cut expenses on relevant items (education, health, transportation, among others) due to shocks. Figure 6-a shows that households that experienced these shocks did cut expenses in several items, but that those effects are smaller for those that obtained bank credit. In particular, households that dealt with shocks using bank credit cut expenses for an average of 7.5 p.p less items than those that dealt with shocks using other means. These results suggests that reduced credit access may harm consumption smoothing, similar to findings in Morse (2011).

Additionally, we study whether credit access upon shocks affects household ability to repay their financial commitments. In particular, we focus on whether households stopped paying bills (health bills, rent, mortgage payments, loan payments, among others). Figure 6-b shows that households that obtained credit access upon hardships do not display any differential behavior relative to households that did not experience hardships. However, households that did not access credit are significantly more likely to have unpaid bills than the latter. In particular, households that dealt with shocks using bank credit are 36 p.p less likely to have any unpaid bill than those that dealt with economic hardships using other means. This suggests that credit access might provide liquidity to avoid financial distress episodes, as in Zinman (2010).

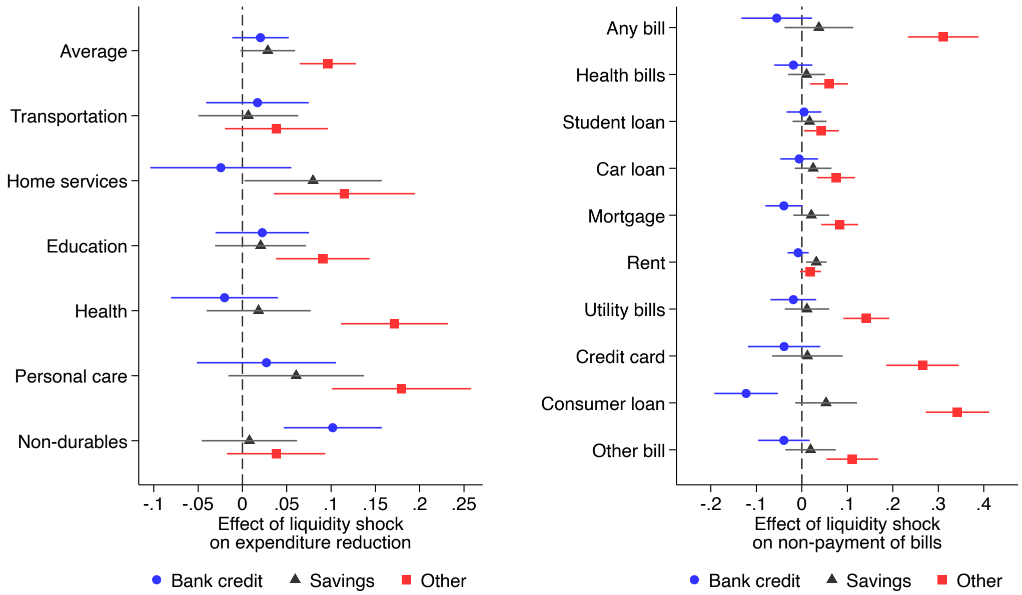
These results suggest that credit access aids consumption smoothing and alleviates financial distress upon shocks, although we do not claim that they describe a causal relationship. This evidence complements our welfare analysis. These results are in contrast with research finding adverse effects of payday borrowing on financial distress (Melzer, 2011; Gathergood *et al.*, 2018; Skiba and Tobacman, 2019). This contrast may be driven by interest rates in our context being substantially lower than in the payday market.

7 Counterfactual Analysis of Interest Rate Regulation

7.1 Effects of Interest Rate Regulation beyond the Reform

We start by studying the effects of a range of interest rate caps. Figure 7-a shows that regulation than that in December 2015 would further reduce both the number of loans and average monthly payments. In particular, setting interest rate caps for loans in \$0-\$8,000 to 25 p.p would decrease

Figure 6: Survey evidence for effects of reduced credit access on household outcomes



(a) Credit access and household expenses (b) Credit access and unpaid bills

Notes: Results from equation (14) for indicators for household that suffered shocks and dealt with them using bank credit (blue), savings or assets (gray), or some other way (red). Panel (a) display results for reductions in household expenses. Panel (b) display results for unpaid bills. Markers indicate coefficients. Lines indicate 95% confidence intervals.

the number of loans by 46% relative to baseline. On the other hand, there would be limited gains in terms of quantity outcomes from setting caps higher than those in December 2013.

