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Regulatory Interventions in Consumer Financial Markets: The Case of Credit Cards*

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August 2020

Abstract

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1 Introduction

After the financial crisis, policymakers in several countries began intervening in markets for consumer financial products more aggressively than before, both through new legislation and the creation of new regulatory agencies, such as the Consumer Financial Protection Bureau (CFPB) in the U.S. and the Financial Conduct Authority (FCA) in the U.K. Although the interventions have taken different forms, two broad, prevalent directions are a break from the recent past: 1) the imposition of direct constraints on some prices and fees of financial products, because policymakers viewed them as "predatory,", that is, as targeting unsophisticated and poorly-informed households;[1] and 2) a tighter supervision of lenders, which often increased compliance and operating costs for these financial institutions.

An important question is what effects these policies will have on the operation of markets for consumer financial products. Standard competitive theory predicts that binding price caps and higher operating costs reduce market efficiency and lower market access, particularly for marginal borrowers. Policymakers' primary motivation, however, is that markets for consumer financial products do not satisfy the conditions of perfectly-competitive markets, because of informational and other frictions.[2] Nevertheless, the theoretical analysis of frictional markets provides ambiguous predictions on the effects of these policies on consumer surplus and on aggregate welfare. For example, although price caps have the direct effect of lowering some prices, they also reduce incentives to become informed, which may increase market power and lead to higher, rather than lower, average prices (Fershtman and Fishman, 1994; Armstrong, Vickers, and Zhou, 2009). Therefore, determining the overall effect of these policies is an empirical/quantitative question.

The objective of this paper is to quantitatively study the effects of the two types of intervention on the market for consumer financial products. We focus on the U.S. credit card market, for which we have been able to combine several sources of data. Our data build on Stango and Zinman (2016) (henceforth SZ) and display two key patterns that appear, at first sight, somewhat contradictory. First, the interest rates that borrowers pay on their credit cards

[1] Specifically, the 2009 U.S. Credit Card Accountability Responsibility and Disclosure Act explicitly prohibited lenders from charging some fees on credit cards (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2015). Similarly, in the U.K. the FCA has introduced regulatory caps for several financial products: in November 2014 it enacted a price structure for payday loans, capping the initial cost of a loan to a maximum of 0.8 percent per day; in November 2016, it restricted fees for individuals who want to access their pensions to a maximum of one percent. Furthermore, the financial press reports that the FCA is currently evaluating limits on fees for other products, such as mutual fund fees (*The Financial Times*, Funds' lucrative entry fees under attack, May 26, 2016) and mortgage origination fees (*The Financial Times*, Mortgage lenders under FCA review for masking high fees, December 12, 2016).

[2] Sirri and Tufano (1998) and Hortaçsu and Syverson (2004) show that information frictions play a prominent role in mutual fund markets, and Allen, Clark, and Houde (2019) and Woodward and Hall (2012) in mortgage markets.

are high in comparison to funding costs, and they are very dispersed, even after controlling for observable borrower characteristics—including their creditworthiness, as captured by their credit score—or card characteristics (e.g., rewards). Thus, this first pattern suggests that lenders enjoy a significant amount of market power. Second, the average consumer receives several pre-approved credit card offers every month and these offers advertise very different interest rates. This second pattern suggests that lenders face considerable competition, because borrowers can choose low-interest-rate credit cards among the offers that they receive. Interpreting these seemingly contradictory patterns and deriving the policy implications of our interpretation are the main contributions of our paper.

We develop a rich but tractable modeling framework that accounts for these patterns. Our framework includes two features to help interpret high and dispersed interest rates: information frictions, such as costs of examining and evaluating different offers, and product differentiation.[3] In our model, lenders, which are heterogeneous in their funding costs, choose whether to enter a particular market characterized by borrower creditworthiness (i.e., subprime, near-prime, prime, and super-prime), choose what interest rate to offer, and send credit card offers to borrowers. Borrowers, who are heterogeneous in their willingness to pay for a loan, choose how much effort to exert in examining the offers that they receive and decide which offer, if any, to accept. The acceptance decision depends on the offer's interest rate and on an offer-specific attribute, interpreted as product differentiation. Hence, a borrower might reject a low-interest-rate credit card because he does not examine it or because he does not like the offer-specific attribute, thereby leading to a high level of and a large dispersion in accepted interest rates.

We calibrate the model to match the statistics on the distribution of interest rate offers, on the distributions of accepted offers, and on the fractions of borrowers in each market, as well as lenders' average funding costs and charge-off rates. The model fits the data well. The calibration implies that, while product differentiation affects borrowers' choice and lenders' pricing, our model requires borrowers to have high cost of examining offers, leading to low examination effort, in order to match all empirical patterns in the data. The intuition is that, although both high examination costs and high product differentiation are potentially consistent with the high level of and the high dispersion in accepted interest rates, high examination costs can additionally account for the high dispersion of offered rates and the moderate fraction of borrowers in the data. By contrast, high product differentiation leads to a lower dispersion of offered rates and a larger fraction of borrowers in the population than those observed in the data.

[3] Carlin (2009) argues that producers of retail financial products strategically make their prices more complex for consumers, thereby increasing consumers' costs of evaluating different products. Similarly, Ellison and Wolitzky (2012) develop a search model of obfuscation and Ellison and Ellison (2009) provide empirical evidence on obfuscation among online retailers.

We use our calibrated model to perform counterfactual experiments. First, we consider the effect of the introduction of a 25-percentage-point interest rate cap. Our calibrated model predicts that the cap has a relatively small effect on outcomes in the markets for creditworthy borrowers (prime and super-prime) because it is rarely binding in our data. In markets for riskier borrowers, that is, sub-prime and near-prime, where the cap is binding for 35 and 25 percent of borrowers in our data, respectively, the effect is more pronounced: the average accepted interest rate declines by more than 10 percent, while the number of people getting a loan declines modestly, by less than four percent. The decline in loans is modest because, although the number of offers falls by more than 10 percent in the sub-prime market, borrowers respond to the more favorable interest rate distribution by examining a larger share of the offers that they receive. The overall effect is a large redistribution of surplus from lenders to borrowers—consumer surplus increases substantially, by more than 10 percent in the sub-prime and near-prime markets, whereas lender profits decline quite steeply, by more than 50 percent in the sub-prime market—and a small decline in aggregate welfare of at most three percent.

We view the large positive effect of an interest rate cap on the consumer surplus of sub- and near-prime borrowers to be an interesting result: in a perfectly-competitive market with complete information such caps will reduce supply precisely toward marginal borrowers and will, therefore, negatively affect their surplus. Our results are reminiscent of monopolistic markets, though our model explicitly accounts for the large number of credit card offers that borrowers receive. Most notably, the presence of informational frictions, that is, the costs of examining and evaluating credit card offers, rationalizes the appearance of a competitive market with the reality of high lender market power.

We further use the calibrated model to understand the effect on market outcomes of higher operating costs, which we model as an increase in lenders' fixed costs. In this case, we are interested in the effect of cost-increasing policies on borrower outcomes, admittedly neglecting some of the potential benefits that motivate the policies, such as greater financial stability and/or fewer abusive lending practices. We calibrate an increase in entry costs to replicate the reduction in entry of our price-cap case to facilitate the comparison of market outcomes between these two cases. We find again that higher operating costs have only minor effects on the markets for safer borrowers. However, in markets for riskier borrowers, higher operating costs trigger the exit of lenders with high marginal costs; because competition is lower than in the baseline case, all surviving lenders increase their interest rates. These changes in supply lead to approximately a 10-percent drop in the fraction of borrowers with credit card loans and a 15-percent drop in consumer surplus in the sub-prime market. Hence, in contrast to the price-cap case, higher operating costs unambiguously harm borrowers and decrease aggregate welfare.

The paper proceeds as follows. Section 2 reviews the literature, highlighting our contribution. Section 3 describes the data. Section 4 presents the theoretical model. Section 5 presents our calibration of the model and illustrates its main quantitative implications. Section 6 performs our counterfactual analyses. Section 7 concludes. The appendices report further results and collect all proofs.

2 Related Literature

The paper contributes to several strands of the empirical literature. The first is the literature that studies imperfect competition and frictions in credit card markets. In an important contribution, Ausubel (1991) showed that interest rates on credit cards are substantially higher than lenders' funding costs and display limited intertemporal variability, citing search frictions as a potential departure from a competitive market. Calem and Mester (1995) present empirical evidence on consumers' limited search and switching behavior. Stango (2002) studies credit card pricing when consumers have switching costs. Grodzicki (2015) analyzes how credit card companies acquire new customers. We contribute to this literature by building a framework that allows us to quantify the effects of product differentiation and choice frictions on lenders' loan pricing and on consumers' cost of borrowing.

Second, a vast literature in household finance studies whether consumers behave optimally in credit markets: among others, Agarwal, Driscoll, Gabaix, and Laibson (2008) analyze consumer mistakes in the credit card market and Ru and Schoar (2016) study how credit card companies exploit consumers' mistakes. In this strand of literature, the most related paper is Woodward and Hall (2012), who study consumers' shopping effort in the U.S. mortgage market. We contribute to this literature by developing and calibrating an equilibrium model of a differentiated product market with endogenous consumers' shopping effort, which allows us to analyze how it adjusts after regulatory interventions.

