Market Power in Credit Markets*

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Abstract

We study limits on lender market power in the unsecured credit market, in an imperfectly competitive model where credit pricing depends on default risk and on households' current and future outside options. We discipline market power with the empirical distribution of credit card interest rates and measured lending costs. Through general equilibrium effects, an interest rate cap that directly binds for few contracts shifts the entire rate distribution down, expanding credit access and reducing bankruptcies. Welfare gains peak at caps of 15 to 25 percent, depending on income and education. Without outside options, the same policy reduces credit and welfare.

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1 Introduction

The scope and impact of lender market power in the unsecured credit market has long been a topic of intense debate in academic and policy circles[1], especially in the context of regulating financial products. On the one hand, regulating lenders' ability to extract profits can lead to credit rationing and welfare losses if the market is close to competitive. On the other hand, regulating high markup contracts can benefit borrowers if these markups are due to monopoly rents. These considerations spurred a variety of regulatory actions affecting the unsecured credit market, most recently the 2009 CARD Act, which regulated financial re-pricing and fee structures, and the proposals by the Trump administration (10% cap) and the earlier Loan Shark Prevention Act (15% limit on credit cards nationwide).[2] Empirical evidence is consistent with departures from perfect competition in the unsecured credit market,[3] which suggests that accounting for these features of the market is important for any policy discussion about potential interventions in consumer credit markets. A growing quantitative literature studies lender market power in consumer credit and, more recently, its interaction with interest rate regulation.[4]

We contribute to this literature by providing a theoretical and quantitative analysis of the effect of limiting market power, isolating a channel through which a cap on the highest rates passes through to the entire distribution, generating strong general equilibrium effects through households' outside options, current *and* future. Specifically, we explore the implications of market power of lenders in a parameterized quantitative dynamic incomplete markets model with income risk. Borrowers search for loans in a competitive search market, but households that fail to obtain a competitive offer are not excluded from credit markets. Instead, they receive a loan from a lender that recognizes their weaker bargaining position and offers less favorable terms, determined through

[1] See, for example, Ausubel (1991), Evans and Schmalensee (2005), Galenianos and Gavazza (2022), Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), Herkenhoff and Raveendranathan (2025), Herkenhoff and Morelli (2026) and Cuesta and Sepúlveda (2021).

[2] For corresponding bill details, see U.S. Congress (2009), Sanders and Ocasio-Cortez (2019), and Sanders, Hawley, Ocasio-Cortez, and Luna (2025), with the Trump administration's proposal also covered in Sweet and Kim (2026).

[3] For an overview of empirical evidence, see Herkenhoff and Raveendranathan (2025), Dempsey and Ionescu (2021), Drechsler, Jung, Peng, Supera, and Zhou (2025), Stango and Zinman (2016), Consumer Financial Protection Bureau (2024) and Agarwal et al. (2015).

[4] Recent quantitative treatments of interest rate caps under lender market power include Raveendranathan, Stefanidis, and Sublet (2026) and Bethune, Saldain, and Young (2024); relative to these, our distinguishing feature is the general equilibrium pass-through from capped high markup contracts to all offered rates through changing outside options.

bilateral bargaining. This option captures reduced borrowing opportunities faced by households who fail to obtain a more competitive contract. As a consequence, the search friction determines markups in the competitive search market and the outside option market, but does not imply credit rationing. That is, if there exists a credit contract for a household that generates positive surplus, then the household is able to borrow. Depending on how attractive the household is as a borrower, the markups on the contract vary endogenously in both markets. Crucially, because the borrowing decision is dynamic, future borrowing terms affect current borrowing opportunities, which in turn influence households' incentives to default. Because lenders price loans based on expected repayment, any policy that changes future outside options also changes current default risk and therefore current loan pricing. This feedback creates a powerful general-equilibrium mechanism: policies such as interest-rate caps need not only affect the contracts that are directly constrained. Instead, by improving borrowers' outside options, they not only reduce lenders' market power but also lower default risk, which makes it feasible for the entire equilibrium distribution of offered interest rates to shift down, even when only a small fraction of contracts initially bind.

We parameterize the model to two groups of households using income processes for High School and College in Guvenen (2009), and set the empirical targets for debt and default for the two groups using the Survey of Consumer Finances, which contains information on education. Our main parameterization, called *Benchmark*, matches aggregate debt and default statistics well, as well as untargeted average interest rates, charge-off rates, and additionally gives a good account of the distribution of interest rates vis-à-vis the data. We discipline the market power of the outside option directly: the lender's Kalai bargaining weight is calibrated to the 90th percentile of the interest rate distribution in an account-level panel used in Stango and Zinman (2016). We also include two elements of the lender's cost side, with a proportional transaction cost parameterized using Agarwal et al. (2015) and an up-front cost benchmarked against industry data on customer acquisition. The calibrated bargaining weight is modest, 15 percent, yet market power still has large policy consequences.

In addition to the Benchmark model, we parameterize two other versions of the setup. The first is the *No Outside Option* model, which features the same competitive search framework but no high markup contract, so that unmatched households must either save or default; it serves as a contrast that isolates the impact of outside borrowing options on equilibrium outcomes. The second is the

Competitive model, which establishes a baseline for the other two. The parameterized Benchmark and Competitive models match the aggregate debt and default statistics well, whereas the No Outside Option model has a harder time matching aggregate debt and charge-offs and requires implausibly low values of the time discount factor. The predictions of the models differ significantly for pricing and profitability. The Benchmark model matches well the distribution of interest rates in the Stango and Zinman (2016) data, while the No Outside Option and Competitive models struggle, with the No Outside Option overshooting all the percentiles and the Competitive model over-predicting the median, the ninetieth percentile, and the mean. For the cross-section of profitability (profit per unit of debt), in the data, profits per dollar of debt are high for the riskiest borrowers and feature a high-risk hump (Drechsler et al. (2025), Agarwal et al. (2015)).[5] The two search-based models reproduce this pattern, with profitability generally *decreasing* in repayment probability and the Benchmark additionally featuring the hump-shaped relationship. The Competitive model implies a counterfactual increasing relationship. These non-targeted moments are the cleanest cross-sectional evidence favoring our market-power mechanism.

Next, we show that modeling market power, and more specifically outside options, has significant implications for the evaluation of regulation and policies that impact markups and profitability of the lenders, even if the regulation directly applies to only a small number of contracts. Specifically, we consider the policy of introducing universal interest rate caps on credit contracts, in line with some of the proposed policies. In the baseline parameterization, the cap is set at 100%, which means that it is virtually not binding and we treat this as a reflection of the current state of regulation in the U.S.[6] In our experiment, we tighten the cap on interest rates gradually from 100% to 15%, and additionally consider an extreme cap of 10%.

We find that in the Benchmark model, limiting market power of lenders has a significant negative effect on the interest rates, but a significant *positive* effect on debt and fraction of households borrowing. Crucially, the pricing of *all* loans is more favorable: the entire distribution of interest

[5] In Agarwal et al. (2015), profitability has a second peak at high credit scores, driven by interchange (transaction-fee) income. Transactions-driven revenues and incentives are outside of the scope of our model and analysis. Drechsler et al. (2025) make the separation explicit: transactors pay no interest, so interest income is earned only on borrowing accounts, while net interchange income accounts for the bulk of the return banks earn on transactors and is a marginal component of the return on borrowers, about 0.4 cents per one dollar of balances.

[6] Even though in principle each state has an interest rate cap policy (on credit cards), in practice the applicability of the caps is limited. The 1978 Supreme Court ruling in Marquette National Bank v. First of Omaha Corp. implies that lenders can apply the interest rate cap of the state where they headquarter rather than the state of the location of the borrower, which limited the ability to enforce strict state-level usury limits.

rates shifts down as a result of the cap, even though only a small fraction of interest rates are actually directly constrained by the cap. This confirms significant general equilibrium effects of regulating just the top interest rates. More favorable pricing of debt implies more households decide to borrow in equilibrium, and borrow more while they do. Additionally, debt becomes safer in response to cheaper borrowing and roll-over costs: both the charge-off rate and the bankruptcy rate go down under tighter interest rate caps, even though borrowing increases. The response to the policy across the two income groups differs substantially. At the preferred 20% cap, the High School group sees little change in debt and the fraction borrowing but a near-halving of the bankruptcy rate, while the College group sees a large increase in debt and in the fraction borrowing. For both groups, we find significant welfare gains from the policy, ranging from about 3% (College) and 4% (High School) of lifetime consumption equivalent for the poorest households to about 0.2% for the median household. The gains are not monotonic in the cap: they peak between 15 and 20 percent for the poorest households and between 15 and 25 percent for the median, and at the recently proposed 10 percent cap the High School market shuts down almost entirely, that group's welfare turns to losses, and the College gains largely vanish. To show the importance of accounting for the high markup option, we compute the response to the cap in the No Outside Option and Competitive models, both of which behave very differently from the Benchmark. In the No Outside Option model, interest rates also fall, but access to credit declines on both the intensive and extensive margins, and the policy generates a welfare loss of about 0.1% and 0.6% of lifetime consumption for the median College and High School household, respectively. The Competitive model behaves similarly: its interest rates contain no upper tail of very high rates, so loose caps do not bind, but once the cap binds for a large fraction of contracts it renders them unprofitable and shuts those loans down, with almost no general equilibrium pass-through to the rates that remain below the cap. The result is lower debt and eventual shut-down of the loan market, with a welfare loss of about 1% of lifetime consumption for the median-income household and as much as 17% for the lowest incomes. In both models, in contrast to the Benchmark, the cap works mainly through the extensive margin of credit and lacks the general equilibrium repricing that delivers the Benchmark's welfare gains.

We shed light on the mechanism behind the model responses by analyzing the policy functions in the Benchmark and No Outside Option models, and their responses to the caps. The main difference

between the two models is in how contracts respond to interest rate caps. In the Benchmark model, lower interest rates (due to the cap) are associated with *higher* borrowing, and significantly reduced default rates. Intuitively, making high markup contracts more attractive *in the future* reduces incentives to default and hence expected default probability *now*. That allows lenders to maintain positive lending while at the same time lowering rates and increasing loan size. In the No Outside Option model, interest rates drop together with *reduced* lending. That is the main way default is reduced in that model as the caps affect the only market: the competitive search market. Making the competitive search contracts less profitable reduces matching probabilities for households, and in the No Outside Option model unmatched households can only save or default. The reduction in lending mitigates the impact of that on default rates, which fall slightly.

We provide further evidence of strong general equilibrium effects of interest rate caps in the Benchmark model in two counterfactual exercises. First, we fix the matching probabilities in the competitive search market at their baseline values, controlling for the extensive margin of switching between the high markup and search market contracts while leaving contract pricing free to respond. We find that the impact on debt outcomes is small, implying the overwhelming importance of loan pricing. Second, holding the sorting between contract types at its baseline probabilities, we decompose the aggregate response into the contributions of the two contract types. The contribution of the directly capped high markup contracts is small: more than 80 percent of the increases in debt and in the fraction borrowing arise on search market contracts, which the cap mostly does not constrain directly. We conclude that the endogenous response of competitive search pricing to households' changing outside options, rather than the reallocation of households across contracts, accounts for the bulk of the equilibrium effects of the interest rate caps.

Related Literature A growing body of empirical evidence on lender market power in consumer credit and on the effects of price regulation motivates our analysis. On pricing, the literature documents credit card markups not accounted for by default risk (Drechsler et al., 2025), additional interest rate markups of large banks (Consumer Financial Protection Bureau, 2024), large interest rate dispersion after conditioning on risk (Stango and Zinman, 2016), and loan spreads above those that default risk justifies (Dempsey and Ionescu, 2021). The direct evidence on the effects of binding caps is more limited, because a binding cap on mainstream revolving credit is rarely observed and

the available episodes each cover only a segment of the market or a different setting. The closest structural estimate, Cuesta and Sepúlveda (2021), finds that a usury ceiling rationed unsecured installment loans in Chile, but does not analyze substitution patterns with credit cards. In their model analysis, welfare effects depend on concentration and turn positive for highly concentrated markets. Some of the remaining evidence points in different directions. Fekrazad (2020) finds no lender exit under a tighter payday cap and Financial Conduct Authority (2017) that a binding cap improved borrower outcomes without a shift to other high-cost products. Chakrabarti, Leonard, Morgan, Pham, and Seltzer (2026a) and Chakrabarti, Leonard, Morgan, Pham, and Seltzer (2026b) argue that recent 36% caps on non-bank lenders rationed the riskiest borrowers and reallocated credit toward safer ones. Our reading of this literature is that we need a structural model in order to be able to assess the full general equilibrium impact of interest rate regulation, especially the effect of the cap on the entire interest rate distribution.

Our study relates to the broader literature on policies that can potentially improve the functioning of credit markets. In the context of behavioral biases, this literature includes Heidhues and Kőszegi (2010), Heidhues and Kőszegi (2017) and Exler, Livshits, MacGee, and Tertilt (2025) and in the context of frictions in credit markets that lead to lender market power it includes Herkenhoff (2019), Herkenhoff and Raveendranathan (2025), Raveendranathan (2020), Galenianos and Gavazza (2022), Nelson (2025), Stango (2002), Grodzicki (2022) and Herkenhoff and Morelli (2026).[7] Generally, relative to search-based credit market frictions modeled in the literature, we are the first to explicitly include the endogenously determined outside option to unmatched households, which, as we show, is quantitatively very important. The idea that heterogeneous outside options shape equilibrium prices in search markets and bound the market power of posting firms goes back at least to Albrecht and Axell (1984), where workers' values of leisure pin down the equilibrium wage distribution; relative to that mechanism, in our setup both current and *future* outside options shape today's contract, since the option of borrowing from the high markup lender tomorrow disciplines the terms a household accepts today. A related mechanism, in which an endogenous outside option shapes the price a trader is offered, appears in Zhu (2012) in the context of over-the-counter

[7] This work spans the macroeconomic and industrial-organization traditions; recent structural treatments of competition and regulation in credit markets include Benetton (2021) and Robles-Garcia (2020) in mortgage markets, Cuesta and Sepúlveda (2021) in consumer installment lending, Nelson (2025) in credit cards, and Grodzicki (2023) on the evolution of credit card competition.

asset markets, where a trader's outside option is the set of remaining counterparties. We share this basic idea but embed it in a dynamic, quantitative model of consumer credit with default and use it to evaluate the general equilibrium effects of interest rate caps. We discuss several closely related papers in turn. Herkenhoff and Raveendranathan (2025) study the effects of improved competition through entry in the unsecured credit market in an oligopolistic setup. They focus on equilibria with interest rate collusion and quantity competition, reflecting early evolution of the credit market. By contrast, we model a simpler contract structure, in which we allow contracts to vary by household state and focus on the general equilibrium effects of policy via the endogenous response of the price distribution. Galenianos and Gavazza (2022) study the aggregate response of the credit market to interest rate caps in an incomplete information environment in which the equilibrium response works through household search effort. Relative to that paper, we provide a fully dynamic consumption/saving model with full information in which the impact of interest rate caps comes from the general equilibrium impact of households' changing dynamic outside options. Raveendranathan (2020) studies the determinants of average profitability in a search environment with credit lines, focusing on the effects of information frictions on changes in profitability. We focus on the impact of market power on the distribution of profitability and study its consequences for the effects of regulation.

Most closely related, Raveendranathan et al. (2026) study interest rate caps in a quantitative model of long-term revolving credit lines with search and Nash bargaining. Under a uniform cap, credit access contracts in their model, just as in our No Outside Option model - the access *expansion* in our Benchmark therefore comes from the outside option available to unmatched households (not present in Raveendranathan et al. (2026)), rather than from the contract horizon. Both frameworks generate welfare gains from caps when lenders have market power, ours being larger and accompanied by an expansion of access. A caveat to this comparison is the contract horizon itself - while long-term contracts insure borrowers against future repricing, a cap may compress that insurance, offsetting part of the markup reduction gain. Our one-period contracts abstract from this margin.

Bethune et al. (2024) reach a related conclusion in a default model with search and informed versus uninformed borrowers: ceilings lower welfare under perfect competition but can raise it under lender market power; their gain requires that some households be uninformed and runs through the

changing composition of low- and high-cost lending, whereas ours requires no information friction and works through the repricing of competitive search contracts as outside options change. Finally, our Competitive model closely follows the perfectly competitive setups in Chatterjee, Corbae, Nakajima, and Rios-Rull (2007), Livshits, MacGee, and Tertilt (2007) or Livshits, MacGee, and Tertilt (2010), where we allow for a non-negative up-front cost of making loans.