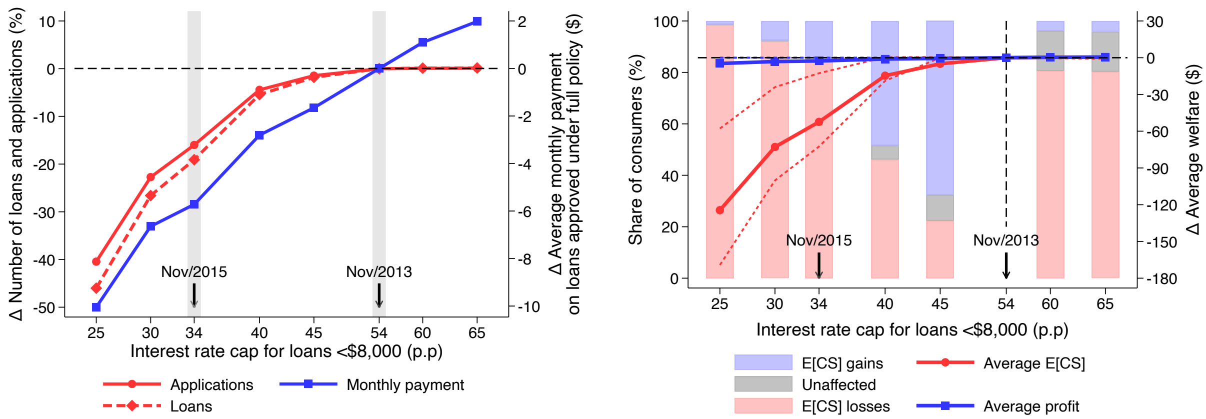
In terms of welfare, Figure 7-b shows that the share of consumers that benefit from changes in regulation is higher than 50% for moderate decreases in interest rate caps relative to December 2013, but remains below 20% for decreases larger than the actual policy change. However, average gains in expected consumer surplus for consumers who benefit are small across the range of policies, such that the average change in expected consumer surplus is negative throughout.

7.2 The Interaction between Market Power and Interest Rate Regulation

The usual motivation for implementing interest rate regulation is to limit usurious behavior, which we define as limiting the exercise of market power by banks. In Section 6, we showed that stronger interest rate regulation indeed reduced average bank profit margins while simultaneously increasing rejections and reducing the number of loans and overall welfare in the market. In this section, we study how those results vary under alternative competitive environments.

To study the role of the competitive environment, we simulate reforms to interest rate caps under different market structures. In particular, we vary how borrowers form consideration

Figure 7: Equilibrium effects of interest rate regulation



(a) Applications, loans and monthly payments

(b) Welfare effects

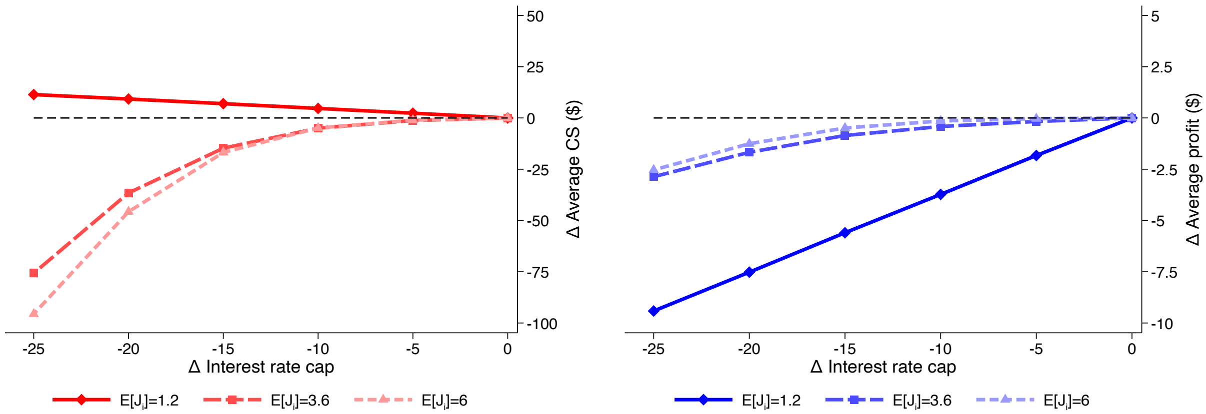
Notes: These figures display effects of interest rate regulation for a range of regulation scenarios relative to the November 2013 baseline. Panel (a) displays the change in quantity and price outcomes. Panel (b) displays changes in average expected consumer surplus and average profit, along with the share of consumers that experience experience consumer surplus gains, losses or none of them. Solid lines indicate averages and dotted lines indicate the 25th and 75th percentiles.