Third, many countries have recently enacted reforms and introduced new regulations in markets for consumer financial products (Campbell, Jackson, Madrian, and Tufano, 2011a,b). Several recent contributions provide descriptive analyses of the effects of these reforms. In the case of U.S. credit card markets, Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015) and Nelson (2020) analyze how regulatory limits on credit card pricing introduced by the 2009 CARD Act affect borrowing costs exploiting rich administrative data. Similarly, in a contemporaneous contribution, Cuesta and Sepúlveda (2019) study price regulation in the Chilean consumer loan market. We complement these papers by analyzing some of these regulatory interventions in a quantitative model that features product differentiation and borrowers' cost of examining offers, and we evaluate their importance for market power and pricing in the credit card market.

Finally, this paper is related to the literature on the structural estimation of consumer search models. Recent contributions include Hortaçsu and Syverson (2004), Hong and Shum (2006), Wildenbeest (2011), Allen, Clark, and Houde (2019), Gavazza (2016), Galenianos and Gavazza (2017), and Salz (2017). Our theoretical framework innovates on these previous empirical papers by building on the models of Butters (1977) and Burdett and Judd (1983) and by combining product differentiation, search frictions, and consumers' endogenous shopping effort. Fershtman and Fishman (1994), Armstrong, Vickers, and Zhou (2009), Janssen and Moraga-González (2004) show that consumers' shopping effort could potentially offset the effects of the regulations that we focus on; thus, our framework that incorporates it seems well suited for a quantitative analysis of these policy interventions.[4]

3 Data

The available data dictate some of the modeling choices of this paper. For this reason, we describe the data before presenting the model. This description also introduces some of the identification issues that we discuss in more detail in Section 5.2.

3.1 Data Sources

Our quantitative analysis combines several sources of data. More specifically, we exploit some of the datasets that SZ use in their descriptive analysis of households' credit card terms, supplementing them with some statistics obtained from credit card market reports of the CFPB and from the Survey of Consumer Finances. We now describe these datasets in more detail.

The first dataset is an account-level panel that samples individuals and reports the main terms of their credit card accounts during (at most) 36 consecutive months between January 2006 and December 2008, including their credit limit, the end-of-month balance, the revolving balance, the annual percentage rate (APR), and the cash advance APR. The dataset also reports limited demographic characteristics of the cardholders, most notably their FICO credit score.[5]

The second dataset reports the terms of all pre-approved credit card offers that a sample of individuals received in January 2007.[6] This second dataset samples different individuals

[4] Knittel and Stango (2003) show that price ceiling served as a focal point for tacit collusion in the U.S. credit card market during the 1980. However, they also show that price dispersion was a lot more limited in that period than in the period of our data.

[5] We are grateful to Victor Stango for sharing this dataset with us.

[6] In the U.S. market, lenders often send personalized pre-approved credit card offers in the mail committing to terms with borrowers.

than those in the first dataset, but allows us to measure the number of offers that individuals receive in a given month, as well as the dispersion in the interest rates of these offers. As SZ emphasize, the dispersion in interest rates on all credit cards offered to a given individual in a given month removes any effect of individual-specific factors on the cross-sectional distribution of interest rates on credit cards that individuals hold. We should point out that we do not have access to the individual survey data, and thus we exploit data reported in tables of SZ.

We complement these datasets with some additional statistics: the shares of sub-prime, near-prime, prime, and super-prime borrowers in the U.S population, calculated using the distribution of FICO scores reported in Consumer Financial Protection Bureau (2012);[7] the fraction of individuals with credit cards, computed from Campbell, Haughwout, Lee, Scally, and van der Klauuw (2016) and the 2007 Survey of Consumer Finances; the charge-off rate on credit card loans in the first quarter of 2007, reported by the Board of Governors of the Federal Reserve System; the interest rate of the one-year Treasury bill on January 16, 2007, which we use as the risk-free rate;[8] and Standard & Poor's U.S. Credit Card Quality Index at January 2007, which is a monthly performance index that aggregates information of securitized credit card receivables, most notably reporting an average cost of funding (i.e., excluding expected charge-offs) for credit card loans.

3.2 Data Description

We use the first dataset on individuals' credit card terms to sum up and extend one of the main results of SZ's descriptive analysis: a large dispersion of the interest rate distribution persists, even after taking into account: 1) different default risk across individuals, as measured by their FICO scores; 2) different card characteristics across borrowers, such as rewards; and 3) different revolving balances across borrowers.

Specifically, the basic framework for this analysis is the following equation:

$$R_{ijt} = \gamma_X X_{it} + \gamma_Z Z_{ijt} + \epsilon_{ijt}, \tag{1}$$

where the dependent variable R_{ijt} is the APR that individual i pays on credit card j in month t; X_{it} are characteristics of individual i in month t, namely his default risk, measured by the FICO score;[9] Z_{ijt} are characteristics of individual i's credit card j in period t, namely the

[7] These shares equal 0.215, 0.140, 0.166, and 0.479, respectively.

[8] We retrieved the values of the charge-off rate and of the interest rate of the one-year Treasury bill from FRED, Federal Reserve Bank of St. Louis, series `https://fred.stlouisfed.org/series/CORCCT100S` and `https://fred.stlouisfed.org/series/DGS1`, respectively.

[9] The dataset reports household income brackets for approximately 50 percent of the individuals in the sample. In order to have larger sample sizes, we choose to report results obtained without including income among the individual characteristics, but we have estimated equation (1) including income among the

credit limit, rewards, and the credit balance; ϵ_{ijt} are residuals.

Based on regression equation (1), we calculate the centered interest rate residuals as

$$R'_{ijt} = \hat{\gamma}_X \overline{X}_{it} + \hat{\gamma}_Z \overline{Z}_{ijt} + \hat{\epsilon}_{ijt}, \tag{2}$$

where $\hat{\gamma}_X$ and $\hat{\gamma}_Z$ are the coefficient estimates, $\overline{X}_{it}$ and $\overline{Z}_{ijt}$ are the sample averages of the covariates of each regression, and $\hat{\epsilon}_{ijt}$ are the estimates of the residuals. Hence, (2) removes the variation in R_{ijt} due to the variation in X_{it} and in Z_{ijt}, while keeping that due to ϵ_{ijt}.

We perform regression (1) and calculate interest rate residuals according to equation (2) separately for four different groups of cardholders based on their FICO score: 1) sub-prime borrowers, with FICO score strictly below 620; 2) near-prime borrowers, with FICO scores between 620 and 679; 3) prime borrowers, with FICO scores between 680 and 739; and 4) super-prime borrowers, with FICO scores above 740. These different groups constitute the main classification of borrowers used in the credit card industry (Consumer Financial Protection Bureau, 2015). Hence, performing separate regressions for each group allows us to capture in a flexible way the heterogeneity across them, and thus to obtain a reasonably accurate measure of the dispersion in interest rates within each group of borrowers.

Table 1 reports coefficient estimates of several specifications of equation (1) and the main percentiles of the resulting distribution of interest rates based on equation (2). Column (1) uses the raw data over the entire sample period, which exhibit a large dispersion of interest rates: the difference between the 90th and the 10th percentiles equals 18 percentage points for subprime borrowers; it decreases for more-creditworthy borrowers, reaching a difference of 10 percentage points for super-prime borrowers. Column (2) restricts the data to January 2007 (the date of our other data sources), showing the large dispersion of interest rates is almost identical to that in column (1), for two reasons: a) limited aggregate variation exists in interest rates over time; and b) limited within-account variation exists in interest rates. Column (3) further restricts the data to cards without introductory "teaser" rates (i.e., low initial rates that reset to higher rates after an initial offer period); of course, interest rates increase relative to those displayed in column (2), but the increase is minimal; for example, the difference between the 90th and the 10th percentiles slightly decreases to 16 percentage points for subprime borrowers and 9 percentage points for super-prime borrowers.

The specification of column (4) introduces the main individual characteristic that should affect pricing, that is, the credit risk of the individual, measured by the FICO score. Within all groups, higher-risk individuals face higher interest rates. Averaging across all groups, a 10-point increase in the FICO score corresponds approximately to a 30-basis-point decrease in interest rates, which is almost identical to the magnitude that Nelson (2020) estimates.[10]

individual characteristics as well, and obtained very similar results to those reported in Table 1.

[10] Moreover, Nelson (2020) shows that: 1) the interest rate on a credit card changes in response to a change

However, the corresponding distribution of residual interest rates constructed as in equation (2) displays a dispersion that is almost identical to that computed from the raw data in column (3). The specification of column (5) further controls for other card characteristics, such as the credit limit and an indicator variable that equals one if the card features some rewards (e.g., frequent flier miles or cash back), and zero otherwise, as well as the revolving balance. The specification of column (6) further restricts the sample to cards with a revolving balance (i.e., cards used for borrowing beyond the 25-day grace period). Nevertheless, the large dispersion of residual interest rates persists almost unaffected.[11] Moreover, Appendix A presents robustness checks that weigh each observation by the size and the persistence of its revolving balance which leads to qualitatively similar results. This finding bolsters the argument that interest rate dispersion is a robust feature when we focus our attention on individuals who use their credit cards to borrow (and, hence, pay interest on their balances) rather than transactors (who pay off their credit card balance at the end of each month).[12]

Overall, Table 1 attests to some remarkable features of credit card markets. First, although more creditworthy borrowers on average pay lower interest rates, the difference in interest rates within groups is substantially larger than the difference across groups. Notably, the difference between the 90th and the 10th percentiles equals approximately 16 percentage points for sub-prime borrowers, near-prime borrowers, and prime borrowers, whereas it equals approximately 13 percentage points for super-prime borrowers. Hence, because the average outstanding revolving balance of borrowers equals approximately \$4,000 in our sample, moving from the 90th percentile to the 10th percentile of interest rates would reduce borrowers' annual payment by approximately \$500-\$600. Second, observable credit card characteristics do not seem to have a major effect on card pricing. A consequence of these two features is that a large dispersion of interest rates persists once we account for borrower and card characteristics.