2 The Model

In this section, we set up a quantitative model of unsecured borrowing with endogenous level of competition for borrowers.

Time is discrete, and the economy is populated by ex-ante identical, infinitely lived households, who receive income shocks y that are stochastic and follow a Markov process: denoting the current period's income by y, next period's income y' is drawn from a distribution $G(y', y)$ with finite support $Y \times Y$. Markets are incomplete and households use unsecured credit to smooth consumption in the face of the income shocks. The state of a household at the beginning of the period consists of its default status d, debt level b (negative if the household is a saver) and current income y, where we define *household type* as $x \equiv (b, y)$. Default status $d = 1$ indicates that the household ended the previous period in default and $d = 0$ indicates that it did not.

The timing of actions within a period is as follows. The household enters the period with default status $d \in \{0, 1\}$ and type $x \equiv (b, y)$. Then, households who are not in default (enter the period with $d = 0$) choose whether to become savers, borrowers or default on their debt obligations. Households in default are restricted to be savers. After the saving, borrowing and default decisions are made, households draw next period income y'. Those households who enter the period in default transition out of default, i.e., enter next period with $d = 0$.[8] Households die stochastically at the end of each period with probability δ.

The value function of a household with default status d, debt b and income y at the beginning of the period is $V_d(b, y)$. Denote the value function of saving for a household by $V^S(b, y)$ and the

[8]This sets the period of exclusion from financial markets to the period of default plus 1 model period. This is consistent with the empirical literature finding that post-bankruptcy exclusion from borrowing is short (Jagtiani and Li, 2015). Longer, stochastic exclusion lengths do not change any of the conclusions from our quantitative analysis.

value functions of borrowing and defaulting by $V^B(b,y)$ and $V^D(y)$, respectively. Then:

$$\begin{aligned} V_0(b,y) &= \max\Big[V^D(y), V^S(b,y), V^B(b,y)\Big], \\ V_1(y) &= V^S(0,y). \end{aligned} \tag{1}$$

Denote the next period's debt (or savings, if negative) of the household by b'. A household has access to a competitive saving market at the risk-free rate r, which gives the value of being a saver:

$$\begin{aligned} V^S(b,y) &= \max_{c,b'}\Big(u(c)+\beta(1-\delta)\int_{y'\in Y} V_0(b',y')dG(y',y)\Big) \\ \text{s.t.} &\quad b' \le 0 \\ \text{and} &\quad y-b = c - \frac{b'}{1+r} \end{aligned} \tag{2}$$

A household can only default if it is not currently in default. A defaulting household's debt is erased ($b=0$) and the default state next period switches to $d'=1$. The household's borrowing or saving during the period is zero (i.e., consumption equals current income) and it incurs a one-off utility cost Δ.[9] We denote the value of defaulting by $V^D(y)$:

$$V^D(y) = u(y) - \Delta + \beta(1-\delta)\int_{y'\in Y} V_1(y')dG(y',y). \tag{3}$$

A household can only borrow if it is not currently in default ($d=0$). We denote the value of borrowing by $V^B(b,y)$, which is pinned down by the equilibrium of the loan market. We discuss the details of this market next.

2.1 The loan market

Lenders are risk neutral, have access to borrowing at the risk-free rate r, and pay cost κ to make an offer of a one-period loan to a customer of a specific type $x=(b,y)$.[10] A loan specifies the amount that the household receives in the current period, qb', and the amount that the household

[9] Our specification uses a one-off utility cost rather than a proportional income loss; the two are isomorphic under log utility and lead to qualitatively similar predictions under CRRA.

[10] We abstract from asymmetric information, so the competitive search market faces no adverse selection. In this context, the up-front cost κ can be viewed as also covering the screening and data-analysis costs (for example, credit scoring) that lenders incur to overcome it. We leave the interaction between adverse selection and the outside option to future work.

repays in the following period, b'.

The loan market is subject to frictions and consists of two options for the household. The first one is modeled as a competitive search equilibrium. Lenders post loans for each type x at cost κ (if profitable) and households observe all posted loans and decide which loan to search for. The probability of getting a loan in the competitive search market depends on the matching function and the household-lender ratio at loan (q, b') and type x. Specifically, denote the measure of lenders posting loan (q, b') targeted at type x by $L_x(q, b')$, the measure of households of type x searching for that loan by $H_x(q, b')$ and the resulting household-lender ratio (tightness) by $\theta_x(q, b') = \frac{H_x(q,b')}{L_x(q,b')}$. When the household-lender ratio is $\theta_x(q, b')$, a lender makes a loan with probability $\alpha_L(\theta_x(q, b'))$, the household receives a loan with probability $\alpha_H(\theta_x(q, b'))$ and, with the complementary probabilities, they are left unmatched. We make the following standard assumption about the matching probabilities:

Assumption 1. The trading probabilities satisfy $\alpha_L(\theta) = \theta\alpha_H(\theta)$, $\alpha_L(\theta)$ is increasing and concave in θ, $\alpha_H(\theta)$ is decreasing and convex in θ, $\lim_{\theta\to\infty} \alpha_L(\theta) = \alpha_H(0) = 1$ and $\alpha_L(0) = \lim_{\theta\to\infty} \alpha_H(\theta) = 0$.

The second part of the lending market consists of an option of a *high markup contract*, which the household can get with probability 1. Specifically, when a household fails to match with a lender, we assume that it is matched to a *high markup lender*, who bargains with the household over the surplus from the loan according to the Kalai (1977) bargaining solution with Kalai share ω going to the lender and $1 - \omega$ to the borrower. The household's outside option in this case is the value of default or saving, whichever is higher. The outside option of the lender is not matching at all. This assumption is intended to capture the fact that households with low probability of obtaining a competitive offer may still be able to obtain a loan, just at less attractive terms. What is crucial is that it prevents the households who fail to match with a lender in the search market from being forced into bankruptcy by the requirement that they repay their debt immediately. The existence of the high markup contract option means that the level of competition for a specific household type pins down the markup in the competitive search market and the probability of getting the competitive search contract versus the high markup contract, which then determines average markups. Crucially, however, it does not lead to credit rationing, i.e., households whose

surplus from a lending relationship is positive always get a contract offer.

Given the above, the net value to a household of type $x = (b, y)$ of receiving loan (q, b') in the competitive search market, measured relative to the high markup outside option, is:

$$v_x(q, b') \quad = \quad u(y - b + qb') + \beta(1 - \delta) \int_{y' \in Y} V_0(b', y') dG(y', y) - V^{HM}(b, y),$$

where V^{HM} is the value to the household of the high markup contract, defined below, which serves as the outside option in the search market. Given that, the value function of borrowing satisfies:

$$V^B(b, y) = \max_{(q,b')} \Big(\alpha_H\big(\theta_x(q, b')\big) v_x(q, b') + V^{HM}(b, y) \Big) \tag{4}$$

where the maximization is over loans offered to type-x households, i.e., subject to

$$\kappa = \alpha_L(\theta_x(q, b')) \Big(- qb' + \frac{b' \rho(b', y)}{1 + r} \Big) \tag{5}$$

where $\rho(b', y)$ is the repayment probability, given by

$$\rho(b', y) = (1 - \delta) \left(1 - \int_{y' \in Y} \mathbb{1}_{\{V^D(y') > \max\{V^B(b', y'), V^S(b', y')\}\}} dG(y', y) \right). \tag{6}$$

Intuitively, default happens when the value of defaulting exceeds the value of saving and the value of borrowing. That is the only point at which the household would potentially choose default, and in equilibrium this is only going to happen if markets are closed, since the values delivered by contracts in open markets exceed the value of default. That comes from the fact that, per (4), $V^B \geq V^{HM}$, and that the high markup contract's surplus treats $\max\{V^D, V^S\}$ as the outside option.

Equation (5) above pins down the tightness level $\theta_x(q, b')$ associated with each loan (q, b') in market x: lenders offer loans (q, b') in market x as long as expected profits cover the up-front cost κ.

The joint equilibrium determination of the offered contract (q, b') and the market tightness

$\theta_x(q, b')$ can be characterized by defining the profits of delivering net value v to household type x:

$$\begin{aligned} \Pi_x(v) &= \max_{q,b'} \; -qb' + \frac{\rho(b', y)b'}{1+r} \\ &\quad \text{subject to} \\ v &= u(y - b + qb') + \beta(1-\delta) \int_{y' \in Y} V_0(b', y') dG(y', y) - V^{HM}(b, y) \end{aligned} \tag{7}$$

In equilibrium, entry determines the optimal contract (q^*, b'^*) and corresponding market tightness $\theta_x(q^*, b'^*)$ such that the free entry condition is satisfied:

$$\alpha_L(\theta_x(q^*, b'^*))\, \Pi_x(v^*) = \kappa, \qquad v^* \equiv v_x(q^*, b'^*). \tag{8}$$

Finally, we characterize the high markup contract bargaining problem. Specifically, the loan offered to a type-x household by the high markup lender splits the surplus from the contract according to the Kalai (1977) bargaining solution with lender power ω:

$$\begin{aligned} \max_{q,b'} \; -qb' &+ \frac{\rho(b', y)b'}{1+r} \\ \text{s.t.} & \\ (1-\omega)(-qb' + \frac{\rho(b', y)b'}{1+r} - \kappa) = \omega(u(y - b + qb') &+ \beta(1-\delta) \int_{y' \in Y} V_0(b', y') dG(y', y) - \max[V^S(b, y), V^D(y)]) \\ -qb' + \frac{\rho(b', y)b'}{1+r} &\geq \kappa \\ u(y - b + qb') + \beta(1-\delta) \int_{y' \in Y} V_0(b', y') dG(y', y) &\geq \max[V^S(b, y), V^D(y)] \end{aligned} \tag{9}$$

The first constraint is the Kalai surplus splitting condition. The LHS gives the surplus from the contract that is obtained by the lender, given by expected profits net of the up-front cost (which is identical across all lenders). The RHS is the surplus from the contract attained by the borrower, net of outside option. A value of $\omega = 1$ gives the monopolistic solution: the borrower is held exactly indifferent between outside options and the contract. $\omega = 0$ gives the perfectly competitive solution where the expected profit just covers the up-front cost. In the quantitative section, we use the upper percentiles of the interest rate distribution to calibrate the value of ω. The second and third constraints are the participation constraints.

Notice that if no (q, b') admits an open market, then there is no lender entry and the household can only choose between default and saving. Otherwise, let (q^{hm}, b'^{hm}) be the solution to (9). Then the value of the high markup contract to the household is:

$$V^{HM}(b, y) = u(y - b + q^{hm} b'^{hm}) + \beta(1 - \delta) \int_{y' \in Y} V_0(b'^{hm}, y') dG(y', y).$$

2.2 Equilibrium

An equilibrium consists of:

1. Value functions $V_0(b, y)$, $V_1(y)$, $V^S(b, y)$, $V^D(y)$, $V^B(b, y)$ and $V^{HM}(b, y)$;
2. Household decision rules: the default/save/borrow choice from (1), the saver's consumption–savings policy, the search-market contract $(q^*(b, y), b'^*(b, y))$, and the high markup contract $(q^{hm}(b, y), b'^{hm}(b, y))$;
3. A repayment probability $\rho(b', y)$ and a market tightness function $\theta_x(q, b')$;

such that:

1. Given ρ, θ_x and V^{HM}, the value functions V_0, V_1, V^S, V^D and V^B satisfy (1), (2), (3) and (4), and the household's decision rules attain their respective maxima.
2. Tightness at each posted loan $\theta_x(q, b')$ is consistent with lenders' free entry condition (5), and the search-market contract $(q^*(b, y), b'^*(b, y))$ attains $V^B(b, y)$.
3. Given ρ and the household's outside option $\max[V^S(b, y), V^D(y)]$, the high markup contract $(q^{hm}(b, y), b'^{hm}(b, y))$ and value $V^{HM}(b, y)$ are consistent with (9).
4. The repayment probability $\rho(b', y)$ is consistent with households' optimal default decisions next period, as given by (6).

All equilibrium contracts and prices depend only on the household's individual type $x = (b, y)$ and the exogenous risk-free rate r, not on the cross-sectional distribution of households.[11]

[11] This recursive structure keeps the model tractable under aggregate income shocks, which can be added at low computational cost but would add little, since they shift realized income without inducing distributional pricing effects. An aggregate shock with non-trivial equilibrium consequences would instead require endogenizing the risk-free rate or adding a production block, as in Chatterjee et al. (2007), at substantially higher computational cost.

3 Parameterization and Model Fit

3.1 Parameterization

In this section, we detail the choices of our functional forms and parameter values. The utility function is CRRA, with relative risk aversion coefficient of $\sigma = 2$: $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$. The matching function $m(H, L)$ is

$$m(H, L) = LH(L^\gamma + H^\gamma)^{-1/\gamma},$$

which gives the matching probabilities as functions of the market tightness $\theta \equiv H/L$:

$$\alpha_H = m(H, L)/H = (1 + \theta^\gamma)^{-1/\gamma}, \quad \alpha_L = m(H, L)/L = (\theta^{-\gamma} + 1)^{-1/\gamma}.$$

In the benchmark parameterization, we set $\gamma = 1$.

The period in the model is one year, and accordingly, we set the death hazard rate to $\delta = 2\%$ (so that households live for 50 years in expectation, i.e., enter the economy at 21 and reach age 71 in expectation). We set the real risk-free rate to $r = 1.26\%$, which is the real yield on 3-month T-bills over the period 1990–2004.[12] We focus our calibration on this period whenever possible, as it covers the years before both the 2005 BAPCPA overhaul of the bankruptcy filing regulation and the Great Recession, hence avoiding any regime changes or unusually large shocks to the credit market. We set the lenders' per-period transaction cost, covering servicing, collection, and processing, to $\tau = 0.029$ (2.9% of the balance), which we take from Agarwal et al. (2015) following the calculation in Raveendranathan et al. (2026).[13]

We calibrate the income processes for two groups of households, identified in the data by their educational attainment. Specifically, we take the income process estimates from Guvenen (2009) for 'High School' and 'College' and approximate the process for each group as

$$\ln(Y_t) = \ln(z_t) + \varepsilon_t,$$

[12] We use the 3-month US Treasury bill secondary-market rate (FRED series `TB3MS`), which averages 4.11% over 1990–2004, and deflate it by the average year-over-year CPI inflation (`CPIAUCSL`), 2.85% over the same period. Computed from the unrounded monthly averages, the real rate is 1.2587%, which we round to 1.26%.

[13] Total operating costs in Agarwal et al. (2015) are about 3.4% of average daily balances; the 0.5% marketing-and-acquisition component is excluded, as our entry cost κ already captures it, leaving $\tau = 2.9\%$.

where the persistent part is

$$\ln(z_t) = \phi \ln(z_{t-1}) + \eta_t,$$

and η_t and ε_t are i.i.d. with means zero and standard deviations σ_η and σ_ε. Both the persistence parameter and the volatilities of innovations are education-group-specific. We map the above continuous log processes into a 25-state Markov chain for each education group, using the method in Rouwenhorst (1995).[14]

We calibrate the remaining 6 parameters: the discount factor by education group g, β_g, the utility cost of default by education group, Δ_g, the common Kalai bargaining power, ω, and the entry cost of lenders, κ, using the targets defined below.

Details of data targets For our targets, we use the education group-specific debt-to-income ratios, bankruptcy rates, percent of households holding credit card debt, and the 90th percentile of the credit card interest rate distribution. To compute the data moments, we use micro-data from the Survey of Consumer Finances (SCF) in 2001 and 2004, aggregate data from the Flow of Funds for 2000–2004, and filing rates for Chapter 7 bankruptcy over 2000–2004. Finally, for the interest rate distribution, we use one of the datasets from Stango and Zinman (2016), an account-level panel that samples individual credit-card holders.[15]

First, using the SCF, we place a household in the 'High School' group if the household head has less than 16 years of education (i.e., this includes 'some college'); this group accounts for 69.11% of all households in our sample. We place a household in the 'College' group if the household head has 16 years of education or more, which accounts for 30.89% of households in our sample. We use these group weights to calculate the aggregates for the various outcomes. The data targets from the SCF are calculated using survey years 2001 and 2004, in order to avoid using the data after the introduction of the bankruptcy reform of 2005 (BAPCPA).[16] For the education group-specific debt/income targets, we first calculate the average debt on major credit cards relative to average income for each of the two educational groups, averaged over survey years 2001 and 2004. Since unsecured debt is underreported in the SCF relative to aggregate data, as documented by Brown,

[14] Specifically, the persistence and the variances of the η and ε shocks are taken from Table 1 in Guvenen (2009).