sets by shifting their consideration probabilities. Smaller consideration sets imply that banks face less competition. We implement this by adjusting consideration probabilities ϕ_{ij} such that $E[\phi_{ij}] = \{0.1, 0.3, 0.5\}$ on average across consumers. Given our model covers 12 banks, the average borrower considers $E[|\mathcal{J}_i|] = \{1.2, 3.6, 6\}$ banks. For each environment, we start by simulating an unconstrained equilibrium. Using those results, we follow the Chilean institutional framework and set a baseline cap at 1.5 times the average interest rate in each policy loan size bracket. Finally, we simulate reforms that decrease interest rate caps from that baseline by between 5 and 25 p.p.

Market power plays a key role in determining the effects of interest rate regulation. Our main finding is that a lower interest rate cap can increase consumer surplus in a concentrated enough market, as shown by Figure 8-a. In contrast, we find that bank profits decrease upon decreases in interest rate caps throughout the range of market structures we consider, as displayed by Figure 8-b.[36] This result suggests that when banks have more market power and therefore charge higher prices, interest rate regulation might be able to play a role in constraining the exercise of such market power by banks, shifting rents from banks to borrowers and possibly increasing welfare. However, in a competitive market where banks do not have substantial market power, the trade-off between exclusion and protection becomes less appealing, as profit margins are already low.

[36]We report results for a broader set of outcomes and market structures in Table A.4.

Figure 8: The effects of interest rate regulation under different market structures



(a) Effects on consumer surplus

(b) Effects on bank profits

Notes: Each line displays the effect of a decrease in the interest rate cap of the magnitude indicated in the x-axis relative to baseline regulation, for a different level of competition as measured by the average number of banks in the consideration set. Panel (a) displays effects on average consumer surplus. Panel (b) displays effects on average profits.

7.3 Risk-Based Interest Rate Caps

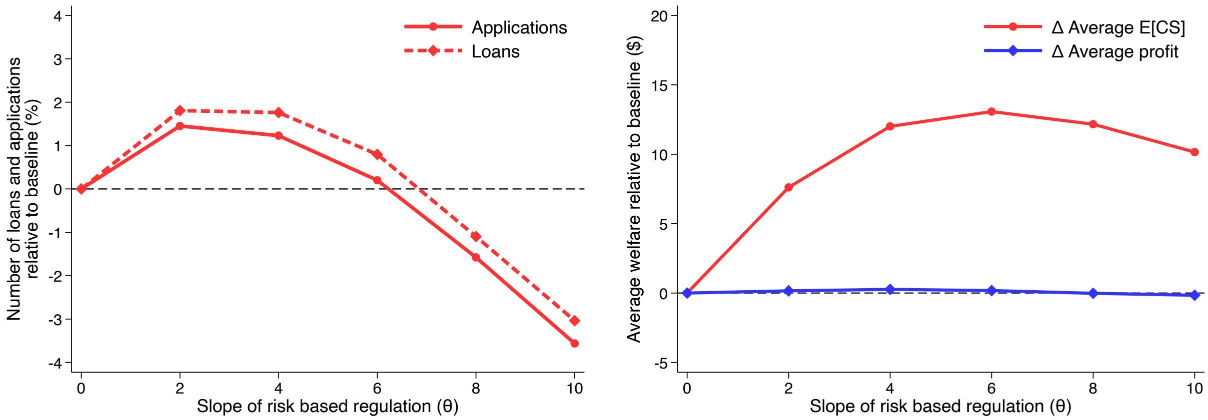
The trade-off between consumer consumer protection and credit access is partly caused by the mismatch between unsophisticated regulation in the form of constant interest rate caps and sophisticated risk pricing by banks. However, innovation in the design of this regulation has been scant. Risk-based regulation might better account for borrower risk heterogeneity and risk pricing.