Table 2 combines all empirical targets of our quantitative model. Panel A reproduces the percentiles of the distributions of interest rates derived in Table 1. Panel B reports statistics on credit card offers that SZ document. Specifically, Section 5.1 of SZ recounts that approximately 75 percent of individuals received two or more credit card offers during January 2007; among them, the median and the mean number of offers was three and four,

in the credit card holder's FICO score over time; and 2) the magnitude of the change in response to a change in the FICO score over time is almost identical to the cross-sectional difference between individuals with different FICO scores at credit card origination. These two observations imply that the long-term nature of the credit card contract does not affect the magnitude of the correlation between the FICO score and the interest rate in our data.

[11] The R^2 of the regressions of Table 1 are lower than those reported in Table of 3 of SZ. The difference is due to the fact that we perform our regressions separately within each of the four groups of cardholders based on their FICO score.

[12] Some people use their credit cards as a means of payment and repay their balance in full at the end of each month. For such transactors the interest rate is arguably not a salient feature of their credit card, since they never actually pay interest charges.

Table 1: Dispersion of Interest Rates, by Borrower Group

Subprime Borrowers	(1)	(2)	(3)	(4)	(5)	(6)
FICO Score				-0.018	-0.017	-0.018
				(0.006)	(0.006)	(0.006)
Reward Card					0.863	0.405
					(0.618)	(0.674)
Credit Limit					-0.170	-0.158
					(0.094)	(0.125)
Credit Balance					0.197	0.174
					(0.110)	(0.140)
R^2				0.010	0.015	0.013
Observations	27,024	903	877	877	871	766
10th Percentile	11.90	12.74	14.24	14.30	14.41	14.39
25th Percentile	16.15	16.95	17.24	17.55	17.46	17.58
50th Percentile	20.65	21.20	21.74	21.72	21.65	21.93
75th Percentile	27.49	27.99	27.99	27.52	27.45	27.80
90th Percentile	29.99	30.24	30.24	30.06	30.01	30.16
Near-prime Borrowers						
FICO Score				-0.046	-0.043	-0.052
				(0.011)	(0.011)	(0.013)
Reward Card					0.494	0.562
					(0.453)	(0.565)
Credit Limit					-0.211	-0.255
					(0.046)	(0.078)
Credit Balance					0.242	0.225
					(0.064)	(0.100)
R^2				0.019	0.044	0.043
Observations	27,059	944	900	900	885	661
10th Percentile	10.49	11.24	12.99	13.16	13.09	13.20
25th Percentile	14.90	14.99	15.94	16.01	16.06	16.55
50th Percentile	18.24	18.99	19.24	19.09	19.31	20.20
75th Percentile	23.15	23.24	23.30	24.07	23.87	25.72
90th Percentile	28.99	29.24	29.24	29.03	28.75	29.16
Prime Borrowers						
FICO Score				-0.053	-0.048	-0.051
				(0.011)	(0.011)	(0.015)
Reward Card					0.084	-0.257
					(0.374)	(0.520)
Credit Limit					-0.093	-0.070
					(0.026)	(0.049)
Credit Balance					0.080	0.019
					(0.038)	(0.058)
R^2				0.024	0.039	0.029
Observations	31,115	1,003	953	953	932	605
10th Percentile	9.90	9.90	11.99	11.79	11.85	11.56
25th Percentile	12.99	13.99	14.31	14.65	14.64	14.81
50th Percentile	16.74	17.31	18.24	17.74	17.70	17.93
75th Percentile	19.99	20.24	20.34	21.04	20.97	21.90
90th Percentile	25.99	27.24	28.15	27.32	27.25	28.68
Super-prime Borrowers						
FICO Score				-0.008	-0.008	-0.024
				(0.004)	(0.005)	(0.010)
Reward Card					0.442	0.346
					(0.220)	(0.471)
Credit Limit					0.010	0.028
					(0.014)	(0.031)
Credit Balance					0.058	-0.040
					(0.032)	(0.051)
R^2				0.002	0.007	0.012
Observations	56,880	1,741	1,645	1,645	1,611	546
10th Percentile	9.90	9.90	11.24	11.33	11.20	10.79
25th Percentile	12.99	13.24	14.15	14.05	13.97	13.82
50th Percentile	15.98	16.74	16.99	17.02	16.91	16.84
75th Percentile	18.24	18.24	18.24	18.48	18.52	19.54
90th Percentile	20.24	20.24	20.31	20.56	20.81	23.98

Notes: This table reports OLS coefficient estimates of equation (1) and the corresponding percentiles of the distribution of centered interest rates as in equation (2).

respectively. For these individuals who received two or more offers, Table 4 of SZ reports key percentiles of the distribution of the difference between the highest and the lowest offered interest rates charged after the expiration of any introductory "teaser" period (if any).

Panel C reports auxiliary statistics on credit card markets. We compute the fraction of credit card revolvers in each group by combining the share of individuals with a credit card in 2007 reported in Campbell, Haughwout, Lee, Scally, and van der Klauuw (2016) with the probability of revolving conditional on having a credit card, which we compute directly as the ratio of observations in column (6) to observations in column (5) in Table 1. Interestingly, the share of individuals with a credit card is lower for borrowers with lower credit scores, whereas the probability of revolving conditional on having a credit card is higher, exceeding 80 and 90 percent for near-prime and sub-prime borrowers, respectively. Hence, the fraction of credit card borrowers is non-monotonic in borrowers' credit scores; on average, 46 percent of individuals borrow on their credit card.[13] Finally, the aggregate charge-off rate approximately equals four percentage points and the average funding cost reported by Standard & Poor's Credit Card Quality Index is approximately two percentage points above the risk-free rate.

3.3 Implications for Modeling

Table 2 provides an interesting description of the credit card market and informs the model that we develop in Section 4. We focus on two key data patterns.

First, as we noted above, Panel A shows that the dispersion in the interest rates that similar borrowers pay on their credit card debt is very large, even after we control for observable borrower and card characteristics. Second, Panel B points out that many individuals receive several credit card offers at substantially different interest rates. Hence, public information about individuals' repayment probability, as measured by FICO scores, does not account for the dispersion observed in Panel A and, even more so, in Panel B. Moreover, if all individuals chose the credit card with the lowest interest rate among all their offers, the level and the dispersion of the accepted interest rate distributions would be considerably lower than those reported in Table 2.

These striking patterns motivate some of our key modeling assumptions. We focus on borrowers (rather than transactors) and we allow two possible explanations for why these borrowers do not accept the credit card offers with the lowest interest rates: 1) They may not examine all the offers that they receive; and 2) They may have idiosyncratic preferences for card attributes that our data do not report. The calibration of Section 5 aims to quantitatively

[13]The aggregate share of the population with a credit card and the aggregate share of revolvers, computed as the weighted averages of the corresponding group shares in our data, equal 0.76 and 0.46, respectively. These shares closely match the corresponding aggregate statistics in the 2007 Survey of Consumer Finances, which equal 0.73 and 0.44, respectively.

Table 2: Empirical Targets

Panel A: Accepted Offers	
10th Percentile Accepted Offer Distribution, Sub-Prime Borrowers	14.39
25th Percentile Accepted Offer Distribution, Sub-Prime Borrowers	17.58
50th Percentile Accepted Offer Distribution, Sub-Prime Borrowers	21.93
75th Percentile Accepted Offer Distribution, Sub-Prime Borrowers	27.80
90th Percentile Accepted Offer Distribution, Sub-Prime Borrowers	30.16
10th Percentile Accepted Offer Distribution, Near-Prime Borrowers	13.20
25th Percentile Accepted Offer Distribution, Near-Prime Borrowers	16.55
50th Percentile Accepted Offer Distribution, Near-Prime Borrowers	20.20
75th Percentile Accepted Offer Distribution, Near-Prime Borrowers	25.72
90th Percentile Accepted Offer Distribution, Near-Prime Borrowers	29.16
10th Percentile Accepted Offer Distribution, Prime Borrowers	11.56
25th Percentile Accepted Offer Distribution, Prime Borrowers	14.81
50th Percentile Accepted Offer Distribution, Prime Borrowers	17.93
75th Percentile Accepted Offer Distribution, Prime Borrowers	21.90
90th Percentile Accepted Offer Distribution, Prime Borrowers	28.68
10th Percentile Accepted Offer Distribution, Super-Prime Borrowers	10.79
25th Percentile Accepted Offer Distribution, Super-Prime Borrowers	13.82
50th Percentile Accepted Offer Distribution, Super-Prime Borrowers	16.84
75th Percentile Accepted Offer Distribution, Super-Prime Borrowers	19.54
90th Percentile Accepted Offer Distribution, Super-Prime Borrowers	23.98
Panel B: Received Offers	
Fraction Receiving 2+ Offers (%)	75.00
Median Number of Offers Received, Conditional on 2+ Offers	3.00
Average Number of Offers Received, Conditional on 2+ Offers	4.00
10th Percentile Distribution of Differences in Offered Rates	0.00
30th Percentile Distribution of Differences in Offered Rates	2.25
50th Percentile Distribution of Differences in Offered Rates	4.34
70th Percentile Distribution of Differences in Offered Rates	7.25
90th Percentile Distribution of Differences in Offered Rates	9.25
Panel C: Auxiliary Statistics	
Fraction with Credit Card Debt, Sub-Prime Borrowers	54.56
Fraction with Credit Card Debt, Near-Prime Borrowers	55.33
Fraction with Credit Card Debt, Prime Borrowers	54.00
Fraction with Credit Card Debt, Super-prime Borrowers	36.02
Charge-Off Rate	4.01
Average Funding Cost	7.02

Notes: This table provides the empirical targets of our calibrated model. Panel A reports statistics on the interest rates that borrowers pay on their credit cards. Panel B displays statistics on credit card offers that SZ report. Panel C reports auxiliary statistics.

match the dispersion of interest rates as well as the sizable number of offers that individuals receive, and it allows us to assess the contributions of the two theoretical explanations for the empirical patterns. Nevertheless, our calibration admits other (unmodeled) factors which may feed into the large variance of the cross-sectional distribution of accepted rates, such as adjustment of the interest rate after the offer is accepted, as in Nelson (2020).