[15] We are grateful to Victor Stango and Jonathan Zinman for graciously sharing their data with us.

[16] As Albanesi and Nosal (2025) show, the reform had major effects on the bankruptcy and delinquency behavior of households, and it is not within the scope of the current paper to address these responses.

Haughwout, Lee, and van der Klaauw (2015), we scale both groups' debt/income by the same proportion so that the aggregate implied revolving debt/income matches the Flow of Funds 2000–2004 average of 9.24%. That gives two debt/income targets: 12.45% for High School and 6.7% for College. To calculate the education group-specific proportion of households with unsecured debt, we compute the fraction of households in the SCF that carry a positive balance *and* pay interest on their credit cards, for each education group on average over the survey years 2001 and 2004.[17] The proportion of households with credit card debt is 39.77% for the High School group and 39.41% for the College group. Finally, for the default rate, we first compute the fraction of households in the SCF with a new bankruptcy over the last 3 years, for each education group on average over the survey years 2001 and 2004. We then rescale these fractions so that the aggregate bankruptcy rate equals the aggregate filing rate for Chapter 7 bankruptcy over 2000–2004, which is 5.82 per thousand.[18] The default rates for the High School group and the College group are then 7.73 and 1.54 per thousand, respectively. Finally, we target the 90th percentile of the credit card interest rate distribution, which is 23.8% in real terms for both the High School and College groups. This number is the 90th percentile of non-teaser interest rates among holders that carry a balance and pay interest in the dataset of Stango and Zinman (2016).[19]

The above strategy gives us 6 calibrated parameters, $(\beta_{HS}, \beta_C, \Delta_{HS}, \Delta_C, \omega, \kappa)$ in total to match 7 moments in the data: debt/income, the bankruptcy rate, the fraction with debt for 2 education groups, and the 90th percentile of the real interest rate distribution.

In addition to the Benchmark calibration of the model of Section 2, we calibrate two other versions of the model. The first one is the No Outside Option (NOO) model, in which the high markup contract is not offered, so an unmatched borrower must either save (i.e., repay any outstanding debt) or default.[20] The different predictions of the Benchmark and No Outside Option

[17] Requiring interest payments, not just a positive balance, restricts attention to households who use their credit cards for borrowing rather than purely transaction purposes. We also use this gross measure of debtors instead of net debtors, a measure which nets out assets, for three reasons: many assets are partially or fully exempt in bankruptcy, so net worth understates the debt that is actually dischargeable; seizing assets is costly and we do not observe whether a household's assets would in fact be available to repay unsecured debt after an adverse shock; and credit card debt is underreported in the SCF Brown et al. (2015). Most of the quantitative consumer-credit literature likewise targets gross unsecured debt.

[18] Default in the model is a formal discharge, so we target the Chapter 7 filing rate, the standard choice in the quantitative literature, and treat the charge-off rate, which reflects formal and informal default together, as an untargeted validation moment.

[19] For details, see Appendix A.1.

[20] That means that V^{HM} is replaced by $\max[V^D, V^S]$ in model equations.

models highlight the quantitative impact of the outside option on the equilibrium of the model. The second is the Competitive model, which is based on the standard model of default with competitive pricing of default risk, with entry cost for lenders (κ) and no matching frictions. This serves as a useful point of comparison for our analysis, as this model features ex-post perfect competition, the standard assumption in much of the literature. Specifically, the loan size (b') and price (q) are determined by the following zero profit condition:

$$-qb' + \frac{b'\rho(b', y)}{1+r} = \kappa. \tag{10}$$

For each model, we pick the calibration which minimizes the sum of square deviations from the targets, with the one difference that the NOO and Competitive models are not required to match the 90th percentile of the interest rate distribution, as they do not have a market power parameter to help the model hit that moment.[21] Parameter values are reported in Table 1.

In terms of the calibrated cost of making an offer, κ corresponds to about \$73 per offer in the Benchmark model, \$251 in the No Outside Option model, and \$784 in the Competitive model. Translating into a cost per account opened gives about \$142 in the Benchmark, averaging search-market and high markup entry costs over all accounts, against \$603 in the No Outside Option model and \$784 in the Competitive model. Because matches in our model last one period, the natural empirical counterpart is the marketing cost per open account per year, roughly \$100 to \$200 in the data, which the Benchmark's \$142 matches closely; the two alternative models imply higher per-account costs. Appendix A.2 details the comparison. The interest rate net of the risk-free rate, charge-offs, and the transaction cost τ is about 6 percentage points in the data. The Benchmark comes closest, at about 7.5, whereas the No Outside Option and Competitive models imply substantially larger net spreads of about 21 and 12 percentage points. The Benchmark thus matches the data most closely, on both the net spread and the interest rate distribution (Section 3.3). What remains after netting these real costs covers the lenders' markup together with the up-front entry cost κ.

To interpret the stigma parameters Δ_C and Δ_{HS}, we express them in consumption terms.

[21] Introducing the 90th percentile as a target and forcing these models to match it nonetheless results in a much deteriorated fit for the aggregate statistics.

For the average bankrupt, the calibrated stigma equals a one-time one period consumption loss of about 44% (College) and 36% (High School). The other two models imply comparable values, about 49% and 44% (College/High School) in the No Outside Option model and 42% and 43% in the Competitive model. These values are comparable with the default cost in the consumer-credit literature, which most commonly uses an income garnishment or a utility cost. That cost is typically calibrated to garnishment rates ranging from about 35% of income in Livshits et al. (2007) to 82% above an exemption in Exler et al. (2025), while Athreya, Sánchez, Tam, and Young (2018) use a utility cost worth roughly 65% of one period's consumption. For reference, the Consumer Credit Protection Act caps garnishment of consumer debt at 25% of disposable earnings.[22] The calibrated costs exceed this ceiling because they capture the full cost of default, which also includes filing and legal fees and the non-pecuniary and exclusion costs of default.

3.2 Model fit and aggregate statistics

We now discuss the quantitative fit of our three model versions: Benchmark, No Outside Option and Competitive. Table 2 presents the aggregate statistics and Table 3 presents model fit by education group. In addition to the targeted moments, we also report the untargeted charge-off rate and average interest rate.

Both the Benchmark and Competitive models match aggregate debt and bankruptcy statistics reasonably well, and additionally come close to matching the untargeted charge-off rates and average interest rates. The NOO model offers a significantly worse aggregate fit (Table 2): it under-predicts aggregate debt/income and over-predicts the fraction with debt, and, on untargeted moments, under-predicts charge-off rates by about half while over-predicting the average interest rate by roughly 80% (27.43% versus 15.37% in the data).

The NOO model's calibration also requires setting borrower time discount factors as low as 0.52 (0.517 for High School and 0.663 for College; Table 1), which is very low relative to discount factors implied by the empirical rates of return on savings. For the Benchmark and Competitive calibrations, the required discount factors fall into the more standard range of roughly 0.8–0.9. This calibration outcome follows directly from the credit rationing implied by the search friction:

[22] 15 U.S.C. §1673(a): the garnishable amount is the lesser of 25% of disposable earnings or the amount by which they exceed thirty times the federal minimum wage.

Table 1: Model parameters.

Parameter		Value
	Common Parameters	
σ	risk aversion	2
γ	elasticity of the matching function	1
δ	death hazard rate	2%
r	risk free rate	1.26%
τ	transaction cost	2.9%
ϕ_C, ϕ_{HS}	persistence of income process	0.979, 0.972
$\sigma_\varepsilon^2, \sigma_\eta^2$ College	variances of the income innovations	0.047, 0.0099
$\sigma_\varepsilon^2, \sigma_\eta^2$ High School	variances of the income innovations	0.052, 0.011
	Benchmark	
β_C, β_{HS}	time discount factors	0.873, 0.817
Δ_C, Δ_{HS}	bankruptcy stigma	3.244, 1.778
κ	loan upfront cost	0.0017
ω	lender's surplus share	0.15
	No Outside Option	
β_C, β_{HS}	time discount factors	0.663, 0.517
Δ_C, Δ_{HS}	bankruptcy stigma	3.7917, 2.190
κ	loan upfront cost	0.00584375
	Competitive	
β_C, β_{HS}	time discount factors	0.880, 0.795
Δ_C, Δ_{HS}	bankruptcy stigma	3.367, 2.448
κ	loan upfront cost	0.01828125

because unmatched households must repay or default in the NOO model, aggregate debt is lower in equilibrium, and the model requires high impatience to try to reproduce the debt/income target, which still falls short of the data.[23]

Table 3 presents the model fit by education group. Three patterns stand out. First, the Benchmark and NOO models under-predict the High School debt-to-income ratio while the Competitive model matches it fairly well: against a data target of 12.45%, the models deliver 11.13% (Benchmark), 9.18% (No Outside Option), and 12.25% (Competitive). The miss is sizable for the NOO model. Second, the bankruptcy rates are matched closely across both education groups in all models. Third, the fraction with debt is over-predicted for the High School group by the Benchmark

[23] We are not claiming that, given enough degrees of freedom, the NOO model cannot be calibrated to match the moments better. The calibration presented by us reflects the minimized mean squared deviation target for the 6 free parameters we have.

Table 2: Data and model outcomes.

Targeted Moments:	Data 2000-04	Benchmark	No Outside Option	Competitive
Debt/Income %	9.24	8.73	7.34	9.25
Bankruptcies per 1000	5.82	5.79	5.64	5.92
Fraction with debt %	39.66	43.51	47.37	37.01
90th interest percentile %	23.80	23.73	45.11	33.37
Untargeted Moments:				
Average interest rate %	15.37	15.62	27.43	20.25
Charge-Off Rate %	4.90	4.00	2.55	3.95

Table 3: Data and model outcomes by education group.

Targeted Moments:	Data 2000-04		Benchmark		No Outside Option		Competitive	
	College	*HS*	*College*	*HS*	*College*	*HS*	*College*	*HS*
Debt/Income %	6.70	12.45	6.84	11.13	5.88	9.18	6.88	12.25
Bankruptcies per 1000	1.54	7.73	1.55	7.69	1.50	7.49	1.47	7.91
Fraction with debt %	39.41	39.77	34.15	47.70	44.08	48.84	30.69	39.84
Untargeted Moments:								
Average interest rate %	14.78	15.80	12.83	16.51	19.34	30.69	13.40	22.99
Charge-Off Rate %	4.90	4.90	2.87	4.50	2.16	2.73	2.64	4.54

and NOO models, while the Competitive model matches it closely; for College it is under-predicted by the Benchmark and Competitive models and over-predicted by the NOO model.

Beyond the aggregate fit, the models' predictions differ starkly in their predictions for the cross-sectional distribution of prices and profitability. We turn to these results next.

3.3 Cross-sectional fit: pricing and profitability

Figure 1, panel (a), shows that in both models featuring search, interest rates fall steeply as the repayment probability rises, while in the Competitive model, interest rates vary much less with default probabilities and exhibit a more pronounced U-shape.[24] As for debt balances, presented in panel (b) of Figure 1, all models imply a hump-shaped relationship between repayment probability and debt balances, although for the NOO model, this hump is much less pronounced. Across all of

[24]This is a feature of the competitive model with an up-front cost of making a loan $\kappa > 0$. The low-risk borrowers borrow less (panel (b) of Figure 1) and hence in order for the contracts to break even, the interest rates have to be relatively high. For the case of $\kappa = 0$ in the Competitive model, interest rates qualitatively mimic those in the Benchmark model, but profitability is just flat at zero.

the range the Benchmark and Competitive models imply higher debt balances per capita than the NOO model. The emerging pattern is that the NOO model prices default risk much more elastically on the interest rate side, while keeping borrowing low, which is consistent with the aggregate fit differences in Table 2.

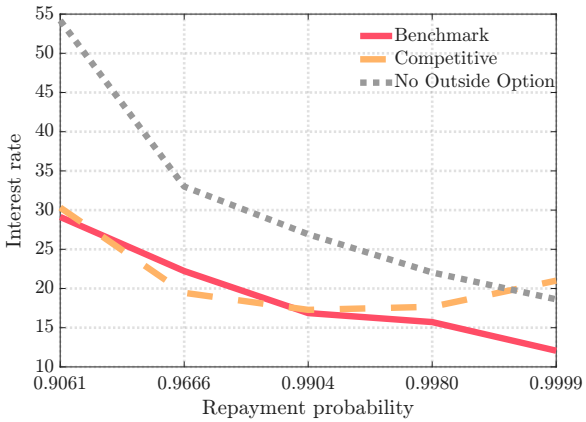
The distinction in the predictions of the models is more pronounced in the distribution of profitability as a function of default risk, as presented in Figure 2. Profitability in the Benchmark and NOO search-based models is high for high-risk borrowers and generally decreases with repayment probability, in stark contrast to the Competitive model, which implies that profitability *increases* with repayment probability. Intuitively, the difference in these models' predictions for the distribution of profitability is driven by the fact that in the Competitive model, pricing is exclusively determined by the risk of default, as in equation (10), while in the Benchmark model, it is additionally affected by the market tightness and outside options, as implied by the problem defined by (7) (and its simplified version for the NOO model). This implies that the search-based frameworks come closer to the empirical pattern, documented in Agarwal et al. (2015) and confirmed in the later, post-crisis data of Drechsler et al. (2025), that profitability is generally higher at lower credit scores.[25] Agarwal et al. (2015), with its finer cross-section of credit scores, additionally documents that this relationship is hump-shaped, with profitability peaking at low but not the very lowest scores. The Benchmark reproduces this hump in its aggregate profitability, as well as for both the competitive search and high markup markets (Figure 2, panel (b)). In magnitude, this peak of about 11% is comparable to the roughly 11% return on the lowest-FICO balances that Drechsler et al. (2025) document over 2015–2023, whereas the No Outside Option model overshoots substantially.

Table 4 reports the percentiles and mean of the interest rate distribution for the three models against the data. The Benchmark fits the distribution far more closely than the other two models: it comes close at the tenth percentile (9.67 against 8.24), essentially hits the targeted ninetieth percentile, and reproduces the mean almost exactly, under-predicting only the median (12.36 against 14.65). The No Outside Option model over-predicts at every percentile and overshoots the mean by nearly a factor of two, and the Competitive model over-predicts the median, the ninetieth

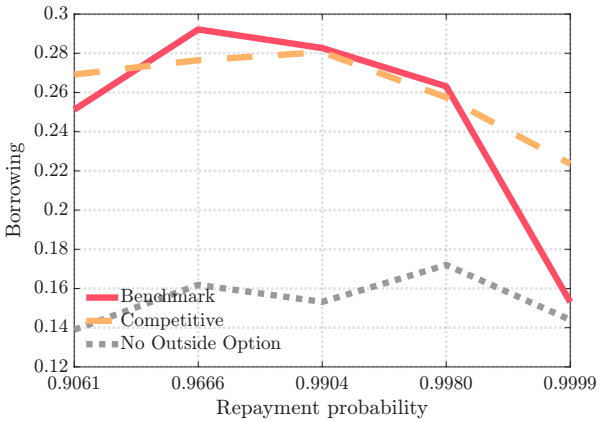
[25] We take the repayment probability as a proxy for credit scores, with lower repayment probability corresponding to lower scores, in line with the empirical and theoretical literature, for example Musto and Souleles (2006), Chatterjee, Corbae, Dempsey, and Ríos-Rull (2023) or Albanesi, DeGiorgi, and Nosal (2022).

Figure 1: Interest rates and debt by repayment probability.