We consider a design that sets interest rate caps according to borrower attributes. Perfect risk-based regulation would involve setting interest caps at the cost of each borrower for the most efficient bank. Such design is hardly feasible, as it would require perfect knowledge of cost by the regulator. Instead, we study a feasible version of risk-based regulation, with the broad structure of the current design. Using the notation of equation (1), interest rate caps can be written as $\bar{\iota}_{\ell t} = \bar{\iota}^r(\tilde{\iota}_{\ell t-1}; \psi, \alpha_{\ell t})$, which is a function of a reference interest rate, a multiplier on that rate ψ, and a mark-up parameter $\alpha_{\ell t}$. We consider a case in which $\bar{\iota}^r_{\ell t} = \bar{\iota}(\tilde{\iota}_{\ell t-1}, x_{i\ell t}; \psi, \alpha_{\ell t}, \theta)$. If $x_{i\ell t}$ is a measure of risk and $\frac{\partial \bar{\iota}^r}{\partial x_{i\ell t}} > 0$, then this design sets a higher cap to observably riskier borrowers. We study a simple linear example of it and compare it to the design currently in place. In particular, let:

$$\bar{\iota}^r_{\ell t} = \bar{\iota}_{\ell t} + f(x_{i\ell t}), \quad f(x_{i\ell t}) = \theta \frac{x_{i\ell t} - \bar{x}_{\ell t}}{\bar{x}_{\ell t}}$$

be the risk-based interest rate cap for borrower i with risk score $x_{i\ell t}$, where $\bar{x}_{\ell t}$ is the average risk score and θ controls the incidence of risk in interest rate caps. Note that the average level of regulation in the market is the same as under the baseline design for each loan-size bracket p,

Figure 9: Risk-based interest rate caps



(a) Applications and loans (b) Welfare effects

Notes: These figures display results for different levels of risk-based regulation given by θ. Baseline outcomes for $\theta = 0$ correspond to simulated equilibrium outcomes for November 2015 under the baseline regulation. Panel (a) displays changes in number of loans relative to the baseline level, while Panel (b) displays changes in consumer surplus.

given $E[f(x_{i\ell t})] = 0$, but the interest rate cap is higher (lower) for riskier (safer) borrowers.

Risk-based interest rate caps recover part of the losses in credit access and welfare induced by constant interest rate caps. We set the reference level of regulation to November 2015, once the policy change is fully in place. We simulate outcomes for values of θ between 0 and 10. Figure 9-a shows that for a range of values of θ, risk-based interest rate caps increase the number of loans relative to constant interest rate caps. Figure 9-b shows a similar pattern for welfare. At its best, risk-based interest rate caps increase the number of loans and average expected consumer surplus by around 1.5% and $13 respectively, while average profits remain constant.[37]

These results suggest that risk-based interest rate caps may manage the trade-off between consumer protection and credit access better than constant caps. This result stems from banks implementing risk pricing. In absence of risk pricing, adverse effects of risk-based caps on safe borrowers may be larger than under constant caps. The case we analyze here is of course an example, and other variants of risk-based regulation could further improve outcomes relative to designs that do not account for risk.

[37] To further illustrate the effects of risk-based interest rate caps, we study heterogeneity across borrower risk. We compare the case of $\theta = 4$ to $\theta = 0$. Figure A.21-a shows that risk-based caps affects application outcomes by increasing approval rates for risky borrowers, while slightly decreasing approval rates for safe borrowers. On the other hand, Figure A.21-b shows that average monthly payments increase (decrease) for risky (safe) borrowers as they face relatively weaker (stronger) regulation. How this heterogeneity across borrower risk aggregates depends on the joint distribution of demand, risk and cost. Our estimates imply that risky borrowers value loans more than safe borrowers, which explains that the effects of risk-based regulation are stronger in terms of expected consumer surplus than in terms of loans: as caps become more aggressive, the benefits of limiting losses in credit access diminish, but the policy increases the share of risky borrowers in the market and thus still increases average expected consumer surplus.