Despite all of their advantages, however, we should acknowledge that our data have some limitations. First, they are mostly cross-sectional, and therefore we do not observe borrowers' and lenders' behavior over time. Specifically, we cannot precisely assess how frequently borrowers switch across credit cards. Hence, in the absence of more-detailed measurement on borrowers' switching behavior, we seek to match the cross-sectional distribution through a static model.[14] Moreover, although the theory can accommodate large multidimensional heterogeneity of borrowers, our cross-sectional data make identifying such a model difficult. Hence, our framework allows for flexible heterogeneity across markets (i.e., sub-prime, near-prime, prime, and super-prime), as well as within-market heterogeneity in borrowers' willingness to pay for credit and in borrowers' valuation of non-price card attributes, whereas some other parameters are common across borrowers within markets. Most notably, we do not observe individual default and, thus, we abstract from within-market heterogeneity in repayment risk, as well as from asymmetric information between lenders and borrowers (though we should note again that differences in observable FICO scores across individuals do not account for the dispersion in interest rates in Panel A and in Panel B). We discuss the implications of these data limitations for our results further in Section 7.

4 The Model

The economy consists of J different markets, labeled by j, which are populated by borrowers and lenders. The different markets operate independently from each other, and each agent (borrower or lender) participates in a single market. Our calibration of Section 5 will consider four different markets corresponding to the general classifications of creditworthiness used in the credit card industry: sub-prime, near-prime, prime, and super-prime.

Each market j has measure 1 of borrowers (a normalization) who have market-specific default risk ρ_j, want to take a loan of market-specific size b_j and are heterogeneous in their marginal valuation of a loan, $\tilde{z}$. We abstract from within-market heterogeneity in repayment probability for reasons we describe in Section 3.3. Furthermore, we abstract from the intensive-margin decision of how much to borrow for the sake of tractability, following Allen, Clark, and Houde (2019), Crawford, Pavanini, and Schivardi (2018), and Nelson (2020), among others. We allow for unobserved heterogeneity in borrowers' marginal valuation $\tilde{z}$ which is

[14] Galenianos and Nosal (2016) develop a dynamic search model of unsecured credit and default.

distributed according to a market-specific discrete distribution $\tilde{M}_j(\cdot)$ with an N_j-point support $\tilde{Z} = \{\tilde{z}_1, ..., \tilde{z}_{N_j}\}$, where $\tilde{z}_1 \leq ... \leq \tilde{z}_{N_j}$.[15] We define $s_{\tilde{z}}$ to be the share of type-$\tilde{z}$ borrowers, where $\tilde{z} \in \tilde{Z}$.

Each market j has measure Λ_j of *potential* lenders who face entry cost χ_j to enter the market and are heterogeneous in their marginal cost of providing a loan, $\tilde{k}$. The marginal cost $\tilde{k}$ is distributed according to a market-specific smooth distribution $\tilde{\Gamma}_j(\cdot)$ with connected support $[\underline{\tilde{k}}_j, \overline{\tilde{k}}_j]$. The measure of lenders who choose to enter market j and the distribution of their marginal costs are L_j and $\tilde{G}_j(\cdot)$, respectively. Every entering lender can give one loan of size b_j.[16]

Matching between borrowers and lenders in a market is subject to frictions. Each lender sends one loan offer with an associated interest rate to a random borrower. Each borrower chooses his examination effort and then receives a random number of offers that follows a Poisson distribution, examines every offer with a probability that depends on his effort, and decides which, if any, offer to accept.[17] The effective number of offers (i.e., offers received *and* examined) to a borrower who exerts examination effort e in a market with L_j lenders follows a Poisson distribution with parameter $e * L_j$. A borrower who exerts examination effort e incurs cost $q_j(e, L_j)$, where $q_j(\cdot, \cdot)$ is strictly increasing and convex in the effort e and satisfies $q_j(0, L_j) = 0$, $\lim_{e \to 0} \partial q_j(e, L_j)/\partial e = 0$ and $\lim_{e \to 1} q_j(e, L_j) = \infty$.

Borrowers consider two components to rank loan offers. The first component is the net interest rate R, which is chosen by the lender and is drawn from the equilibrium offer distribution $F_{R_j}(\cdot)$. The second component is an idiosyncratic (i.e., borrower-specific) attribute a, which is stochastic and represents every other aspect of the loan that might affect the borrower's valuation. The attribute draw captures the importance of horizontal product differentiation in this market, whose value may vary across borrowers. Idiosyncratic attribute a is drawn from an exogenous distribution $F_{a_j}(\cdot)$ that is smooth, has zero mean, and has support in a connected set $[\underline{a}, \overline{a}] \subset (-\infty, \infty)$. In this section and in the calibration of Section 5, we assume attribute draw a is independent across lenders. Appendix D considers the case where some lenders' offers might consistently draw better values of a. We call the sum $c = R + a$ the (net) cost of a loan to the borrower, which might be higher or lower than R depending on the attribute a.

If the borrower does not default, which occurs with probability $1 - \rho_j$, he pays the cost of

[15]We assume a discrete distribution of borrower types to facilitate some technical derivations. The interaction between borrowers and lenders does not hinge on that assumption.

[16]A lender should be interpreted as a loan contract rather than a lending (or credit card) company. We do not model lending companies explicitly.

[17]The random allocation of offers across borrowers in an environment with finite numbers of borrowers and lenders leads to urn-ball matching, which, as the numbers of borrowers and lenders grow large, is approximated by a Poisson distribution. See Butters (1977) for an early application of urn-ball matching to a similar setting.

the loan; if he defaults, which occurs with probability ρ_j, he incurs the utility cost of default $\tilde{\delta}_j$.[18] The expected utility of a type-$\tilde{z}$ borrower in market j who takes a loan with interest rate R and attribute a is $b_j\left(\tilde{z}-(1-\rho_j)(1+R+a)-\rho_j\delta_j\right)$, where $\delta_j \equiv \frac{\tilde{\delta}_j}{b_j}$. The borrower's utility from not taking a loan is zero.

We define a borrower's preference for a loan net of expected default cost and principal repayment by $z=\frac{\tilde{z}-\rho_j\delta_j}{1-\rho_j}-1$ and note that it is distributed according to $M_j(z)=\tilde{M}_j\big((1-\rho_j)(z+1)+\rho_j\delta_j\big)$ with support $Z=\{z_1,...z_{N_j}\}$. We can therefore rewrite the utility of a type-z borrower from taking a loan with cost $R+a$ as

$$b_j\left(1-\rho_j\right)\left(z-R-a\right).$$

Anticipating equilibrium behavior, a type-z borrower chooses the loan offer with the lowest cost among the offers that he examines, conditional on the cost being less than z. A loan offer with a higher cost generates negative utility, and thus the borrower will never accept it. The ex-ante value of a type-z borrower in market j equals the expected value of his best loan offer $V_{z,j}(e)$ (which depends on effort e) net of the cost of effort, $q_j(e,L_j)$:

$$V_{z,j}(e)-q_j(e,L_j). \tag{3}$$

We denote the optimal (utility-maximizing) effort choice of a type-z borrower in market j by $e_j(z)$.

The expected profits per dollar lent for a type-$\tilde{k}$ lender in market j equal the difference between the expected revenues, given by the gross interest rate $(1+R)$ times the market-specific repayment probability $(1-\rho_j)$, and the costs, given by the lender's gross cost of funds $(1+\tilde{k})$: $(1+R)(1-\rho_j)-(1+\tilde{k})$. We define the lender's expected marginal cost inclusive of non-repayment risk as $k=\tilde{k}+\rho_j$, which means that per-dollar expected profits equal $R(1-\rho_j)-k$. We note that for potential lenders k is distributed according to the smooth distribution $\Gamma_j(k)=\tilde{\Gamma}_j(k-\rho_j)$ with support $[\underline{k}_j,\overline{k}_j]$, where $\underline{k}_j=\underline{\tilde{k}_j}+\rho_j$ and $\overline{k}_j=\overline{\tilde{k}}_j+\rho_j$; for entrants, k is distributed according to $G_j(k)=\tilde{G}_j(k-\rho_j)$.