(a) Interest rates



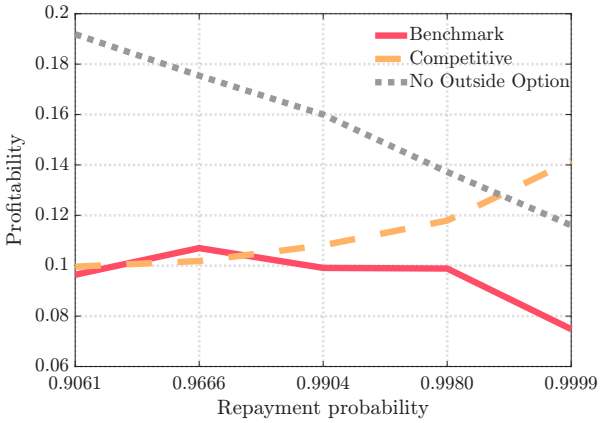
(b) Borrowing b'



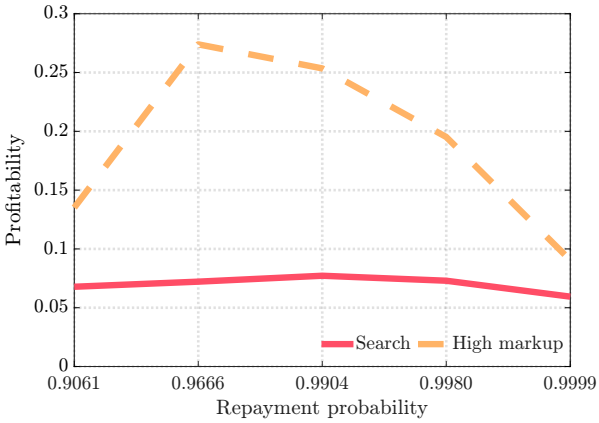
Note: The repayment probabilities shown on the horizontal axis correspond to the average *ex-ante* repayment probability within bins of the Benchmark model's repayment probability distribution, pooling both the search and high-markup options. The bin cutoffs are defined by the percentiles of the Benchmark distribution: 0–10, 10–20, 20–30, 30–40, and 40–100.

Figure 2: Profitability (profit per unit of debt) by repayment probability.

(a) Profitability



(b) Search Market and High Markup Market



Note: The repayment probabilities shown on the horizontal axis correspond to the average *ex-ante* repayment probability within bins of the Benchmark model's repayment probability distribution, pooling both the search and high-markup options. The bin cutoffs are defined by the percentiles of the Benchmark distribution: 0–10, 10–20, 20–30, 30–40, and 40–100.

percentile, and the mean. The one moment the Benchmark misses is the ninety-fifth percentile, where all three models over-predict the data (34.89, 50.08, and 35.48 against 25.80). The very top of the distribution, however, is also where the model and the data potentially capture somewhat different objects. Our model prices a one-period loan through a single interest rate, with no separate fee schedule, so the model rate is most naturally read as a total cost of borrowing, whereas the Stango and Zinman (2016) moments are interest rates only. As reported by Agarwal et al. (2015) and Nelson (2025), the cost of borrowing on credit cards, including interest and fee charges, relative to balances reaches or exceeds 45% for the high end of the distribution. Read in this light, the Benchmark's over-prediction at the very top is considerably smaller than the interest-only comparison suggests.

The education-group distributions in Table 4 confirm this ranking. The aggregate over-prediction of the ninety-fifth percentile comes predominantly from the *High School* group, for which all three models over-predict the top of the interest rate distribution as well as the mean. For the *College* group the fit is closer and mixed across models: the Benchmark comes closest at the ninety-fifth percentile (23.39 against 25.59), the Competitive model at the median and the mean (11.78 and 13.40 against 13.93 and 14.78), and the No Outside Option model over-predicts the College median and upper tail (17.57 and 30.58 against 13.93 and 25.59). Taken together with its aggregate spread, the interest rate distribution is the dimension on which the Benchmark most clearly outperforms both alternatives.

An additional test of the distributional fit of the models, especially important given the interest rate cap experiments of the next section, is presented in Figure 6, panel (b). For each interest rate threshold, it plots the fraction of contracts priced at or above that rate, in the three models and in the data. The Benchmark tracks the empirical distribution far more closely than the No Outside Option and Competitive models, which place far too little mass at rates below 20%. At the 15% threshold, for instance, 29% of Benchmark contracts lie at or above it, against 47% in the data, compared with 80% in the Competitive and 97% in the No Outside Option model.

In our last cross-sectional comparison, Table 5 takes the model to the cross-section of credit access, reporting rates of denial/discouragement from applying, the interest rate differential, and differences in debt-to-income ratios, by within-group income tercile for the Benchmark model alongside the SCF. Mapping the model to these data requires care, because being denied is a different

Table 4: Distribution of interest rates in the model and data, overall and by education group (in %).

Moments	p10	p50	p90	p95	Mean
All borrowers					
Benchmark	9.67	12.36	23.73	34.89	15.62
No Outside Option	16.23	23.73	45.11	50.08	27.43
Competitive	11.42	18.72	33.37	35.48	20.25
Data Stango and Zinman (2016)[a]	8.24	14.65	23.80	25.80	15.37
College					
Benchmark	8.81	10.30	15.57	23.39	12.83
No Outside Option	14.92	17.57	24.99	30.58	19.34
Competitive	10.37	11.78	19.13	21.32	13.40
Data Stango and Zinman (2016)[a]	7.95	13.93	23.12	25.59	14.78
High School					
Benchmark	10.37	12.63	24.83	37.93	16.51
No Outside Option	20.33	26.54	46.49	65.91	30.69
Competitive	15.99	20.38	33.37	37.58	22.99
Data Stango and Zinman (2016)[a]	8.49	15.17	24.19	25.86	15.80

[a] Cross-sectional percentiles and mean of the person-level, balance-weighted average purchase APR on revolving, non-promotional accounts in the Stango and Zinman (2016) panel (January 2006 through December 2008), equally weighted across panelists, shown for all borrowers and separately for the College (four-year degree or higher) and High School groups. Expressed in real terms, deflating nominal APRs by 3.31%, the average of the monthly year-over-year CPI inflation (FRED series CPIAUCSL) over January 2006 through December 2008. See Appendix A.1 for construction.

object in the model and in the survey. In the model, no household that participates in the search market is rationed on the extensive margin: a household that fails to match in the search market still borrows, through the high markup contract, so failing to match means borrowing on worse terms rather than losing access to credit. From that perspective, the empirical measures which *condition on applying* don't map into denial rates in the model, where the rationing in that case shows up as a difference in loan terms. On the other hand, the model predicts which types of borrowers will be rationed on the extensive margin through markets being closed. That would correspond to unconditional denials and/or discouragement rates in the SCF. The cleanest model-data comparisons are therefore the ones stated in prices and quantities, the interest rate and debt-to-income differentials between denied and not-denied borrowers, followed by the unconditional constrained rate, which measures how much of the population is affected by constraints in any form. Finally, the denial rate conditional on applying is the noisiest map, for the reasons we discuss below. Panel A of Table 5 uses the most encompassing measure, the share of households that are credit constrained,

having been turned down, given less credit than requested, or discouraged from applying. This is a population measure, not conditioned on applying, and we compute the model counterpart the same way, as the unconditional probability of being denied the competitive search contract. On this measure the Benchmark does reasonably well: it reproduces the decline of constraints with income within each group and is of comparable magnitude, although the match deteriorates for high incomes.

Panel B instead reports the narrower rate of being denied conditional on applying, and here the model and the data diverge, for the reasons outlined above. In the data this conditional rate falls with income, while in the Benchmark it rises, reaching 77% and 84% for the highest-income College and High School households. However, this divergence shows data measurement issues rather than true divergence of model versus data, and its interpretation turns on a feature of the model: households that fail to match in the search market receive the high markup contract. Whether that amounts to a meaningful denial depends on how far the high markup rate lies above the competitive one, which Panel C reports. For high-income borrowers that gap is essentially zero, 0.6 and 0.7 percentage points in the top College and High School terciles, so a household that fails to match still obtains a contract almost identical to the competitive one, at a low rate, with probability one. That is true both for interest rates in Panel C and debt in Panel D. This is the paper's mechanism at work: a borrower with a strong outside option, here a low-risk, high-income household, can be charged only a negligible markup even by the high markup lender. The Benchmark's high conditional denial rate for these households therefore does not signal lost access; it counts as denied borrowers who are, in effect, served competitively. The economically consequential denial, a high markup contract well above the competitive rate, is concentrated among low-income borrowers, for whom the gap reaches 37 and 26 percentage points (Panel C), and there the model and the data agree that access is most constrained. In the model, this shows up as very large interest rate differentials, well above the data, while in the data this can be seen in very high denial rates, above the model's predictions. Summarizing, the count-based denial measures are not comparable one-to-one between the model and the data, but on the economically meaningful margins, who pays more and who borrows less when constrained, the SCF and the model tell a consistent story: riskier, poorer households are the constrained ones.

Table 5: Denial rates and denied-minus-not-denied differentials by income tercile in the model and the data.

	Data		Benchmark	
	College	High School	College	High School
Panel A: Unconditional denial/constrained rate (%)				
1st tercile	25.5	30.2	14.8	27.2
2nd tercile	17.8	39.0	14.5	26.7
3rd tercile	9.0	26.1	0.4	2.7
Panel B: Conditional denial rate (%)				
1st tercile	34.2	42.2	19.6	30.9
2nd tercile	25.9	44.3	46.5	51.0
3rd tercile	15.5	29.6	77.4	84.4
Panel C: Interest rate differential (denied minus not-denied, pp)				
1st tercile	2.0	2.8	37.1	26.2
2nd tercile	2.6	2.8	6.8	7.5
3rd tercile	2.2	1.9	0.6	0.7
Panel D: Debt-to-income differential (denied minus not-denied, pp)				
1st tercile	0.4	2.4	10.0	5.4
2nd tercile	4.4	1.0	1.5	1.0
3rd tercile	3.7	2.5	0.0	-0.1

Note: Denied means turned down or given less credit than requested; *constrained* also counts discouraged households (those who considered applying but did not, fearing denial). Panel A is unconditional: in the data the share of all households that are constrained, and in the Benchmark, which has no discouragement margin, a pure denial rate. Panel B is the denial rate conditional on applying, computed in the data among revolvers (households carrying a balance). Panels C and D report the denied-minus-not-denied differentials in the interest rate and in debt-to-income, among applicant revolvers, where *denied* is the model's high markup contract and *not denied* the search market contract; the underlying levels are in Table 7. In the aggregate the unconditional rate is 17.4% (Benchmark) versus 27.3% (data) and the rate conditional on applying is 39.1% (Benchmark) versus 33.4% (data revolvers); the Benchmark figure is the per-offer probability of acquiring an account, used for the entry cost κ in Appendix A.2. Data are simple averages across the 2001 and 2004 SCF, household-weighted.

4 Interest Rate Caps

As discussed above, the Benchmark model implies pricing that is linked not only to default risk, but also to households' outside options, which in turn are a function of the distribution of contracts in the market. Intuitively, this can have significant implications for the impact of regulation or policies that limit markups of the lenders, even if the regulation directly applies to only a small number of contracts. The baseline distribution of offered rates in the Benchmark, which tracks the data far more closely than the alternative models (Figure 6, panel (b)), places close to 30% of contracts above a 15% threshold; a partial equilibrium reading would count these as directly constrained, with the cap likely rendering them unprofitable and reducing credit access. When the general equilibrium effects are strong, however, the whole distribution of offered rates

shifts in response: in the capped economy only about a fifth of contracts end up at the 15% cap (Figure 6, panel (a)), the rest repriced below it rather than shut down, with potentially large effects on aggregates. This repricing is a feature of the Benchmark's outside option: in the No Outside Option model the rate distribution barely shifts, the contracts above the cap simply bunching at it, so the partial equilibrium reading is close to right.

In this section, we illustrate this point by considering the effects of the introduction of universal interest rate caps. We vary interest rate caps from the baseline value of 100%, i.e., virtually not binding, which we take as the current state of affairs in the US, to a much tighter level of 15%, and additionally consider an extreme cap of 10%. We discuss the aggregate effects of introducing this policy, as well as the effect on the distribution of interest rates, focusing on the Benchmark and NOO models in order to highlight the role of the high markup outside option in an otherwise similar search-based framework. Then, we discuss the impact of rate caps on policy functions and lenders' profits in order to identify the differential policy responses across these two models. Finally, we conduct counterfactual exercises to shed light on the mechanism behind the model's response, isolating in turn the effects of changing matching probabilities, and the indirect impact of changing the high markup outside option.

4.1 Impact of interest rate caps

Figure 3 presents the average interest rates, debt and fraction borrowing as a function of the interest rate cap. In the Benchmark model, limiting market power of lenders has a significant negative effect on the interest rates, but a significant *positive* effect on debt and fraction of households holding a balance. On the extensive margin, the fractions of households with high markup and with search market contracts both increase under the tighter cap (Figure 4, panel (b)). Both of these markets face more favorable pricing of debt (Figure 4, panel (a)), which explains why more households decide to borrow in equilibrium. Despite growing debt and the fraction borrowing, debt becomes safer in the Benchmark model: both the charge-off rate and the bankruptcy rate go down under tighter interest rate caps (Figure 5). The No Outside Option model behaves in the opposite way: contrary to the Benchmark model, debt and fraction borrowing actually *decline* in response to the tightening caps, falling from a debt-to-income ratio of 7.3% and a borrowing share of 47% absent a binding cap to 4.2% and 29% at the 20% cap, and further to 1.8% and 10% at

the 15% cap. The reason is that, without the high markup option, the general equilibrium effect of the cap is not strong enough to move the aggregate distribution; the tighter caps work mainly by limiting interest rates within matches, reducing the efficiency of the match and eventually making an increasing fraction of them unprofitable, which reduces credit access. This can be seen by calculating the fraction of interest rates *at cap*, presented in panel (a) of Figure 6. The interest rate cap binds for only a small fraction of contracts in the Benchmark model: about 0.2% of contracts are at the cap when it is set at 100%, rising to about 12% at the 20% cap and about 21% at the tightest 15% cap. By contrast, the NOO model implies that the 20% cap binds for about 65% of contracts, climbing to about 94% at the 15% cap. So even though close to 30% of contracts lie above the 15% cap in the baseline distribution (panel (b) of Figure 6), *in equilibrium* only about a fifth are at the cap in the Benchmark: rather than bunching at the ceiling, much of the affected mass is repriced to strictly below the cap, reflecting large general equilibrium shifts in the entire interest rate distribution. The NOO model's predictions come much closer to a partial equilibrium interpretation of the response, implying a binding pattern consistent with the initial distribution in Table 4 and not moving much below the cap.

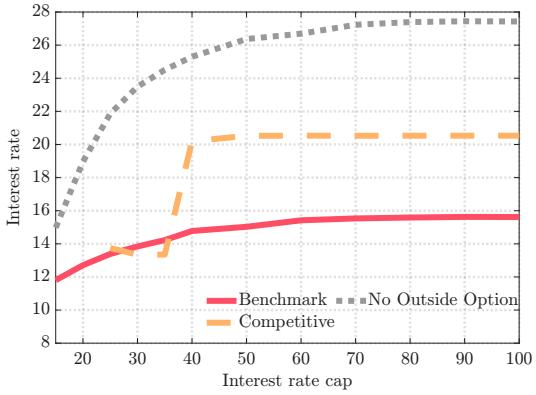
This intuition is confirmed by looking at the response of the entire interest rate distribution to the caps, presented in Figure 7. We can see that the whole distribution of offered interest rates shifts down in response to the cap in the Benchmark model, even though the cap does not directly bind for the majority of the contracts: the 90th percentile of the interest rate distribution is below the cap until the cap falls to about 33%. This illustrates the pure outside-option effect of regulating a small number of high-interest contracts: the fact that with positive probability the household may be directly affected by the cap *in the future* changes the contract received today. This is also reflected in Figure 4, panel (a): both the high markup and search market average interest rates go down significantly in response to the cap. In the NOO model, by contrast, the tightening cap has very little effect except at the very top of the distribution (Figure 7, panel (c)), confirming that this general equilibrium pass-through operates through the high markup outside option.

The increased access to cheaper credit in the Benchmark model results in significant welfare gains, measured as lifetime consumption equivalent variation. Figure 8 presents the welfare gain/loss by income for each of the education groups in the model, evaluated at initial zero debt.[26]

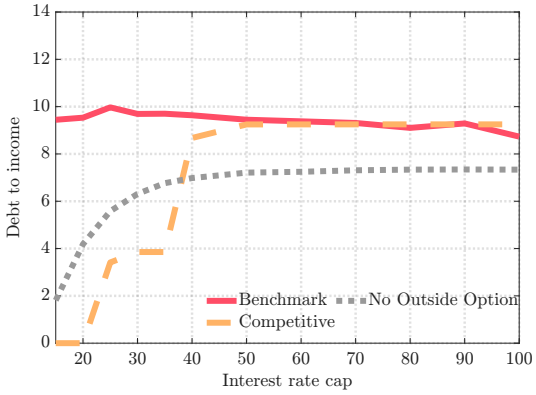
[26]We use income relative to the median for each of the groups in order to be able to express them on the same

Figure 3: Average interest rate, debt, and fraction borrowing under different interest rate caps.