8 Conclusion

Interest rate regulation is widespread in consumer credit markets, but there is disagreement about its effects. Moreover, its design often lacks sophistication, which may lead to unintended consequences. We provide evidence of the effects of interest rate caps on market outcomes and welfare, using the Chilean credit market as a setting. We find that the trade-off between consumer protection and credit access exists, but that adverse effects on credit access dominate consumer protection effects. Thus, while the goal of this regulation is often to protect borrowers from bank market power, we find it ends up mostly harming their credit access.

We develop and estimate a model of the market for consumer loans. Using the model, we estimate welfare effects of interest rate caps and find that welfare mostly decreased in our setting. However, we show that the adverse welfare effects of this regulation are smaller in more concentrated markets, as the consumer protection motive becomes more relevant in such setting. Actually, we find that the same policy can increase welfare in a concentrated enough market. This result highlights the relevance of market structure for the effects of this regulation. Finally, we study risk-based interest rate caps, and find that such design limits the adverse effects of interest rate regulation and recovers part of the losses in credit access and welfare, without increasing bank profits. Such a design may thus provide more consumer protection without harming credit access.

Our welfare analysis follows a revealed preferences approach. We exploit application and repayment behavior to estimate our model, and estimate welfare effects using the model, without accounting for potential behavioral biases (Zinman, 2015; Beshears *et al.*, 2018). We acknowledge that such biases may affect the conclusions of our welfare analysis, and consider them a relevant area for future research. However, evidence from our survey suggests that households that access bank credit upon economic hardships display more consumption smoothing and lower financial distress. These results do not rely on revealed preferences and supports our findings.

Our analysis highlights how a combination of a model and data can inform the design of credit market regulation, by measuring its effects and studying how they depend on the key economic forces at play. While we find mostly adverse effects of interest rate regulation, our model predictions for quantity and welfare effects are ambiguous. This regulation may thus improve market outcomes under different demand and supply conditions. However, most of the literature points towards adverse or null effects, which suggests such a setting might be uncommon.

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A Discussion of Model Assumptions

The model provides a framework to study regulation in consumer credit markets. It accommodates many features of these markets, such as applications, approvals and rejections by banks, risk pricing, price dispersion, the role of relationships for approvals and pricing, and repayment, among others. However, it also has limitations that we discuss.

Static demand. We model borrower application choices as static. Models of credit demand often involve intertemporal optimization problems where the trajectory of interest rates determines optimal borrowing and saving. Such models only yield closed form solutions in restricted cases, which often fail to accommodate heterogeneity in loan contracts (Attanasio *et al.*, 2008). Instead, we focus on the static problem where a borrower chooses whether to finance credit needs by applying for loans or not. Previous empirical research on loan demand also adopts this approach (Alessie *et al.*, 2005; Attanasio *et al.*, 2008; Einav *et al.*, 2012). While this assumption might not be appropriate for large loans such as mortgages—for which consumers often shop over long periods and may react dynamically to market conditions, as shown by e.g., Mian and Sufi (2009)—it is likely appropriate for smaller loans, such as consumer loans. In fact, evidence from our survey suggests that borrowers spend a median of only 7 days searching for consumer loans, as displayed in Figure A.8-b. Moreover, as much as 66% of the respondents say that they search for credit "quickly" in response to financing needs. These patterns suggest that focusing on static choices is meaningful in our context.

Exogenous loan amount and term. We assume that loan amount and term are determined in a previous stage not in the model. This is in line with modeling loan demand as a response to shocks, but imposes a constraint on consumer behavior. This simplification is partly motivated by our focus on the extensive margin of credit access throughout the paper. In practice, the appeal of this assumption is that the application equation becomes a binary choice. The fact that we find no effects of the policy on the distribution of loan size in Appendix A.3, suggests that not modeling this dimension might be a reasonable assumption for our purpose and setting. Finally, the extent to which loan size and term signal borrower cost should be captured by including (L_i, T_i) in our repayment equation.