The expected profits of a type-k lender from market j who offers interest rate R, $\pi_{k,j}(R)$, are given by the probability of making a loan, denoted by $P_j(R)$, times the loan's expected profits:

$$\pi_{k,j}(R) \quad = \quad b_j\big(R(1-\rho_j)-k\big)P_j(R). \tag{4}$$

Notice that the idiosyncratic attribute a affects the lender's payoff only through the probability

[18]We assume defaulting occurs independently of any loan features, that is, the interest rate R or the attribute draw a.

of making a loan.

We denote the optimal (profit-maximizing) interest rate choice of a type-k lender in market j by $R_j(k)$, which, combined with lenders' entry decisions, determines the interest rate distribution in market j, $F_{R_j}(\cdot)$.

We are now ready to define the equilibrium.

Definition 1 *An equilibrium consists of borrowers' effort $e_j(\cdot)$ and lenders' entry and interest rate choices $\{L_j, G_j(\cdot), R_j(\cdot)\}$ such that in every market j, borrowers maximize their ex-ante value (3), lenders maximize their expected profits (4), the expected profits of all entrants exceed the entry cost χ_j, and the expected profits of non-entrants would be strictly below χ_j if they entered.*

To proceed, we first determining borrowers' and lenders' optimal choices separately and then prove the existence of equilibrium. Finally, we characterize the constrained efficient outcome. Because there is no interaction across markets, we henceforth drop the j subscript to ease notation. The reader should keep in mind, however, that all equilibrium outcomes are market specific.

4.1 Borrowers' Choices

We characterize borrowers' optimal effort $e(\cdot)$ of examining offers, taking as given the measure L of lenders in the market and the interest rate offer distribution $F_R(\cdot)$. We should point out that the type distribution of lenders $G(\cdot)$ and interest rate choices $R(\cdot)$ affect borrowers' choices only through $F_R(\cdot)$.

We begin by expressing $V_z(e)$ in a convenient way. Denote the value of a z-borrower from examining n offers by $v_{z,n}$, where $v_{z,0} = 0$. The expected value for a type-z borrower who exerts effort e is

$$V_z(e) \quad = \quad \sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} v_{z,n}. \tag{5}$$

Notice that effort e affects the arrival rate of offers but does not enter $v_{z,n}$; therefore, it is immediate from equation (5) that $V_z(e)$ is continuous and differentiable in e. As a result, the optimal effort choice $e(z)$ solves

$$V_z'(e) \quad = \quad \frac{\partial q(e, L)}{\partial e}. \tag{6}$$

To determine $v_{z,n}$ for $n \geq 1$, recall that the borrower chooses the loan offer with the lowest cost c, if $c \leq z$. Let $F_c(\cdot)$ denote the distribution of c. Because the loan cost c is the sum of two independent random variables (R and a), it is distributed according to

$$F_c(c) = \int_{\underline{R}}^{\overline{R}} F_a(c-R)dF_R(R).$$

The distribution of the *lowest* cost out of $n \geq 1$ draws from $F_c(\cdot)$ is

$$\bar{F}_{c,n}(c) \;\; = \;\; 1-(1-F_c(c))^n \, .$$

Therefore, the value to a z-borrower of examining $n \geq 1$ offers is

$$v_{z,n} \;\; = \;\; b(1-\rho)\int_{-\infty}^{z} (z-c)\, d\bar{F}_{c,n}(c). \tag{7}$$

The following proposition characterizes borrowers' optimal effort $e(\cdot)$ of examining offers, the resulting distribution of accepted rates and the fraction of borrowers who get a loan, conditional on lenders' actions.

Proposition 2 *Given $F_R(\cdot)$ and L:*

1. *The optimal effort of a type-z borrower, $e(z)$, is unique and strictly increasing in z and solves*

$$\sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} \left(v_{z,n+1} - v_{z,n}\right) L \;\; = \;\; \frac{\partial q(e,L)}{\partial e}, \tag{8}$$

where $v_{z,0} = 0$ and equation (7) defines $v_{z,n}$ for $n \geq 1$.

2. *The distribution of accepted offers equals*

$$H_R(R) \;\; = \;\; \frac{1-\sum_{z\in Z} s_z e^{-e(z)L\int_{\underline{R}}^{R} F_a(z-x)dF_R(x)}}{1-\sum_{z\in Z} s_z e^{-e(z)L\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)}}. \tag{9}$$

3. *The fraction of borrowers who get a loan is*

$$Q \;\; = \;\; 1-\sum_{z\in Z} s_z e^{-e(z)L\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)}. \tag{10}$$

4.2 Lenders' Choices

We first characterize the optimal interest rate $R(k)$ of a type-k lender, then aggregate the actions of lenders who enter the market to obtain the interest rate offer distribution $F_R(\cdot)$, and finally characterize lenders' entry decisions L and $G(\cdot)$ given borrowers' effort $e(\cdot)$. To ease notation, we denote the effective arrival rate of offers to a type-z borrower by $\alpha(z) \equiv e(z) * L$.

A borrower accepts a loan offer with interest rate R if he examines this offer, if this offer yields the lowest cost from every offer that he examines (taking into account their attributes a), and if this offer yields net positive utility to the borrower. The next lemma characterizes the probability $P(R)$ that a random borrower accepts a loan offer with interest rate R.

Lemma 3 *Given $F_R(\cdot)$, L, and $e(\cdot)$, the probability $P(R)$ that borrowers accept a loan offer with interest rate R is continuous and differentiable in R and equals*

$$P(R) = \sum_{z \in Z} s_z e(z) \int_{-\infty}^{z-R} e^{-\alpha(z) \int_{\underline{R}}^{\overline{R}} F_a(R+a-x) dF_R(x)} dF_a(a). \tag{11}$$

Furthermore, $P'(R) < 0$.

We proceed to characterize the optimal interest rate schedule $R(\cdot)$, the distribution of interest rate offers $F_R(\cdot)$, the distribution of accepted offers $H_R(\cdot)$, and the fraction of borrowers who get a loan.

Proposition 4 *Given L, $G(\cdot)$, and $e(\cdot)$:*

1. *The profit-maximizing interest rate $R(k)$ of a type-k lender is continuous and strictly increasing in k.*

2. *$R(\cdot)$ solves the following functional equation:*

$$\begin{aligned} &\sum_{z \in Z} s_z e(z) \int_{-\infty}^{z-R(k)} e^{-\alpha(z) \int_{\underline{k}}^{\overline{k}} F_a(R(k)+a-R(x)) dG(x)} dF_a(a) \\ &= \left(R(k) - \frac{k}{1-\rho}\right) \sum_{z \in Z} s_z e(z) \left(\int_{-\infty}^{z-R(k)} e^{-\alpha(z) \int_{\underline{k}}^{\overline{k}} F_a(R(k)+a-R(x)) dG(x)} \left(\alpha(z) \int_{\underline{k}}^{\overline{k}} F_a' \left(R(k) \right.\right.\right. \\ &\left.\left. \left. + a - R(x)\right) dG(x) \right) dF_a(a) + e^{-\alpha(z) \int_{\underline{k}}^{\overline{k}} F_a(z-R(x)) dG(x)} F_a'(z - R(k)) \right). \end{aligned} \tag{12}$$

3. *The interest rate distribution equals $F_R(x) = G\left(R^{-1}(x)\right)$.*

The following proposition completes the characterization of lenders' entry decisions.

Proposition 5 *Given borrowers' effort $e(\cdot)$, lenders' entry satisfies the following:*

1. *A cutoff cost $\hat{k}$ exists such that a lender enters if and only if $k \leq \hat{k}$.*

2. *The measure of lenders in the market equals $L = \Lambda\Gamma(\hat{k})$ and the cost distribution of entrants equals $G(k) = \frac{\Gamma(k)}{\Gamma(\hat{k})}$ for $k \leq \hat{k}$ and $G(k) = 1$ for $k > \hat{k}$.*

3. *The cutoff cost $\hat{k}$ solves*

$$b\left(R(\hat{k})(1-\rho) - \hat{k}\right)\sum_{z\in Z} s_z e(z) \int_{-\infty}^{z-R(\hat{k})} e^{-e(z)\Lambda\Gamma(\hat{k})\int_{\underline{k}}^{\hat{k}} F_a\left(R(\hat{k})+a-R(x)\right)d\frac{\Gamma(x)}{\Gamma(\hat{k})}} dF_a(a) = \chi. \tag{13}$$

4.3 Constrained Efficiency

We now analyze the case of a social planner whose goal is to maximize aggregate welfare subject to frictions. The planner chooses lenders' entry decisions, as well as borrowers' examination effort and trading-decision rules (the interest rate simply redistributes surplus between borrowers and lenders; thus, it does not matter for the planner's problem).

We denote by $e^*(z)$ the planner's optimal solution for the examination of a type-z borrower. The entry decision rule is, trivially, a cutoff rule, and we denote the planner's optimal cutoff cost by $\hat{k}^*$. The surplus of a loan from a type-k lender with attribute a to a type-z borrower is $b(1-\rho)\left(z - a - \frac{k}{1-\rho}\right)$, where $z = \frac{\tilde{z}-\rho\delta}{1-\rho} - 1$ and $k = \tilde{k} + \rho$, as before. The planner's optimal trading-decision rule is that the borrower trades with the lowest-cost lender as long as the surplus is positive.