(a) Average interest rate



(b) Debt-to-income



(c) Fraction of borrowers

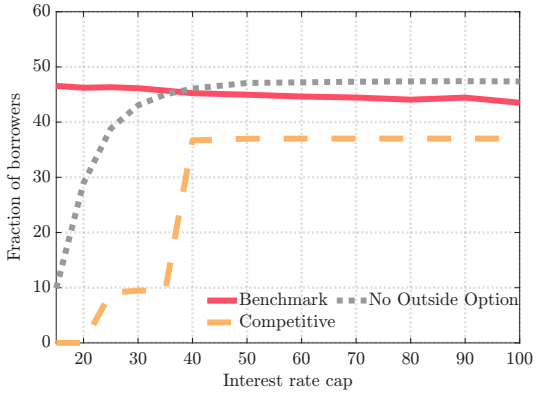
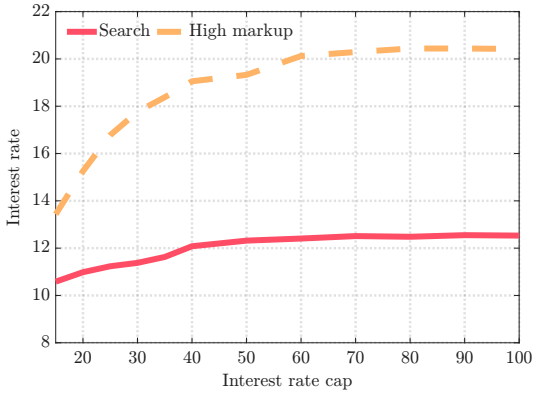


Figure 4: Submarket interest rates and contract shares under different interest rate caps.

(a) Search Market and High Markup Market



(b) Fraction with High Markup and Competitive Search contracts

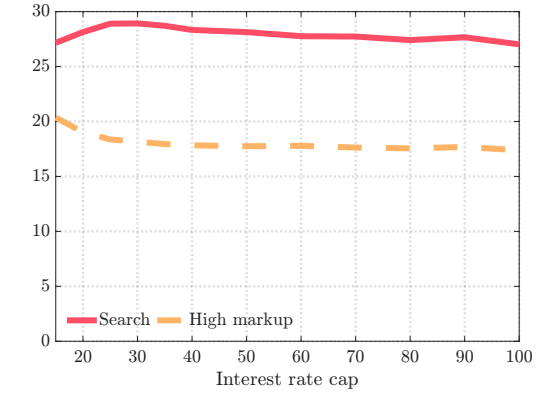
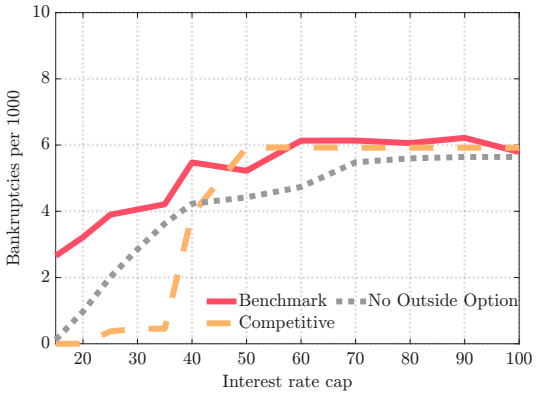


Figure 5: Bankruptcy rates and charge-off rates under different interest rate caps.

(a) Bankruptcies per 1000



(b) Charge-off rate

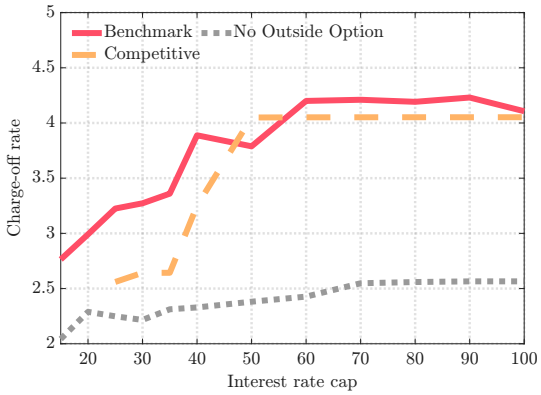
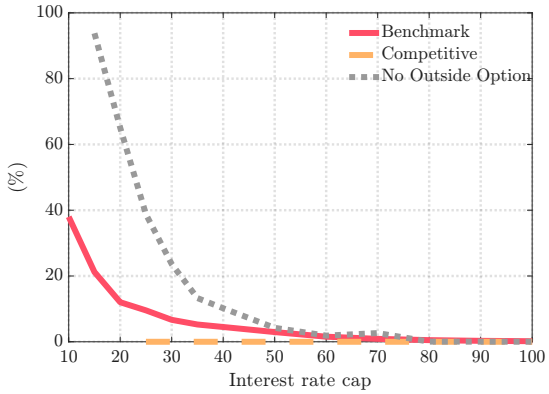


Figure 6: Fraction of interest rates at the cap and above the cap under different interest rate caps.

(a) At the cap in each cap economy



(b) Above the cap in the baseline calibration

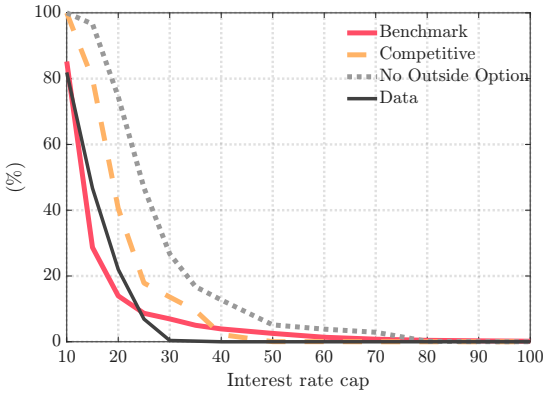
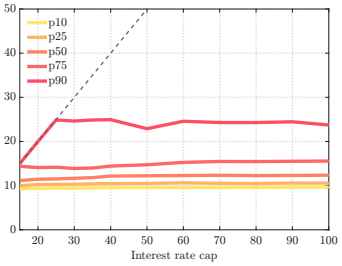
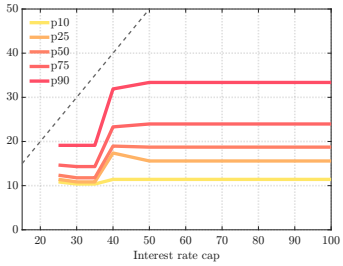


Figure 7: Percentiles of interest rate distribution under different interest rate caps.

(a) Benchmark Model



(b) Competitive Model



(c) NOO Model

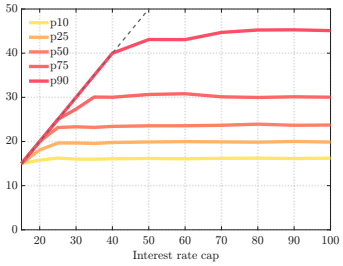
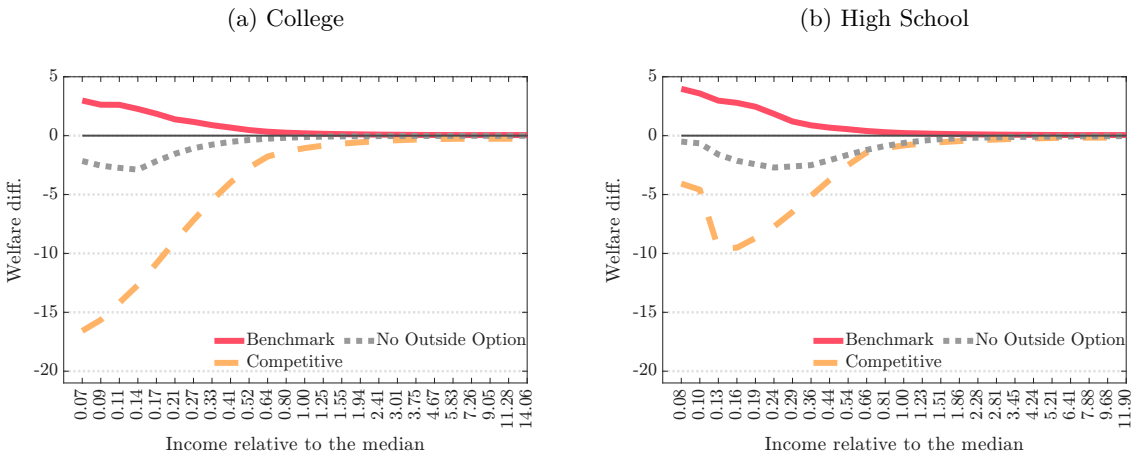


Figure 8: Welfare gain/loss under a 20% interest rate cap relative to the benchmark, as a function of income (relative to the group-specific median).



The welfare gain in the Benchmark model is as high as about 3% (College) and 4% (High School) of lifetime consumption for the lowest incomes, and around 0.2% for the median-income household in both groups. By contrast, the reduced credit access in the No Outside Option model results in a welfare loss for the median-income household of about 0.1% for College and 0.6% for High School.[27]

The interest rate caps affect the two education groups differently in terms of debt and bankruptcy, as presented in Figure 9. For the *High School* group, the preferred 20% cap leaves debt and the fraction borrowing little changed (debt/income from 11.1% to 11.1%, the fraction borrowing from 47.7% to 49.5%) while nearly halving the bankruptcy rate, from 7.7 to 4.0 per thousand, and lowering the group's average interest rate from 16.5% to 13.3%. The *College* group gains most on the debt margin, with debt/income rising by about 22% (from 6.8% to 8.3%) and the fraction borrowing by about 14% (from 34.2% to 38.8%), its bankruptcy rate essentially unchanged (1.55 to 1.53 per thousand), and its average interest rate falling from 12.8% to 10.9%.

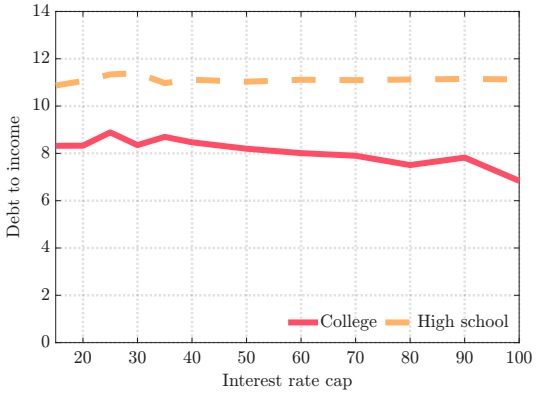
Competitive model's response Finally, for comparison, the aggregate figures also present the prediction of the Competitive model in response to interest rate caps. In the Competitive model, both interest rates and debt barely respond to the interest rate caps initially, followed by a drop in both and then a shutdown of the debt market. Unlike the Benchmark, whose high markup contracts extend to very high rates (2.5% of its contracts carry rates above 50%), the Competitive

axis.

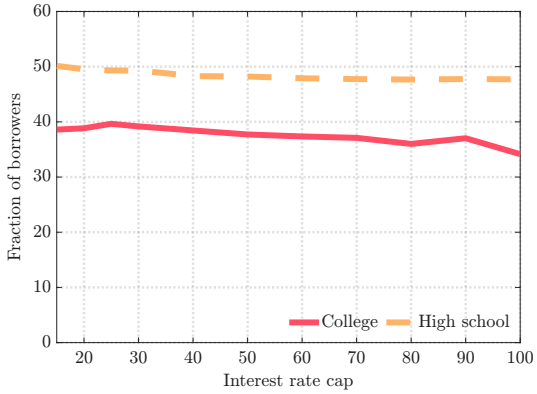
[27] The welfare gain/loss values for a broad set of caps are reported in Table 6.

Figure 9: Debt and default by education group under different interest rate caps.

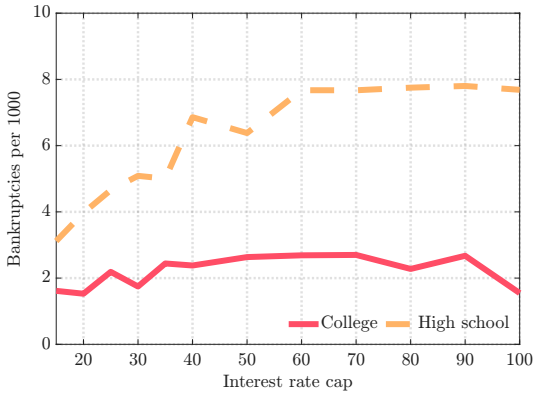
(a) Debt-to-income



(b) Fraction of borrowers



(c) Bankruptcies per 1000



model prices essentially no contracts above 50% (0.04%), and hence initially the tightening cap has little effect. However, when it starts binding for more contracts, markets actually close down, as more constraints render more households unprofitable and there are no markups to cushion the cap tightening. The tightening of the upper bound of the interest rate distribution then mechanically corresponds to an increase in the lower percentiles, contrary to the Benchmark model. Because profits in the Competitive model are brought down to break-even by competition, a binding cap results in households being cut off from credit entirely, with a welfare loss of up to about 17% of lifetime consumption for the poorest households (Table 6). The contrasting predictions of the two models fit into two narratives of the proposed policy: one, supported by the Competitive model, in which regulating interest rates makes credit cards unprofitable and cuts households off from credit; and another, supported by the Benchmark model, in which markups are high and regulating interest rates makes borrowing cheaper and increases access to credit.

Table 6: Welfare effects of interest rate caps.

	College			HS		
Cap (%)	Benchmark	NOO	Competitive	Benchmark	NOO	Competitive
Lowest income						
10	0.36	-2.38	-16.58	-21.05	-0.51	-4.07
15	3.02	-2.34	-16.58	2.94	-0.51	-4.07
20	2.98	-2.16	-16.58	3.98	-0.51	-4.07
25	2.90	-1.94	-10.97	4.00	-0.49	-4.07
30	2.48	-1.67	-10.78	3.48	-0.46	-4.07
40	1.53	-1.33	-9.48	2.17	-0.38	-3.33
50	0.99	-0.89	0.00	1.52	-0.28	-2.70
60	0.59	-0.51	0.00	0.94	-0.20	-2.11
80	-0.19	-0.04	0.00	0.26	-0.10	-0.91
90	-0.35	-0.00	0.00	0.18	-0.03	-0.91
Median income						
10	0.01	-0.53	-1.06	-1.39	-0.89	-0.83
15	0.15	-0.30	-1.06	0.21	-0.89	-0.83
20	0.20	-0.12	-1.06	0.22	-0.62	-0.83
25	0.23	-0.05	-0.13	0.26	-0.37	-0.83
30	0.20	-0.02	0.00	0.23	-0.21	-0.83
40	0.14	-0.01	0.00	0.09	-0.06	-0.05
50	0.08	-0.00	0.00	0.06	-0.02	-0.01
60	0.05	-0.00	0.00	0.03	-0.01	-0.00
80	0.02	0.00	0.00	0.00	-0.00	-0.00
90	-0.00	0.00	0.00	0.00	0.00	-0.00

Can the cap be too tight? The welfare gains are not monotonic in the cap. Table 6 shows the Benchmark's gains peaking at caps between 15 and 20% for the lowest incomes and between 15 and 25% for the median, while at a 10% cap Tables 8 and 9 show aggregate debt collapsing from its 9.5% level at the 20% cap to 4.0% and the High School market closing almost entirely, so that the Benchmark itself turns to welfare losses for that group (about 1.4% for the median High School household, more for the poorest), and the College gains largely vanish. Set tightly enough, a cap eventually renders most contracts unprofitable and shuts the market down even in the Benchmark, in which case even that model implies losses.

4.2 The contract-level pricing mechanism: outside options and pass-through

In this section, we analyze the mechanism at the level of the individual contract. We focus on how equilibrium contracts are shaped by outside options, and then show their response to a tightening cap. To that end, we plot the policy functions for offered interest rates, debt and profits, as well as default policy and matching probabilities for the Benchmark and NOO models. Throughout, we show policy functions for a borrower in the 15th percentile of the income distribution, for different levels of current debt b.