Bank competition as English auction. We model equilibrium interest rates as the result of an English auction, where banks compete for borrowers by offering lower interest rates. The appeal of this approach is that it provides a tractable model that accommodates price dispersion and imperfect competition. Moreover, it avoids the need to specify the prices of all alternatives in consumer choice sets, which are unobserved to us.[38] This approach has been recently used for

[38] An alternative approach would be to model the game between borrowers and banks as a Bertrand-Nash game with posted prices and predict the prices that competing banks would offer to each borrower using information from signed contracts (e.g., Crawford *et al.* 2018). Modeling the game as an English auction avoids that prediction step.

modeling markets with bargained prices (Allen *et al.*, 2019; Salz, 2020), and is isomorphic to modeling the market as a standard Bertrand game with homogeneous goods with heterogeneous costs (Beckert *et al.*, 2018). This aspect of the framework implies that a source of bank market power in our model is cost heterogeneity—the other one comes from consumers considering only a subset of banks. Additionally, survey evidence in Figure A.8-c shows that for a given application 89% of borrowers considered more than two banks, and the median borrower considered three banks. This evidence suggests that borrowers indeed interact with several banks when shopping.

Search frictions. We capture search frictions by assuming that applicants consider a randomly drawn set of banks when shopping for loans, such that search behavior is exogenous in the model. This is unlike recent work that allows for endogenous search behavior in credit market (Allen *et al.*, 2019; Agarwal *et al.*, 2020; Galenianos and Gavazza, 2021). An implication of this assumption is that we disregard potential effects of interest rate regulation on search effort. Price caps reduce price dispersion and thus decrease search effort, which may lead to unintended effects such as increases in equilibrium prices (Fershtman and Fishman, 1994; Armstrong *et al.*, 2009).

Moral hazard. Loan price p_{ij} does not enter into the repayment equation, which implies the model rules out moral hazard in the form suggested by Holmstrom and Tirole (1997). An implication of this assumption is that the effect of interest rate regulation on aggregate loan performance in the model is purely compositional. While restrictive, this assumption substantially simplifies the analysis of bank pricing. Moreover, recent experimental evidence in Castellanos *et al.* (2018) suggests moral hazard might not be a first order concern in consumer credit markets.

B Simulation Details

For all the simulations using the estimated model, we follow the procedure we describe below:

1. Draw shocks for applications, repayment and cost, and draw consideration sets. Specifically, (i) draw application and loan repayment shocks for each borrower in the sample from the estimated joint distribution, $\{\varepsilon_{Ai}, \varepsilon_{Si}\}$; (ii) draw a cost shock for each bank-borrower in the sample, ω_{ij}; and (iii) draw consideration sets $\mathcal{J}_i$ from their distribution Φ_i.

2. Draw shocks and consideration sets for integration steps. Specifically, (i) draw a vector of N_ω bank-borrower cost shocks for integration of prices by borrowers, $\{\omega_{ij}^{(s)}\}_{s=1,j\in\mathcal{J}}^{s=N_\omega}$; (ii) draw a vector of N_S loan repayment shocks per borrower for integration of repayment risk by banks, $\{\varepsilon_{Si}^{(s)}\}_{s=1}^{s=N_S}$; and (iii) draw N_ϕ consideration sets per borrower for integration, $\{\mathcal{J}_i^{(s)}\}_{s=1}^{s=N_\phi}$.

3. Simulate optimal prices and approval decisions for each of the N_ω vectors of cost shocks and N_ϕ consideration sets, for a given interest rate regulation $\bar{p}_i$, which are required for simulating application decisions. This step requires solving a fixed point problem, because banks take the expectation of repayment risk conditional on application, and application in turn de-

pends on expected approval probability and prices. We proceed by: (i) computing simulated unconditional repayment risk as a starting point, (ii) computing simulated application decisions, (iii) computing expected approval probability P_{Ci} and monthly payments conditional on approval $\{p_i^{(s)}\}_{s=1}^{s=N_\omega}$ given simulated repayment risk, (iv) computing simulated conditional repayment risk, and (v) repeating (ii)-(iv) until convergence of simulated monthly payments. The outputs of this step are simulated approval probability P_{Ci}, monthly payments $\{p_i^{(s)}\}_{s=1}^{s=N_\omega}$, and expected repayment risk $E_\varepsilon[\varphi(S_i)]$.

4. Simulate application decisions for each borrower a_i, by computing application probabilities using simulated approval probabilities and monthly payments from Step 3 along with draws for application shocks from Step 1.i.

5. Simulate approval and pricing decisions by banks (L_i, p_i), using draws for cost shocks from Step 1.ii and simulated repayment risk from Step 3.

6. Simulate repayment outcomes for borrowers s_i, using estimates for the repayment equation along with repayment draws in Step 1.i.