The overall surplus given borrowers' effort $e(\cdot)$ and lenders' entry cutoff $\hat{k}$ is

$$\mathcal{W}\left(e(\cdot),\hat{k}\right) \;=\; \sum_{z\in Z} s_z\left(\mathcal{W}_z\left(e(z),\hat{k}\right) - q\left(e(z),L\right)\right) - \chi L, \tag{14}$$

where $\mathcal{W}_z(e(z),\hat{k})$ is the expected surplus that a type-z borrower obtains from the offers that he receives; $q\big(e(z),L\big)$ is a z-borrower's examination effort cost; $L = \Lambda\Gamma(\hat{k})$ is the measure of lenders who enter the market; and χL are aggregate lenders' entry costs. Notice that no interaction occurs among borrowers regarding their examination efforts; thus, $\mathcal{W}_z$ only depends on the effort of the type-z borrower and does not depend on the full effort schedule.

The cost of a loan for the planner is $w \equiv \frac{k}{1-\rho} + a$. The planner's loan cost is distributed according to

$$
\begin{aligned}
F_w(w) &= \int_{\underline{k}}^{\hat{k}} F_a\left(w - \frac{k}{1-\rho}\right) dG(k) \\
&= \frac{1}{\Gamma(\hat{k})} \int_{\underline{k}}^{\hat{k}} F_a\left(w - \frac{k}{1-\rho}\right) d\Gamma(k).
\end{aligned}
$$

The distribution of the lowest w among n offers is

$$
\bar{F}_{w,n}(w) = 1 - \left(1 - \frac{1}{\Gamma(\hat{k})} \int_{\underline{k}}^{\hat{k}} F_a\left(w - \frac{k}{1-\rho}\right) d\Gamma(k)\right)^n .
$$

The social value to a type-z borrower of receiving n offers is:

$$
\mathcal{W}_{z,n}(\hat{k}) = b(1-\rho) \int_{-\infty}^{z} (z-w) d\bar{F}_{w,n}(w), \tag{15}
$$

where $\mathcal{W}_{z,0}(\hat{k}) = 0$. Notice these terms only depend on $\hat{k}$ and do not depend on borrowers' effort e.

The surplus that a type-z borrower who examines offers with effort e generates from the offers that he receives when lenders' entry cutoff is $\hat{k}$ equals

$$
\mathcal{W}_z(e, \hat{k}) = \sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} \mathcal{W}_{z,n}(\hat{k}). \tag{16}
$$

We now characterize the planner's optimal solution.

Proposition 6 *The constrained-efficient allocation is as follows:*

1. *The optimal effort for a type-z borrower $e^*(z)$ satisfies*

$$
\sum_{n=0}^{\infty} \frac{e^{-\alpha(e^*(z),L^*)}(\alpha(e^*(z), L^*))^n}{n!} \left(\mathcal{W}_{z,n+1}(\hat{k}^*) - \mathcal{W}_{z,n}(\hat{k}^*)\right) \frac{\partial \alpha(e^*(z), L^*)}{\partial e} = \frac{\partial q\left(e^*(z), L^*\right)}{\partial e}, \tag{17}
$$

where $\mathcal{W}_{z,n}(\hat{k}^*)$ is defined by equation (15), and $L^* = \Lambda\Gamma(\hat{k}^*)$ is the optimal measure of lenders in the market. A unique solution $e^*(z)$ exists for each z.

2. *The optimal entry-cost cutoff $\hat{k}^*$ for lenders satisfies*

$$
\sum_{z \in Z} s_z \left(\frac{\partial \mathcal{W}_z\left(e^*(z), \hat{k}^*\right)}{\partial \hat{k}} - \frac{\partial q(e^*(z), L^*)}{\partial L} \Lambda\Gamma'(\hat{k}^*) \right) = \chi\Lambda\Gamma'(\hat{k}^*), \tag{18}
$$

where

$$\frac{\partial \mathcal{W}_z(e^*(z), \hat{k}^*)}{\partial \hat{k}} = \sum_{n=0}^{\infty} \frac{e^{-\alpha(e^*(z),L^*)}\left(\alpha(e^*(z), L^*)\right)^n}{n!} \left(b \int_{-\infty}^{z} (z-w) d\left(\frac{\partial \bar{F}_{w,n}(w)}{\partial \hat{k}}\right) \right.$$
$$\left. + \frac{\partial \alpha(e^*(z), L^*)}{\partial L} \Lambda \Gamma'(\hat{k}^*) \left(\mathcal{W}_{z,n+1}(\hat{k}^*) - \mathcal{W}_{z,n}(\hat{k}^*) \right) \right), \tag{19}$$

and

$$\frac{\partial \bar{F}_{w,n}(w)}{\partial \hat{k}} = n \left(1 - \frac{1}{\Gamma(\hat{k})} \int_{\underline{k}}^{\hat{k}} F_a \left(w - \frac{k}{1-\rho} \right) d\Gamma(k) \right)^{n-1} \frac{\Gamma'(\hat{k})}{\Gamma(\hat{k})^2} \left(F_a \left(w - \frac{\hat{k}}{1-\rho} \right) \Gamma(\hat{k}) \right.$$
$$\left. - \int_{\underline{k}}^{\hat{k}} F_a \left(w - \frac{k}{1-\rho} \right) d\Gamma(k) \right).$$

The decentralized equilibrium of the economy features two potential sources of inefficiencies relative to the planner's allocation. First, for a given measure of lenders, some meetings in which trade is efficient (i.e., $z > \frac{k}{1-\rho} + a$) feature no trade, because the interest rate of lenders is excessive (i.e., $R > z - a$) due to lenders' market power. Second, the measure of lenders is not optimal (i.e., $L \neq L^*$).

5 Quantitative Analysis

The model does not admit an analytic solution for all endogenous outcomes. Hence, we choose the parameters that best match moments of the data with the corresponding moments computed from the model's numerical solution. We then study the quantitative implications of the model evaluated at the calibrated parameters.

5.1 Parametric Assumptions

The calibration requires that we make parametric assumptions for each of the four separate markets, that is, sub-prime, near-prime, prime, and super-prime borrowers.

We borrow some parametric assumptions about the distributions of borrowers' and lenders' heterogeneity from papers that structurally estimate search models of the labor market and our prior work on the retail market for illicit drugs (Galenianos and Gavazza, 2017). Specifically, given the similarity in modeling frameworks and empirical targets between this paper and those predecessors, we choose a discretized lognormal distribution with parameters μ_{z_j} and σ_{z_j} and $N_j = 20$ support points for the distribution $M_j(z)$ of buyers' preferences z in market j. Moreover, we assume that the distribution $\tilde{G}_j(\tilde{k})$ of sellers' costs $\tilde{k}$ is common across markets and follow a right-truncated Pareto distribution with shape ξ, scale equal to the risk-free rate—we use the interest rate of the one-year Treasury bill at January 16, 2007, which equals 5.06 percent—and an upper-truncation point $\hat{k}$. The assumption of a common cost distribution across markets means that we implicitly assume that the mass of potential lenders Λ_j varies across markets.

We normalize the loan size to $b_j = 1$. We further assume the following: 1) the effort cost of examining offers $q_j(e, L_j)$ equals $\beta_{0j}e^{\beta_1}$; 2) the charge-off rate in market j equals ρ_j; and 3) attribute a is unobserved in our data, and it follows a normal distribution with mean zero and standard deviation σ_{a_j}, and it is uncorrelated with R (Appendix D reports the results of the calibration in the case in which attribute a is correlated with the costs k and, thus, with the interest rate R as well). Hence, the effort costs of examining offers, the charge-off rates, and the standard deviations of the product attributes vary across markets.

Finally, we assume that the reported accepted rates $\hat{R}_j$ and the "true" accepted rate R are related as $\hat{R}_j = R_j\eta$, where η is a random variable, identically and independently distributed across observations, drawn from a lognormal distribution with parameters (μ_η, σ_η), common across markets, and with mean to equal 1. Hence, reported rates are unbiased and the parameters (μ_η, σ_η) satisfy $\mu_\eta = -0.5\sigma_\eta^2$. The literature that structurally estimates search models of the labor market frequently assumes that wages are measured with error. In our application, surveyed borrowers may report the interest rates that they pay on their credit card debt incorrectly. Moreover, the random variable η may also accounts for some additional factor that our model does not consider, such as adjustment of the interest rate after the offer is accepted, as in Nelson (2020). Table 2 shows that the distributions of accepted rates display a large dispersion, and these random η allow the model to more precisely match this feature of the data quantitatively.

5.2 Calibration

We choose the vector $\psi = \left\{L_j, \mu_{z_j}, \sigma_{z_j}, \xi, \hat{k}, \rho_j, \sigma_{a_j}, \beta_{0j}, \beta_1, \sigma_\eta\right\}_{j\in J}$ that minimizes the distance between the target moments m reported in Table 2 and the corresponding moments of the model. We calibrate two versions of the model: in the first one, we impose $\sigma_\eta = 0$; in the second one, σ_η can take any positive value.