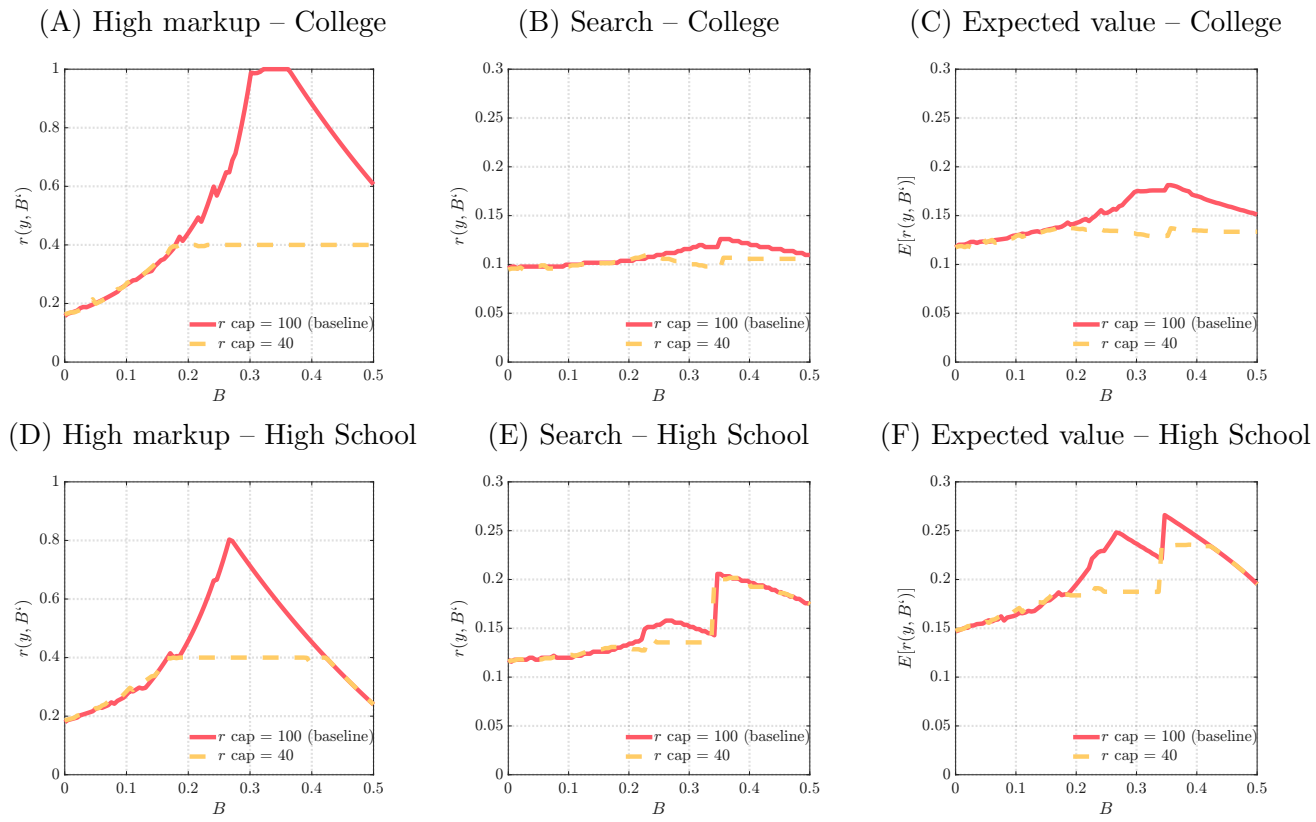
Figure 10 presents Benchmark interest rates. Several things immediately stand out. First, in Panels A and D, the high markup contracts are clearly constrained by the outside options of the household. For low b borrowers, the binding outside option is to stay out of debt and save, so the household will accept only a low rate and the high markup rate is correspondingly low. As b increases, the value of borrowing rises and with it the maximum rate the household is willing to accept, so the rate increases, up to the point where the household would rather default than repay. Beyond that point the binding outside option becomes default, and keeping the household willing to borrow requires a lower rate the larger is b. The high markup rate is therefore hump-shaped in b, low at both ends and highest in the intermediate range of debt. Second, a tightening cap lowers not only the high markup interest rates, but also the competitive search interest rates (Panels B and E), even though those interest rates are well below the cap. As a result, a tightening cap significantly reduces the expected interest rates in equilibrium (Panels C and F).

Figure 11 presents Benchmark loan levels. Interestingly, the lower interest rates in equilibrium are also accompanied by mostly *increased* loan sizes, mostly for the high markup contracts (Panels

A and D). These lower interest rates and higher borrowing correspond to lower realized ex-post profits, shown in Figure 12. How can lower offered interest rates be consistent with profit maximizing behavior and why do markets not close? Figures 13 and 14 provide an explanation. In the Benchmark model, lower rates and higher debt levels are associated with *significantly lower* default probability, especially for the *High School* group, and at the same time, increased probability of matching with a borrower for most borrowing levels. Intuitively, this is driven by the existence of an outside option *in the future*: having a possibility of borrowing from a high markup lender *tomorrow* means the borrower will be offered a value larger than or equal to the value of default and hence stay out of bankruptcy. For the lender *today*, this means the ability to offer lower rates without cutting lending, because the lower default probability allows for this more favorable pricing without negative expected profits.

This point is clear from the comparison of the policy functions of the Benchmark and NOO models. In the NOO model, interest rates also drop in response to the introduction of the cap (Figure 15), but that is accompanied by a *drop* in borrowing (Figure 16). That is the way the NOO model response ensures the bankruptcy rate drops (Figure 13, Panels C and F), although that drop is much smaller in the NOO model. As a result, profits drop by less in the NOO model (Figure 12), and the probability of finding a borrower actually barely moves.

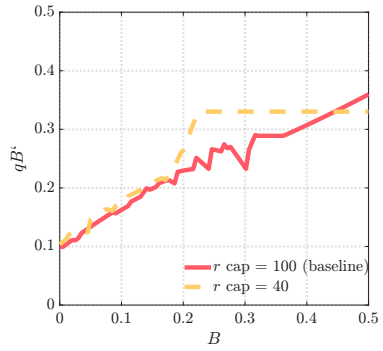
Figure 10: Contract interest rates for different levels of current debt (15th percentile of the income distribution).



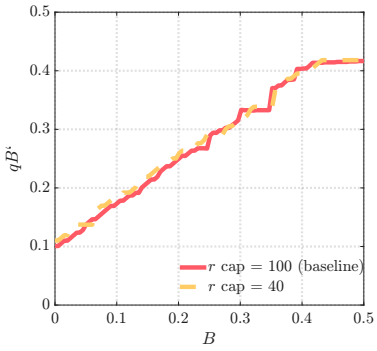
The pricing schedules just discussed are reflected in higher consumption for households who roll over their debt, which helps account for the welfare gains in the model with market power. When we plot $q\,b'$, the effective amount of spendable resources the household receives, we see that, under the high markup contract, the interest rate caps produce a substantial increase. Because the caps also affect the search contracts, the consumption of households under those contracts increases as well (Figure 11). This does not happen when there is no outside option; in that case, borrowing even gets reduced in some places, because otherwise default on debt becomes more likely (Figure 16).

Figure 11: Contract loan sizes for different levels of current debt (15th percentile of the income distribution).

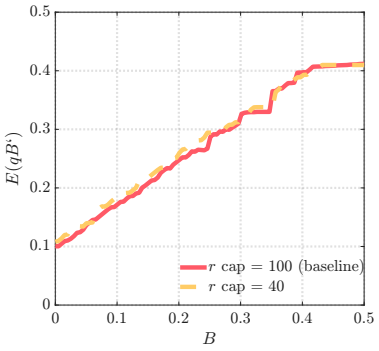
(A) High markup – College



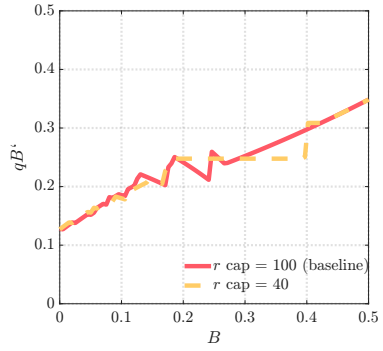
(B) Search – College



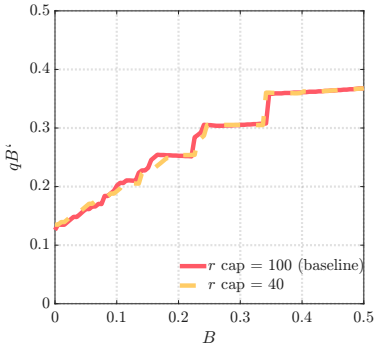
(C) Expected value – College



(D) High markup – High School



(E) Search – High School



(F) Expected value – High School

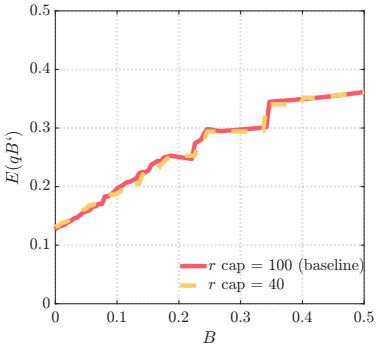
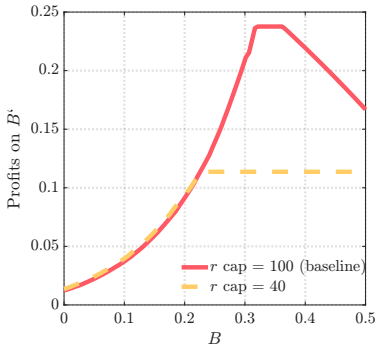
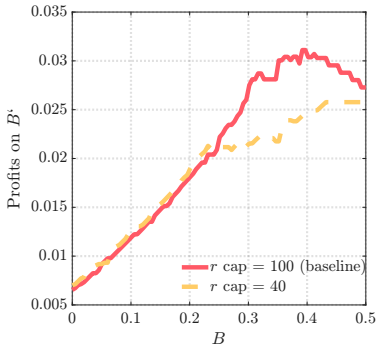


Figure 12: Profits for different levels of current debt (15th percentile of the income distribution).

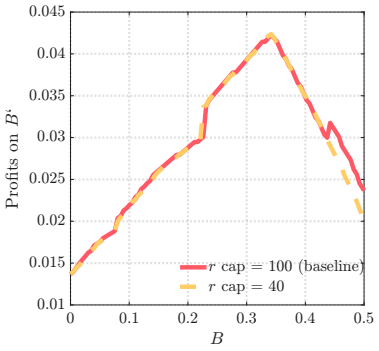
(A) High markup – College



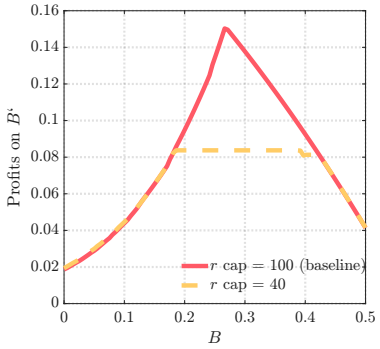
(B) Search – College



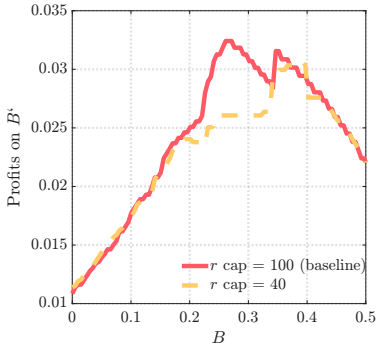
(C) No-Outside – College



(D) High markup – High School



(E) Search – High School



(F) No-Outside – High School

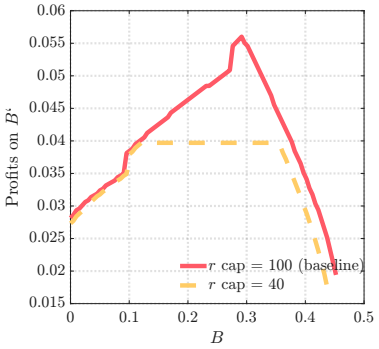
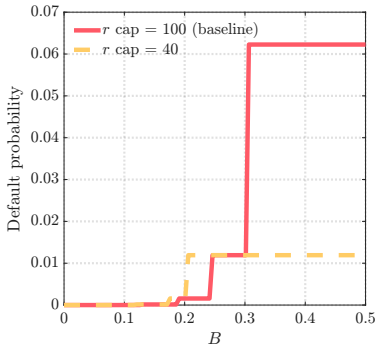
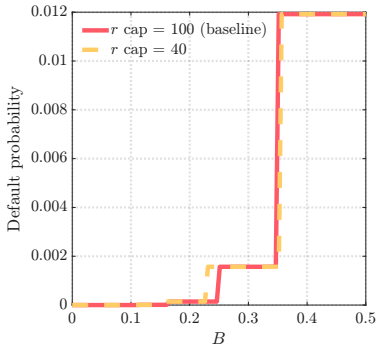


Figure 13: Default probability for different levels of current debt (15th percentile of the income distribution).

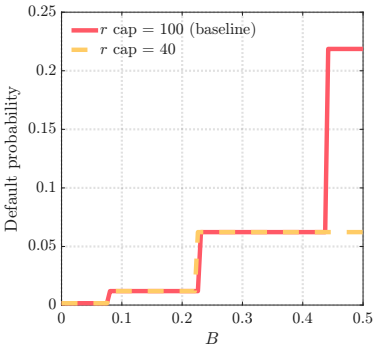
(A) High markup – College



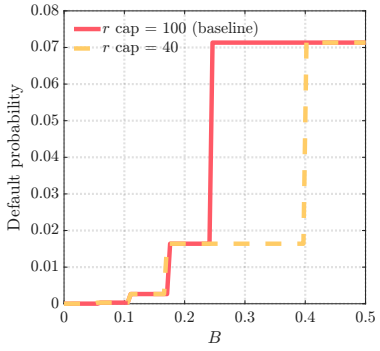
(B) Search – College



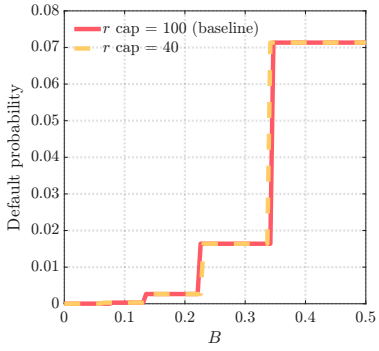
(C) No-Outside – College



(D) High markup – High School



(E) Search – High School



(F) No-Outside – High School

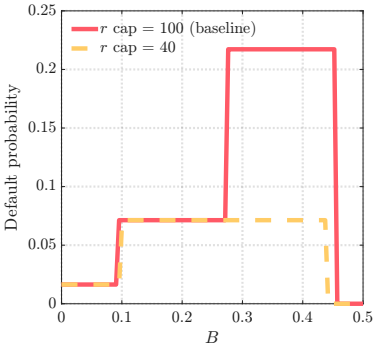


Figure 14: Probability of finding a borrower for different levels of current debt (15th percentile of the income distribution).

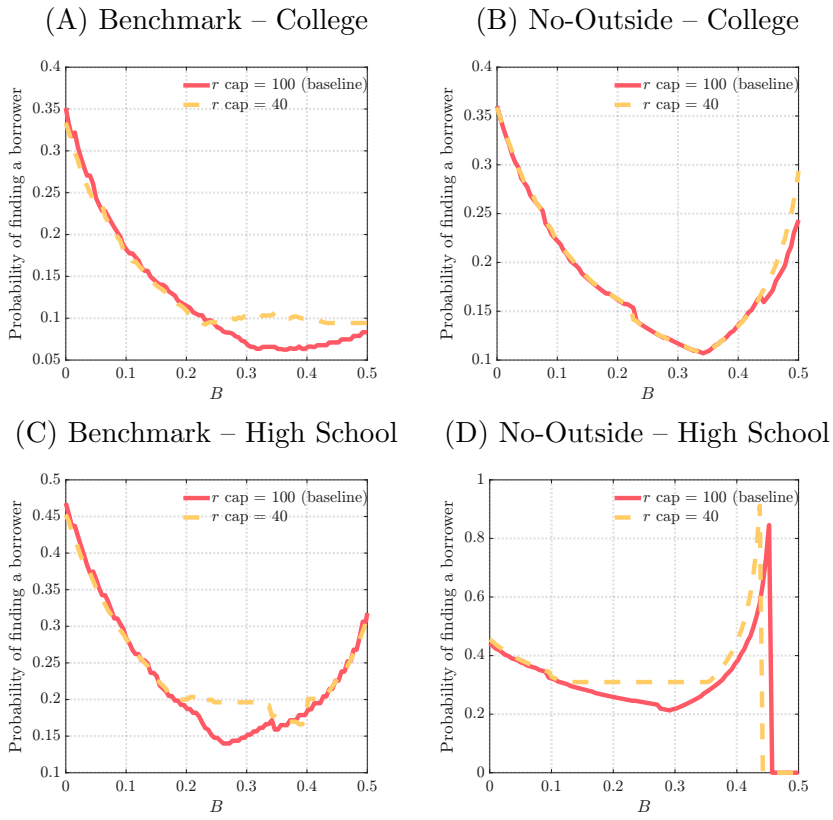


Figure 15: Contract interest rates for different levels of current debt in the No Outside Option model (15th percentile of the income distribution).