Specifically, for any value of the vector ψ, we solve the model of Section 4 to find its equilibrium: the distribution $F_{R_j}(k)$ of offered interest rates and borrowers' effective arrival rate $\alpha_j(z)$ in each market j that are consistent with each other. Once we solve for these policy functions of borrowers and lenders in each market j, we compute the equilibrium distributions of interest rates of received offers and of accepted offers. In practice, we simulate these distributions and compute the moments $\mathbf{m}(\psi)$ corresponding to those reported in Table

2 on received offers and on accepted offers, as well as the aggregate fraction of credit card borrowers in each market j. Panel A and Panel C in Table 2 report the distribution of accepted interest rates and the charge-off rate, respectively, for each group j, whereas Panel B reports moments of the distribution of the number and of the offered rates aggregated for the entire market. Hence, we use weights ω_j corresponding to the population share of each group j (see footnote 7) to aggregate the number of received offers and the distribution of their interest rates.

We choose the parameter vector ψ that minimizes the criterion function

$$(\mathbf{m}(\psi) - m)' \, \Omega \, (\mathbf{m}(\psi) - m),$$

where $\mathbf{m}(\psi)$ is the vector of stacked moments simulated from the model evaluated at ψ and m is the vector of corresponding sample moments. Ω is a symmetric, positive-definite matrix; in practice, we use the identity matrix.

5.3 Data-Generating Process

Matching the moments reported in Table 2 requires that we account for the fact that the data-generating process may be unusual, because we combine two separate datasets, collected for different purposes. Specifically, the dataset on received offers reports *all* offers that borrowers in group j receive, whose arrival rate is L_j, and not exclusively the offers that borrowers examine in equilibrium, which may be lower than the offers received because borrowers' endogenous examination effort e may be less than full effort $e = 1$. We derive in Appendix B the average number of offers and the distribution of the difference between the highest and lowest offers that borrowers receive under the assumption that the arrival rates of these offers equal L_j.

However, lenders send these offers anticipating that borrowers receive and examine them according to their equilibrium $e_j(z) * L_j$. Hence, the moments on the empirical distribution of accepted offers reflect borrowers' endogenous examination effort $e_j(z) * L_j$.

5.4 Sources of Identification

The identification of the model is similar to that of other structural search models. Specifically, although the model is highly nonlinear, so that (almost) all parameters affect all outcomes, the identification of some parameters relies more heavily on certain moments in the data.

The moments on the number of offers that borrowers receive identify the average offer rate $\sum_j \omega_j L_j$ (where ω_j are the known shares of borrowers in each group), and thus contribute to the identification of group-specific offer rates L_j.[19] Similarly, the aggregate charge-off rate is informative about the group-specific default rates ρ_j. Moreover, we identify the parameter ξ of the distribution $G(k)$ of sellers' heterogeneity from the average funding cost reported by Standard and Poor's.

Furthermore, we observe the distribution of the difference between the highest and lowest offered interest rates R that borrowers receive. We show in Appendix B that this distribution depends in a precise way on the offer distribution $F_{R_j}(\cdot)$, which allows us to recover $F_{R_j}(\cdot)$.

With this knowledge, we still have to identify three sets of parameters that determine 1) the distribution of borrowers' preferences; 2) borrowers' examination effort; and 3) the extent of product differentiation (variation in attributes). Proposition 4 shows that these three sets of parameters shape three mappings between observable outcomes: A) the mapping between the distribution $G(k)$ of costs k and the distribution $F_{R_j}(R)$ of offered rates $R(k)$; B) the mapping between the offer distribution $F_{R_j}(R)$ and the distribution of accepted rates $H_{R_j}(R)$; and C) the mapping between the offer distribution $F_{R_j}(R)$ and the fraction of borrowers who get a loan Q_j. Hence, these three outcomes jointly identify the remaining three sets of parameters.

Intuitively, given lenders' costs $G(k)$, the dispersion of offers (i.e., mapping A) increases in the dispersion of borrowers' preferences, and decreases in the standard deviation σ_a of the product attribute a, because lenders (most notably, low-cost lenders) charge similar rates anticipating that consumers' choice depends relatively less on interest rates when a displays larger values. Furthermore, given the offer distribution F_{R_j}, the dispersion of accepted interest rates (i.e., mapping B) increases in examination costs, because borrowers examine fewer offers when costs are high, and in the standard deviation σ_a of the product differentiation, because larger values of a imply that interest rates affect consumers' choice relatively less than smaller values. Similarly, given the offer distribution F_{R_j}, it is apparent from equation (10) that the fraction of borrowers (i.e., mapping C) increases as examination effort $\alpha(z)$ increases. The discussion of the calibrated parameters of Section 5.5 and the comparative statics of Section 5.7 will further clarify how examination costs and product attribute a differentially affect market outcomes.

Finally, lenders' free-entry condition (equation (13)) implies that we can recover lenders' fixed costs χ_j from the variable profits of the highest-cost lender in each market.

[19] We should point out that the main implications of the model do not particularly rely on the specific values of L_j, but rather on borrowers' effective arrival rates $\alpha(z) = e(z)L_j$, which are identified from the distributions of costs, of offered rates, and of accepted rates, as we explain shortly. Hence, different values of L_j would imply different equilibrium values of $s(z)$ (and, thus, different costs β_{0j}), keeping $\alpha(z)$ unchanged.

Table 3: Calibrated Parameters

Panel A: No Measurement Error				Panel B: Measurement Error			
μ_{z_1}	3.613	σ_{z_1}	0.131	μ_{z_1}	3.575	σ_{z_1}	0.121
μ_{z_2}	3.518	σ_{z_2}	0.093	μ_{z_2}	3.528	σ_{z_2}	0.111
μ_{z_3}	3.461	σ_{z_3}	0.131	μ_{z_3}	3.447	σ_{z_3}	0.125
μ_{z_4}	3.251	σ_{z_4}	0.337	μ_{z_4}	3.223	σ_{z_4}	0.192
ξ	3.774	$\hat{k}$	10.182	ξ	4.183	$\hat{k}$	9.656
L_1	1.509	L_2	3.779	L_1	1.550	L_2	3.943
L_3	3.219	L_4	2.999	L_3	3.214	L_4	2.983
ρ_1	0.033	ρ_2	0.020	ρ_1	0.040	ρ_2	0.030
ρ_3	0.015	ρ_4	0.011	ρ_3	0.020	ρ_4	0.010
σ_{a_1}	0.105	σ_{a_2}	0.124	σ_{a_1}	0.081	σ_{a_2}	0.121
σ_{a_3}	0.138	σ_{a_4}	0.153	σ_{a_3}	0.156	σ_{a_4}	0.128
β_{01}	8.637	β_{02}	34.714	β_{01}	8.630	β_{02}	42.264
β_{03}	27.001	β_{04}	28.079	β_{03}	29.002	β_{04}	32.478
β_1	1.627	σ_η	0.000	β_1	1.741	σ_η	0.272

Notes: This table reports the calibrated parameters. Panel A refers to the version without measurement error ($\sigma_\eta = 0$), and Panel B to the version with measurement error ($\sigma_\eta > 0$)

5.5 Calibrated Parameters and Model Fit

Table 3 reports the calibrated parameters of the model. Panel A refers to the version without measurement error ($\sigma_\eta = 0$) and Panel B to the version with measurement error ($\sigma_\eta > 0$). Overall, the parameters are almost identical across versions, and thus we now discuss on those in Panel A of Table 3 only. As we recount above and Table 4 shows in detail, the measurement error η allows the model to capture the dispersion of accepted offers more precisely.

The parameters μ_{z_j} and σ_{z_j} of the distributions of z in group j mean that borrowers' willingness to pay for credit is, on average, large and displays large heterogeneity within group, as well as across groups. Specifically, borrowers' average willingness to pay decreases as their creditworthiness increases. The standard deviation of the willingness to pay, which equals $\sqrt{e^{2\mu_{z_j}+\sigma^2_{z_j}}\left(e^{\sigma^2_{z_j}}-1\right)}$, is non-monotonic in creditworthiness, with super-prime borrowers displaying a standard deviation almost nine times larger than that of near-prime borrowers.

The parameters ξ and $\hat{k}$ of the distribution of costs $\tilde{k}$ imply that the average costs of all entrants (not weighted by market shares) equal 636 basis points (the average funding cost used in the calibration weighs lenders by their market shares, and it equals 613 basis points at the calibrated parameters). Thus, average costs display a small spread of approximately 130 basis points over the risk-free rate. Moreover, the heterogeneity of lenders' costs is small, that is, the standard deviation of costs equals 106 basis points. Thus, the model generates a large dispersion of offered rates even with a small dispersion of costs.

The values of L_j indicate that lenders send, on average, approximately 2.7 credit card offers, with considerable heterogeneity across groups—sub-prime borrowers receive approximately half the offers that near-prime, prime, and super-prime borrowers receive. The number of offers is non-monotonic in the creditworthiness of borrowers, thereby matching the patterns that Han, Keys, and Li (2018) report. However, the parameters β_{0j} and β_1 imply that borrowers examine only a small fraction of these offers: the cost of effort to examine an average number of offers per period equal to $\alpha = 1$ corresponds to approximately 450 basis points, and it increases by almost 1,000 basis points to examine an average number of offers per period equal to $\alpha = 2$.

The value of σ_{a_j} implies that the standard deviation of the product attribute a is not large, relative to the overall heterogeneity in borrowers' preferences. Moreover, the value of σ_{a_j} increases with borrowers' creditworthiness, thereby indicating that non-price card attributes matter relatively more as borrowers' risk scores increase.