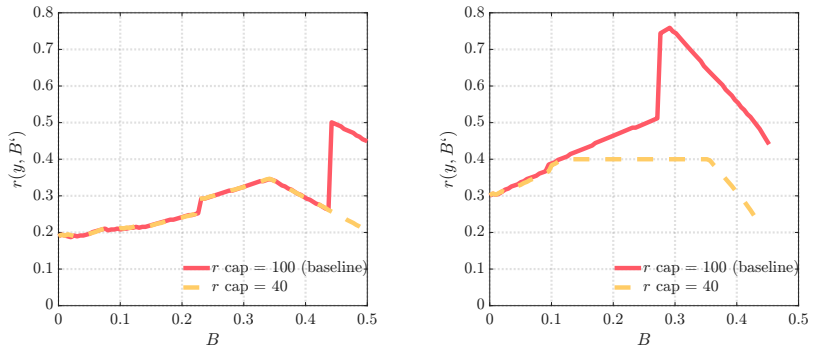
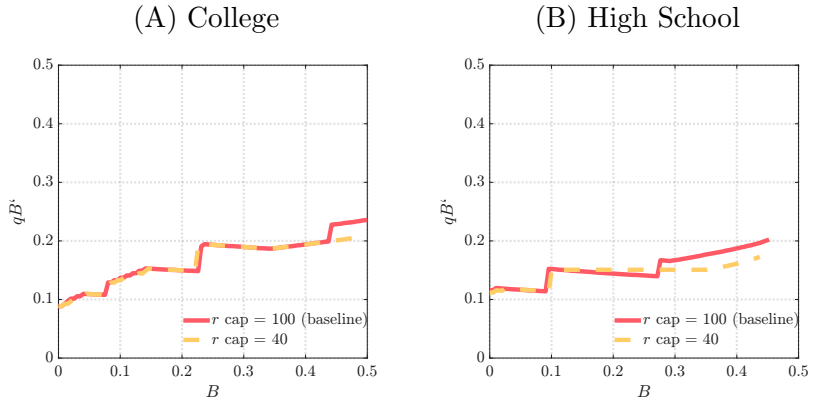


Figure 16: Contract loan sizes for different levels of current debt in the No Outside Option model (15th percentile of the income distribution).



4.3 Mechanism decompositions

The previous sections argued, qualitatively, that the Benchmark economy's response to interest rate caps works through the general equilibrium adjustment of households' outside options. This section sheds light on that mechanism and measures its quantitative bite, by isolating the channels through which the cap operates. The first is an *extensive* margin: a household matches in the competitive search market with probability $\alpha_H(\theta_x)$ and otherwise, with probability $1 - \alpha_H(\theta_x)$, is allocated the high markup contract, so the policy can reshuffle borrowers across the two contracts. The second is a *pricing* margin within the search market: since the value of a search contract is measured relative to the high markup outside option V^{HM} (equation (4)), a cap that lowers high markup rates raises V^{HM} and pulls search rates down even where they already lie below the cap. The two exercises below address each margin in turn: the first holds the matching probabilities at their baseline values, shutting off the extensive margin, and the second decomposes the resulting aggregate response into the contributions of the two contract types. They show that the reallocation of borrowers across contracts matters little, and that the response arises overwhelmingly on search market contracts, which the cap mostly does not constrain directly: the indirect, outside-option pricing channel accounts for the bulk of the aggregate response.

Effects of matching probabilities The Benchmark response to the cap involves changes in the equilibrium matching probabilities, and hence in the fractions of borrowers obtaining the search versus the high markup contract. If the chance of matching in the search market, $\alpha_H(\theta_x)$, rises

with the policy, households are less likely to be pushed into the more expensive high markup contract, and this reallocation could by itself deliver cheaper credit and more borrowing in the aggregate. To gauge the strength of this extensive margin, we solve the Benchmark model in full under the cap, so that all contracts, prices, and policy and value functions respond to the policy, but in the simulation we replace the equilibrium matching probability function α_H with its baseline counterpart. Households therefore face the full equilibrium contracts and prices, while the rate at which they are sorted into the search versus the high markup contract is held at its baseline level, which switches off the extensive margin. Figure 17 reports the result, with panel (a) for the debt-to-income ratio and panel (b) for the fraction of borrowers, comparing the actual Benchmark economy with this fixed-α_H simulation. The two are almost identical, which implies that changes in the matching probabilities, that is in $1 - \alpha_H$, are not a significant driver of the response; the aggregate effect is driven almost entirely by the pricing of contracts within markets.

Direct versus indirect effect of high markup option Having shown that the reallocation of borrowers across markets matters little, we now ask where the credit expansion takes place. The direct effect of the cap falls on the high markup contracts it binds. The indirect effect is the channel highlighted in Section 4: capping high markup rates raises the outside option V^{HM} in equation (4), and search market lenders respond by lowering rates even on contracts below the cap. To separate the two, we return to the fixed-α_H simulation of Figure 17 and split total debt and the number of borrowers by contract type. The two contributions sum to the aggregate response. Since sorting is fixed at its baseline probabilities, the high markup contribution captures the direct effect of the cap, and the search contribution captures the indirect repricing channel.[28] Figure 18 reports the decomposition, with panel (a) for the debt-to-income ratio and panel (b) for the fraction of borrowers. The high markup contribution is nearly flat across caps. At the 20 percent cap, search contracts account for about 85 percent of the increase in the debt-to-income ratio and about 90 percent of the increase in the fraction borrowing. Their share exceeds 80 percent for both responses at all caps of 25 percent and below. We conclude that the credit expansion occurs overwhelmingly on contracts that the cap does not directly constrain. The general equilibrium repricing of households' outside options, not the direct effect of the cap or the reallocation of

[28] At tight caps some search contracts are themselves at the cap (Figure 6(a)), so the search contribution includes a small direct component, bounded by the at-cap fractions.

Figure 17: Economy response under interest rate caps: Benchmark versus fixed matching probabilities (α_H).

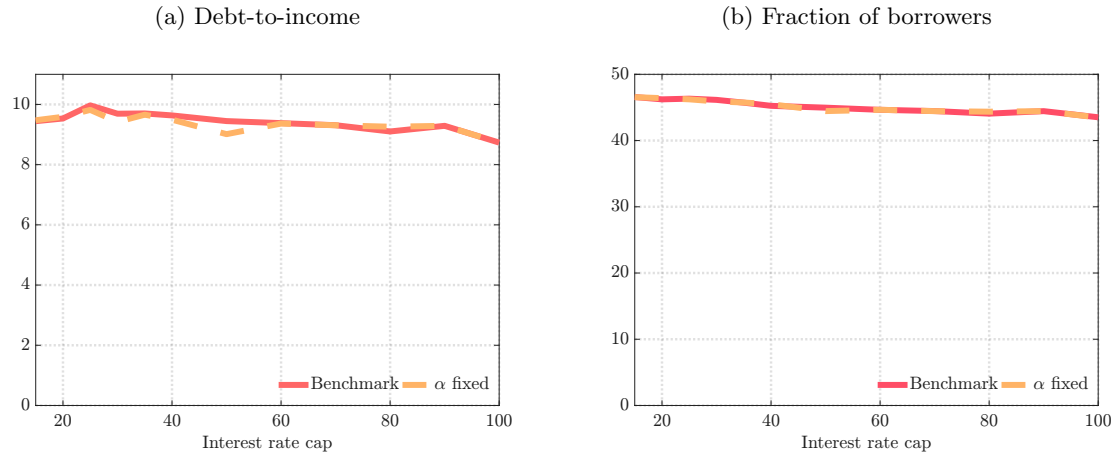
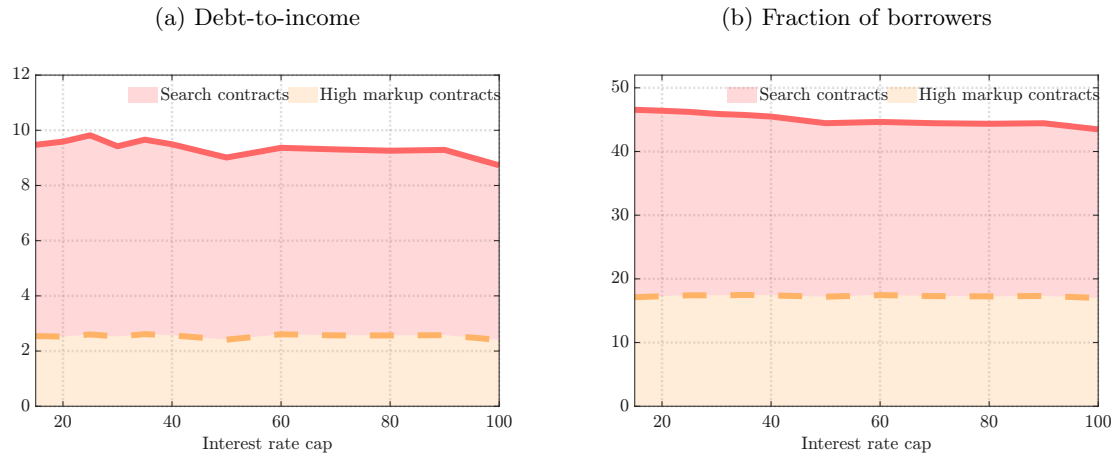


Figure 18: Economy response under interest rate caps: contributions of search and high markup contracts, holding matching probabilities (α_H) fixed at their baseline values.



borrowers across markets, accounts for the bulk of the aggregate response to the policy.

5 Conclusions

We propose a mechanism in which market power emerges due to search and matching frictions in the credit market where a high markup outside option is available. When embedded in a quantitative dynamic model, the mechanism delivers aggregate statistics, interest rates, and a profitability distribution consistent with the data. We show that the Benchmark model outperforms the No Outside Option model as well as the Competitive model. The parameterized model implies

strong general equilibrium effects of households' outside options driving the distribution of offered rates. In the context of a policy limiting market power of lenders in the form of interest rate caps, we show that in the Benchmark model, these general equilibrium effects are responsible for the majority of the aggregate response, and imply increased and cheaper access to credit for all households, as well as lower bankruptcy and charge-offs. The regulation implies significant welfare gains, especially for the poorest households. Our conclusions are in stark contrast to those implied by the Competitive and No Outside Option frameworks, in which the same interest rate cap implies *reduced* access to credit and welfare losses. Our research offers a tool for capturing the aggregate effects of regulation aimed at a small proportion of contracts, as it captures the equilibrium effects these contracts have on the entirety of the interest rate distribution. Although we take the model to the US unsecured consumer credit market, where borrowing is predominantly through credit cards, the mechanism is not specific to it: it applies to any credit market in which rolling over debt and maintaining continued access to future borrowing is important, since it is the value of that future access that disciplines the terms a household is offered today. The forces we identify, and the general equilibrium response to interest rate regulation they generate, therefore extend beyond consumer credit.

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A Empirical Support for the Calibration

This appendix collects two pieces of empirical material supporting the calibration of Section 3: the construction of the interest-rate distribution used as a calibration target (Section A.1), and an assessment of the dollar magnitude of the entry cost κ (Section A.2).

A.1 Stango–Zinman account panel: interest rate measure and distribution

We use data used by Stango and Zinman (2016) and shared with us, to characterize the cross-section of interest rates paid by borrowers (referenced in Section 3.1). The file is an account-month panel covering January 2006 to December 2008, with up to 36 consecutive monthly observations per account. Each row records the purchase annual percentage rate (APR), whether that APR is a promotional rate, the account's average monthly balance, the panelist (individual) identifier, the account identifier, and the panelist's self-reported education.

Sample restriction. We keep account-months that meet two conditions: (i) the APR is not a teaser or promotional rate (teaser = 0) and (ii) the account carried a positive balance from the previous month (revolving = 1). This isolates the rates that borrowers actually pay interest on. We retain rows with non-missing APR and non-missing average monthly balance. The resulting sample contains 11,031 panelists, of whom 6,369 are in the High School group and 4,662 in the College group, as defined next.

Education groups. The survey item records the highest level of education completed in seven categories. Consistent with Section 3.1, we assign panelists to the College group if they report a four-year college degree or a graduate degree (categories 6 and 7) and to the High School group otherwise (categories 1 through 5).

Person-level balance-weighted interest rate. For each panelist i, let S_i denote the set of account-months that survive the sample restriction. We define

$$\bar{r}_i \;=\; \frac{\sum_{(c,t)\in S_i} r_{c,t}\, B_{c,t}}{\sum_{(c,t)\in S_i} B_{c,t}}, \tag{11}$$

where $r_{c,t}$ is the purchase APR on account c in month t and $B_{c,t}$ is its average monthly balance. By construction, $\bar{r}_i$ is the dollar-weighted average rate that panelist i paid on revolving balances during the sample. Panelists whose summed balance is zero across all eligible account-months are dropped, since $\bar{r}_i$ is undefined for them.

Table 4 in the main text reports the resulting cross-sectional distribution of $\bar{r}_i$, in the aggregate and by education group, alongside the model counterparts. Rates are expressed in real terms, deflating the nominal APRs by 3.31%, the average of the monthly year-over-year CPI inflation (FRED series CPIAUCSL) over January 2006 through December 2008.

A.2 The empirical magnitude of the entry cost κ

In our model the entry cost κ is the cost a lender incurs to post an offer of a one-period loan, paid whether or not the offer is taken up (the free-entry condition (5)). It is most naturally interpreted as the cost of acquiring a credit card customer: the marketing, solicitation, and origination outlays an issuer makes to bring a new account onto its books. Section 3.1 reports the implied dollar magnitudes of κ for the three models; this appendix documents the empirical benchmarks behind that comparison, assessing those magnitudes against two independent measures of the cost of acquiring a US credit card customer over our calibration period.

From κ to dollars. As reported in Section 3.1, we map one unit of model income to average US per-capita personal income over 2001–2004, \$42,895.[29] This gives a per-offer cost $\kappa \times$ \$42,895 of about \$73, \$251, and \$784 in the Benchmark, No Outside Option, and Competitive models. The cost per account opened then depends on the matching structure. In the No Outside Option model every account is a search-market match, so the cost per account is the per-offer cost divided by the population-averaged match probability α_L,[30] about \$603; in the frictionless Competitive model $\alpha_L = 1$, so the per-account cost equals the per-offer cost, \$784. In the Benchmark, search-market offers cost κ each and match with probability α_L, while households that fail to match are served by the high markup lender at one further κ; averaging all entry spending over all opened accounts gives about \$142 per account, below the per-match search-market figure because the high markup

[29] Per capita is taken over the adult population aged 16 and over

[30] By the model's matching structure, this per-offer match probability equals the aggregate denial rate conditional on applying ($\alpha_L = 1 - \alpha_H$): 0.391 in the Benchmark and 0.416 in the No Outside Option model.

accounts are each opened at a single κ. The implied average balance per borrowing account is about \$9,994: the data revolving debt-to-income ratio of 9.24% times income gives \$3,963 per capita, which divided by the 39.66% of households that carry a balance yields the per-account figure the measures below use.

Marketing per open account. Drawing on regulatory account-level data covering more than 90% of the US credit card market together with bank-level Call Reports, Drechsler et al. (2025) find that credit card banks spend 1 to 2% of their assets on marketing each year, an order of magnitude more than other commercial banks; since receivables are the bulk of these banks' assets, we read this as a marketing flow of 1 to 2% of balances. Applied to the average balance, this is a marketing cost of about \$100 to \$200 per open account per year. Because matches in our model last one period, so that every account is effectively re-acquired each period, this per-open-account annual flow is the natural counterpart to the model's per-period entry cost.

Issuer marketing and rewards per new card. As an external check resting only on issuer disclosures, we use American Express, the one major issuer reporting both a standalone marketing expense and a gross count of new cards acquired. It began disclosing "proprietary new cards acquired" only in its 2024 Form 10-K, covering 2022–2024 (American Express Company (2024)). Earlier filings bundled the marketing line with promotion, business development, or rewards, so the measure cannot be reproduced nearer the calibration window. Dividing marketing by new cards gives a marketing-only lower bound (\$437 per card in 2022, \$465 in 2024). Adding the average rewards sign-up bonus earned (\$326 in 2022 and \$311 in 2024, Consumer Financial Protection Bureau (2025)) gives a marketing-plus-bonus measure (\$763 and \$776). Adding instead all card member rewards, which accrue to the whole cardholder base and so overstate the per-new-card figure, gives an *upper* bound (\$1,557 and \$1,741). Deflated to 2004 dollars using CPI inflation, these three figures are roughly \$282, \$492, and \$1,005 in 2022 and \$280, \$467, and \$1,049 in 2024, essentially unchanged across years. On a per-new-card, up-front basis, the cost of acquiring a card is marketing plus the one-time sign-up bonus, about \$280 to \$490. The full card-member rewards expense, which raises the figure above \$1,000, is a recurring cost proportional to balances and spending, and in our model corresponds to the transaction cost τ rather than the up-front cost κ.

B Additional Tables

B.1 Interest rates and debt-to-income by income tercile

Table 7: Interest rate and debt-to-income levels by income tercile, denied versus not denied, in the model and the data.

	Data		Benchmark	
	College	High School	College	High School
Panel A: Interest rate, denied (%)				
1st tercile	11.7	13.2	48.1	41.2
2nd tercile	10.4	12.9	15.7	18.2
3rd tercile	9.7	11.0	9.0	11.0
Panel B: Interest rate, not denied (%)				
1st tercile	9.7	10.5	11.0	15.0
2nd tercile	7.8	10.0	9.0	10.7
3rd tercile	7.5	9.1	8.4	10.3
Panel C: Debt-to-income, denied (%)				
1st tercile	16.1	20.3	65.1	62.8
2nd tercile	11.2	11.5	20.3	25.2
3rd tercile	8.7	8.4	6.1	8.0
Panel D: Debt-to-income, not denied (%)				
1st tercile	15.7	17.9	55.1	57.4
2nd tercile	6.8	10.5	18.8	24.2
3rd tercile	5.0	5.9	6.1	8.1

Note: Interest rate and debt-to-income for denied versus not-denied households, conditional on applying and, in the data, among revolvers (households carrying a balance); denied is the model's high markup contract and not denied the search market contract. Interest rates are real, the nominal SCF APR deflated by 2.85%. Debt-to-income (net credit card debt over income) is the mean of household ratios for both the data and the Benchmark, with the data ratio winsorized at the 1st and 99th percentiles. Data are simple averages across the 2001 and 2004 SCF, household-weighted. The denied-minus-not-denied differentials are reported in Table 5.

B.2 Interest rate cap experiments

The following tables report the aggregate outcomes, education-group outcomes, and interest rate distributions under counterfactual interest rate caps of 10% and 20%, complementing the figures in Section 4. For each cap we report the same targeted and untargeted moments as Tables 2 and 3, along with the interest rate distribution reported in Table 4.

Table 8: Data and model outcomes with interest rate cap of 10%.

Targeted Moments:	Data 2000-04	Benchmark	No Outside Option	Competitive
Debt/Income %	9.24	3.99	0.00	0.00
Bankruptcies per 1000	5.82	0.17	0.00	0.00
Fraction with debt %	39.66	11.50	0.00	0.00
90th interest percentile %	23.80	10.00	–	–
Untargeted Moments:				
Average interest rate %	15.37	–	–	–
Charge-Off Rate %	4.90	–	–	–

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

Table 9: Data and model outcomes by education group, with interest rate cap of 10%.

Targeted Moments:	Data 2000-04		Benchmark		No Outside Option		Competitive	
	College	*HS*	*College*	*HS*	*College*	*HS*	*College*	*HS*
Debt/Income %	6.70	12.45	7.14	0.00	0.00	0.00	0.00	0.00
Bankruptcies per 1000	1.54	7.73	0.55	0.00	0.00	0.00	0.00	0.00
Fraction with debt %	39.41	39.77	37.24	0.00	0.00	0.00	0.00	0.00
Untargeted Moments:								
Average interest rate %	14.78	15.80	9.31	–	–	–	–	–
Charge-Off Rate %	4.90	4.90	2.20	–	–	–	–	–

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

C Computational Algorithm

Computing the high markup contract requires, for each candidate b', finding a price q that solves the Kalai surplus-splitting condition in (9). The following lemma shows that this inner subproblem has at most one solution, so a one-dimensional bisection in q for each b' suffices.

Lemma 1. *Fix (b, y) and $b' > 0$. If the Kalai surplus-splitting condition and both participation constraints in (9) admit a solution $q^{hm}(b'; b, y)$, it is unique and the market for b' is open. Otherwise the market for b' is closed and no contract with that b' is offered.*

Proof. Rearranging the Kalai surplus-splitting condition to collect the q-dependent terms on one side gives

$$\omega\, u(y - b + qb') + (1 - \omega)\, qb' \;=\; \bar{C}(b', y, b), \tag{12}$$

Table 10: Distribution of interest rates in the model and data, overall and by education group, with interest rate cap of 10% (in %).

Moments	p10	p50	p90	p95	Mean
All borrowers					
Benchmark	8.04	9.77	10.00	10.00	–
No Outside Option	–	–	–	–	–
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	8.24	14.65	23.80	25.80	15.37
College					
Benchmark	8.04	9.77	10.00	10.00	9.31
No Outside Option	–	–	–	–	–
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	7.95	13.93	23.12	25.59	14.78
High School					
Benchmark	–	–	–	–	–
No Outside Option	–	–	–	–	–
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	8.49	15.17	24.19	25.86	15.80

[a] Cross-sectional percentiles and mean of the person-level, balance-weighted average purchase APR on revolving, non-promotional accounts in the Stango and Zinman (2016) panel (January 2006 through December 2008), equally weighted across panelists, shown for all borrowers and separately for the College (four-year degree or higher) and High School groups. Expressed in real terms, deflating nominal APRs by 3.31%, the average of the monthly year-over-year CPI inflation (FRED series CPIAUCSL) over January 2006 through December 2008. See Appendix A.1 for construction.

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

Table 11: Data and model outcomes with interest rate cap of 20%.

Targeted Moments:	Data 2000-04	Benchmark	No Outside Option	Competitive
Debt/Income %	9.24	9.53	4.19	0.00
Bankruptcies per 1000	5.82	3.22	0.97	0.00
Fraction with debt %	39.66	46.22	28.93	0.00
90th interest percentile %	23.80	20.00	20.00	–
Untargeted Moments:				
Average interest rate %	15.37	12.71	18.96	–
Charge-Off Rate %	4.90	2.97	2.34	–

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

where

$$\bar{C}(b',y,b) \;:=\; \omega\Big(\max[V^S(b,y),V^D(y)]-\beta(1-\delta)\int_{y'\in Y}V_0(b',y')dG(y',y)\Big)+(1-\omega)\Big[\frac{\rho(b',y)b'}{1+r}-\kappa\Big].$$

For a borrowing contract, $b'>0$ and $u'>0$, so the LHS of (12) is strictly increasing in q and (12)

Table 12: Data and model outcomes by education group, with interest rate cap of 20%.

Targeted Moments:	Data 2000-04		Benchmark		No Outside Option		Competitive	
	College	*HS*	*College*	*HS*	*College*	*HS*	*College*	*HS*
Debt/Income %	6.70	12.45	8.33	11.06	4.69	3.54	0.00	0.00
Bankruptcies per 1000	1.54	7.73	1.53	3.97	0.70	1.09	0.00	0.00
Fraction with debt %	39.41	39.77	38.84	49.52	39.67	24.13	0.00	0.00
Untargeted Moments:								
Average interest rate %	14.78	15.80	10.89	13.34	17.59	19.97	–	–
Charge-Off Rate %	4.90	4.90	2.64	3.11	2.05	2.47	–	–

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

has at most one solution.

The two boundary cases pin down useful reference prices. At $\omega = 1$, (12) reduces to

$$u(y - b + qb') \;=\; \max[V^S(b,y), V^D(y)] - \beta(1-\delta)\int_{y'\in Y} V_0(b',y')dG(y',y),$$

which has a unique solution q^m, the household-indifference price used in the algorithm. At $\omega = 0$, (12) reduces to $qb' = \rho(b',y)b'/(1+r) - \kappa$, with unique solution

$$q^c \;=\; \frac{\rho(b',y)}{1+r} - \frac{\kappa}{b'}.$$

By definition of q^m and q^c we have $\bar{C}(b',y,b) = \omega\, u(y - b + q^m b') + (1-\omega)\, q^c b'$, so (12) can be rewritten as

$$\omega\big[u(y - b + qb') - u(y - b + q^m b')\big] + (1-\omega)(q - q^c)\, b' \;=\; 0. \tag{13}$$

Evaluating (13) at $q = q^m$ yields $(1-\omega)(q^m - q^c)b'$, with sign $\text{sgn}(q^m - q^c)$. Evaluating at $q = q^c$ yields $\omega\big[u(y-b+q^c b') - u(y-b+q^m b')\big]$, with sign $\text{sgn}(q^c - q^m)$. Combined with strict monotonicity of the LHS of (12), this yields three cases:

1. $q^m < q^c$. By the intermediate value theorem, there is a unique $q^{hm} \in (q^m, q^c)$ solving (12). At this price, the borrower surplus $u(y - b + q^{hm}b') + \beta(1-\delta)\int_{y'\in Y} V_0(b',y')dG(y',y) - \max[V^S(b,y), V^D(y)] > 0$ (since $q^{hm} > q^m$ and u is increasing), and the lender surplus $-q^{hm}b' + \rho(b',y)b'/(1+r) - \kappa = (q^c - q^{hm})b' > 0$. Both participation constraints hold and the market is open.

Table 13: Distribution of interest rates in the model and data, overall and by education group, with interest rate cap of 20% (in %).

Moments	p10	p50	p90	p95	Mean
All borrowers					
Benchmark	9.37	11.45	20.00	20.00	12.71
No Outside Option	15.77	20.00	20.00	20.00	18.96
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	8.24	14.65	23.80	25.80	15.37
College					
Benchmark	8.70	9.74	16.27	20.00	10.89
No Outside Option	14.81	17.81	20.00	20.00	17.59
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	7.95	13.93	23.12	25.59	14.78
High School					
Benchmark	10.18	11.81	20.00	20.00	13.34
No Outside Option	20.00	20.00	20.00	20.00	19.97
Competitive	–	–	–	–	–
Data Stango and Zinman (2016)[a]	8.49	15.17	24.19	25.86	15.80

[a] Cross-sectional percentiles and mean of the person-level, balance-weighted average purchase APR on revolving, non-promotional accounts in the Stango and Zinman (2016) panel (January 2006 through December 2008), equally weighted across panelists, shown for all borrowers and separately for the College (four-year degree or higher) and High School groups. Expressed in real terms, deflating nominal APRs by 3.31%, the average of the monthly year-over-year CPI inflation (FRED series CPIAUCSL) over January 2006 through December 2008. See Appendix A.1 for construction.

Note: "–" indicates that the corresponding credit market shuts down under the cap, so the statistic is not defined.

2. $q^m > q^c$. Any root of (12) lies in (q^c, q^m), in which case the borrower surplus is negative ($q < q^m$) and the lender surplus is negative ($q > q^c$). Both participation constraints fail, so no contract is offered and the market is closed.

3. $q^m = q^c$. The unique solution is $q^{hm} = q^m = q^c$, with both surpluses equal to zero.

□

Iteration scheme

We solve for the equilibrium by value-function iteration on (V_0, V_1, ρ). Let n index outer iterations and write $E[\cdot \mid y] \equiv \int_{y' \in Y} (\cdot)\, dG(y', y)$. Given $V_0^{(n)}(b, y)$, $V_1^{(n)}(y)$, and $\rho^{(n)}(b', y)$, one outer iteration consists of the following steps.

Step 1: outside-option values. Update the default value V^D from (3) and the saver value V^S from (2):

$$V^D(y) = u(y) - \Delta + \beta(1-\delta)\, E\Big[V_1^{(n)}(y') \,\Big|\, y\Big],$$
$$V^S(b,y) = \max_{b' \le 0} \left\{ u\left(y - b + \frac{b'}{1+r}\right) + \beta(1-\delta)\, E\Big[V_0^{(n)}(b',y') \,\Big|\, y\Big] \right\}.$$

Step 2: high markup contract V^{HM}. For each (b,y) and each candidate $b' > 0$:

(a) Compute the household-indifference price $q^m(b';b,y)$ as the unique root of

$$u(y - b + q^m b') \;=\; \max[V^S(b,y), V^D(y)] - \beta(1-\delta)\, E\Big[V_0^{(n)}(b',y') \,\Big|\, y\Big].$$

(b) Compute the zero-profit price $q^c(b';y) = \rho^{(n)}(b',y)/(1+r) - \kappa/b'$.

(c) By Lemma 1, if $q^m < q^c$ the high markup price $q^{hm}(b';b,y) \in (q^m, q^c)$ is the unique root of (12), found by bisection. If $q^m \ge q^c$, the market for that b' is closed.

Let $b'^{hm}(b,y) \equiv \arg\max_{b'} \left[-q^{hm}(b';b,y)\, b' + \rho^{(n)}(b',y) b'/(1+r)\right]$ over the open markets. Then

$$V^{HM}(b,y) \;=\; u\Big(y - b + q^{hm}(b'^{hm};b,y)\, b'^{hm}\Big) + \beta(1-\delta)\, E\Big[V_0^{(n)}(b'^{hm},y') \,\Big|\, y\Big].$$

If no $b' > 0$ admits an open market, $V^{HM}(b,y) = \max[V^S(b,y), V^D(y)]$.

Step 3: competitive-search contract V^B. For each (b,y), retain candidate contracts (b',q) with $b' > 0$ satisfying (i) lender entry feasibility,

$$-qb' + \frac{\rho^{(n)}(b',y) b'}{1+r} > \kappa,$$

and (ii) strict borrower participation, $v_x(q,b') > 0$, where v_x is defined immediately before (4). For each retained (b',q), free entry (5) pins down the matching probabilities:

$$\alpha_L(\theta_x(q,b')) = \frac{\kappa}{-qb' + \rho^{(n)}(b',y) b'/(1+r)}, \qquad \theta_x(q,b') = \left(\alpha_L^{-\gamma} - 1\right)^{-1/\gamma}, \qquad \alpha_H(\theta_x) = \left(1 + \theta_x^{\gamma}\right)^{-1/\gamma}.$$

Then, from (4),

$$V^B(b,y) \;=\; \max_{(b',q)} \Big\{ \alpha_H(\theta_x(q,b'))\, v_x(q,b') + V^{HM}(b,y) \Big\}.$$

If no (b',q) is retained, $V^B(b,y) = V^{HM}(b,y)$ and the search market is closed for type (b,y).

Step 4: aggregate value functions. From (1),

$$V_0^{(n+1)}(b,y) \;=\; \max\big[V^D(y),\; V^S(b,y),\; V^B(b,y)\big], \qquad V_1^{(n+1)}(y) \;=\; V^S(0,y).$$

Step 5: update repayment probability. From (6),

$$\rho^{(n+1)}(b',y) \;=\; (1-\delta)\left(1 - E\Big[\mathbf{1}\{V^D(y') > \max[V^B(b',y'), V^S(b',y')]\} \,\Big|\, y\Big]\right).$$

Convergence. Iterate Steps 1–5 until $\|V_0^{(n+1)} - V_0^{(n)}\|_\infty < \varepsilon$ and the policy indices for $b'^S(b,y)$, $(b'^*(b,y), q^*(b,y))$, and $b'^{hm}(b,y)$ are stable across consecutive iterations.

Competitive model. The Competitive model of Section 3.1 is solved by the same iteration scheme with three simplifications: Step 2 is dropped and $V^{HM}(b,y) \equiv \max[V^S(b,y), V^D(y)]$; in Step 3 the matching probabilities are degenerate, $\alpha_H \equiv \alpha_L \equiv 1$; and the borrowing value reduces to

$$V^B(b,y) \;=\; \max_{b'>0} \Big\{ u(y - b + q^c(b';y)\, b') + \beta(1-\delta)\, E\Big[V_0^{(n)}(b',y') \,\Big|\, y\Big] \Big\}$$

subject to $-q^c b' + \rho^{(n)}(b',y)b'/(1+r) \geq \kappa$, with q^c given by (10).