To understand why the calibration results in a sizable role for examination costs and a more modest one for product differentiation, we turn to the parts of the model that most contribute to their identification, namely, the mappings from lenders' costs to lenders' offers and from lenders' offers to borrowers' outcomes. Key features of the data are that 1) the level of offered interest rates is high relative to lenders' costs; 2) the distribution of offered rates is very dispersed; 3) the accepted rate distribution is similar to the offered rate distribution; 4) borrowers receive several credit card offers; and 5) the share of households with credit card debt is moderate. The central question is why borrowers do not systematically end up with low interest rates given that they receive many offers from a highly dispersed offer distribution.

Examination costs and product differentiation are two features that could rationalize the fact that individuals do not borrow at low interest rates. If examination costs are high, borrowers examine few of the offers that they receive—often one only—which results in high and dispersed accepted rates. If examination costs are low, borrowers examine several offers, which tends to reduce the level and the dispersion of accepted rates. High accepted rates could still occur with low examination costs if borrowers choose an offer because the value of its attribute a is large, which occurs more often when product differentiation is an important feature of the market, that is, when σ_a is large. However, the combination of low examination cost and high product differentiation leads to the following: 1) On the supply side, lenders set similar interest rates, because they matter less for borrowers' choices when the variance of the attribute a is larger; 2) Holding the distribution of offered rates constant, on the demand side, many borrowers take out loans, because borrowing is attractive due to large values of a. However, the data show that the dispersion of offered rates is very high, and that the aggregate fraction of individuals with credit card debt is moderate (approximately 45 percent).

In summary, the model calls for high examination costs β_{0j} in order to match the moderate fraction of borrowers, as well as the high dispersion of offered and of accepted rates that we observe in the data. The comparative statics of Section 5.7 further illustrate these issues.

Finally, the calibrated σ_η equals 0.272, which means that the standard deviation of the measurement error on the accepted rates equals 0.279. This value is small relative to the calibrated standard deviations of accepted rates R in the version without measurement error, which equal 3.50 in the sub-prime market, 3.45 in the near-prime market, 3.08 in the prime market, and 2.33 in the super-prime market, respectively.

Table 4 presents a comparison between the empirical moments and the moments calculated from the model at the calibrated parameters reported in Panels A and B of Table 3, respectively. The model without measurement error matches the data well, though, as anticipated, it underpredicts the dispersion of accepted rates—i.e., it overpredicts the lower percentiles and it underpredicts the higher percentiles. It matches reasonably well the percentiles of the distribution of the difference between the highest and lowest offered interest rates, and almost perfectly the aggregate statistics on the fraction of credit card borrowers in each group, thereby reproducing the mild non-monotonicity of the fraction of borrowers as their creditworthiness increases observed in the data. The model with a small measurement error on accepted offers matches the data almost perfectly. Perhaps the most notable difference between the model and the data is the fact that the model underpredicts the aggregate charge-off rate.

5.6 Model Implications

We study the implications of the model evaluated at the parameters reported in Panel A of Table 3. Because these parameters are very similar to those of Panel B, the implications of the model evaluated at the latter parameters are very similar as well.

Figure 1 displays lenders' and borrowers' equilibrium policies in each market j, shown in each row. The left column of Figure 1 displays lenders' optimal offered rate $R(k)$ (solid line, left axis) to each group of borrowers as a function of their cost k, as well as the density of lenders' cost k (dotted line, right axis) for values of the cost k from the risk-free rate up to the cutoff value $\hat{k}$ that the free-entry condition (13) determines. Lenders' offered rates are strictly increasing in their costs k, as Proposition 4 states. Markups, computed as $\frac{R(k)(1-\rho_j)-k}{k}$, on

Table 4: Model Fit

	Data	Model $\sigma_\eta = 0$	Model $\sigma_\eta > 0$
10th Percentile Accepted Rate, Sub-prime Borrowers	14.39	18.31	14.64
25th Percentile Accepted Rate, Sub-prime Borrowers	17.58	19.44	17.53
50th Percentile Accepted Rate, Sub-prime Borrowers	21.93	21.88	21.53
75th Percentile Accepted Rate, Sub-prime Borrowers	27.80	25.20	26.51
90th Percentile Accepted Rate, Sub-prime Borrowers	30.16	27.95	31.85
10th Percentile Accepted Rate, Near-prime Borrowers	13.20	17.01	13.68
25th Percentile Accepted Rate, Near-prime Borrowers	16.55	18.12	16.42
50th Percentile Accepted Rate, Near-prime Borrowers	20.20	20.46	20.19
75th Percentile Accepted Rate, Near-prime Borrowers	25.72	23.73	24.99
90th Percentile Accepted Rate, Near-prime Borrowers	29.16	26.32	30.06
10th Percentile Accepted Rate, Prime Borrowers	11.56	15.61	12.43
25th Percentile Accepted Rate, Prime Borrowers	14.81	16.58	14.93
50th Percentile Accepted Rate, Prime Borrowers	17.93	18.65	18.41
75th Percentile Accepted Rate, Prime Borrowers	21.90	21.54	22.75
90th Percentile Accepted Rate, Prime Borrowers	28.68	23.97	27.64
10th Percentile Accepted Rate, Super-prime Borrowers	10.79	14.17	11.31
25th Percentile Accepted Rate, Super-prime Borrowers	13.82	15.00	13.49
50th Percentile Accepted Rate, Super-prime Borrowers	16.84	16.72	16.44
75th Percentile Accepted Rate, Super-prime Borrowers	19.54	19.01	19.95
90th Percentile Accepted Rate, Super-prime Borrowers	23.98	21.05	23.95
Fraction Receiving 2+ Offers (%)	75.00	74.20	74.57
Median Number of Offers Received, Conditional on 2+ Offers	3.00	3.00	3.00
Average Number of Offers Received, Conditional on 2+ Offers	4.00	3.47	3.49
10th Percentile Distribution of Differences in Offered Rates	0.00	1.54	1.19
30th Percentile Distribution of Differences in Offered Rates	2.25	3.68	3.01
50th Percentile Distribution of Differences in Offered Rates	4.34	5.44	4.37
70th Percentile Distribution of Differences in Offered Rates	7.25	7.19	5.81
90th Percentile Distribution of Differences in Offered Rates	9.25	9.27	8.52
Fraction with Credit Card Debt, Sub-Prime Borrowers	54.56	55.87	54.52
Fraction with Credit Card Debt, Near-Prime Borrowers	55.33	56.19	55.29
Fraction with Credit Card Debt, Prime Borrowers	54.00	54.93	54.16
Fraction with Credit Card Debt, Super-prime Borrowers	36.02	36.58	36.17
Charge-Off Rate	4.01	1.90	2.28
Average Funding Cost	7.02	6.07	6.00
Criterion Function		139.15	19.02

Notes: This table reports the values of the empirical moments and of the moments calculated at the calibrated parameters reported in Table 3.

average, exceed 100 percent. They are non-monotonic in borrowers' creditworthiness: they equal 117, 154, 149, and 126 percent in the subprime, near-prime, prime, and super-prime markets, respectively.

The right panel of Figure 1 displays borrowers' effective arrival rate of offers $\alpha(z)$ (solid line, left axis), which is the outcome of borrowers' optimal examination effort e, as a function of their willingness to pay z, as well as the density of borrowers' willingness to pay z (dotted line, left axis). Because the lowest-valuation borrowers have a willingness to pay that is below almost all offered interest rates and the product attribute a has a small variance, these borrowers do not exert any effort to examine offers. More generally, the examination effort is low—on average, borrowers examine approximately 0.7 offers—and only borrowers whose willingness to pay z is in the highest 15 percent of the distribution choose $\alpha(z)$ larger than 1.

Figure 2 displays the probabilities $P_j(R)$ that borrowers accept a credit card offer with an interest rate R. These probabilities are obviously decreasing in R, but perhaps the most striking features of Figure 2 are that 1) for any R, the probability that subprime borrowers accept such an offer is at least twice as high as the probability that borrowers in any other risk group accept it, consistent with the evidence that Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018) report; and 2) because of borrowers' low examination effort, they are quite flat, which means that borrowers' demand is quite inelastic—the average elasticity equals approximately -1.70, which is remarkably similar to the elasticity that Nelson (2020) estimates. These external comparisons seem to suggest that our calibration yields reasonable parameters. Overall, the average acceptance probability $P_j(R)$ equals 0.17, which, scaled up by the mass of lenders $\sum_{j=1}^{J} \omega_j L_j \approx 2.7$, yields the aggregate fraction of individuals with credit card debt of 45.7 percent.

Figure 3 plots the distributions $F_{R_j}(R)$ of offered rates and the distributions $H_{R_j}(R)$ of accepted rates. Of course, the distributions of offered rates first-order stochastically dominate the distribution of accepted rates. However, the differences between the two distributions are small. Two reasons account for these small differences: 1) borrowers' low examination effort implies that the rate $\alpha(z)$ at which they consider offers is low; and 2) borrowers do not always accept the offer with the lowest interest rate, because of the differentiation attribute a. However, this second factor is quantitatively smaller than the first one, because the standard deviation σ_a is small and because, for a to have sizable effect, borrowers would need to consider more than one offer, which happens very infrequently due to their high costs of examining them. Thus, the mean of the distribution of accepted rates would be almost identical if borrowers were to always choose the offer with the lowest interest rates.[20]

[20] Of course, this is not a full equilibrium argument, as the endogenous distribution of offered rates $F_R(\cdot)$ depends on the product attribute a.

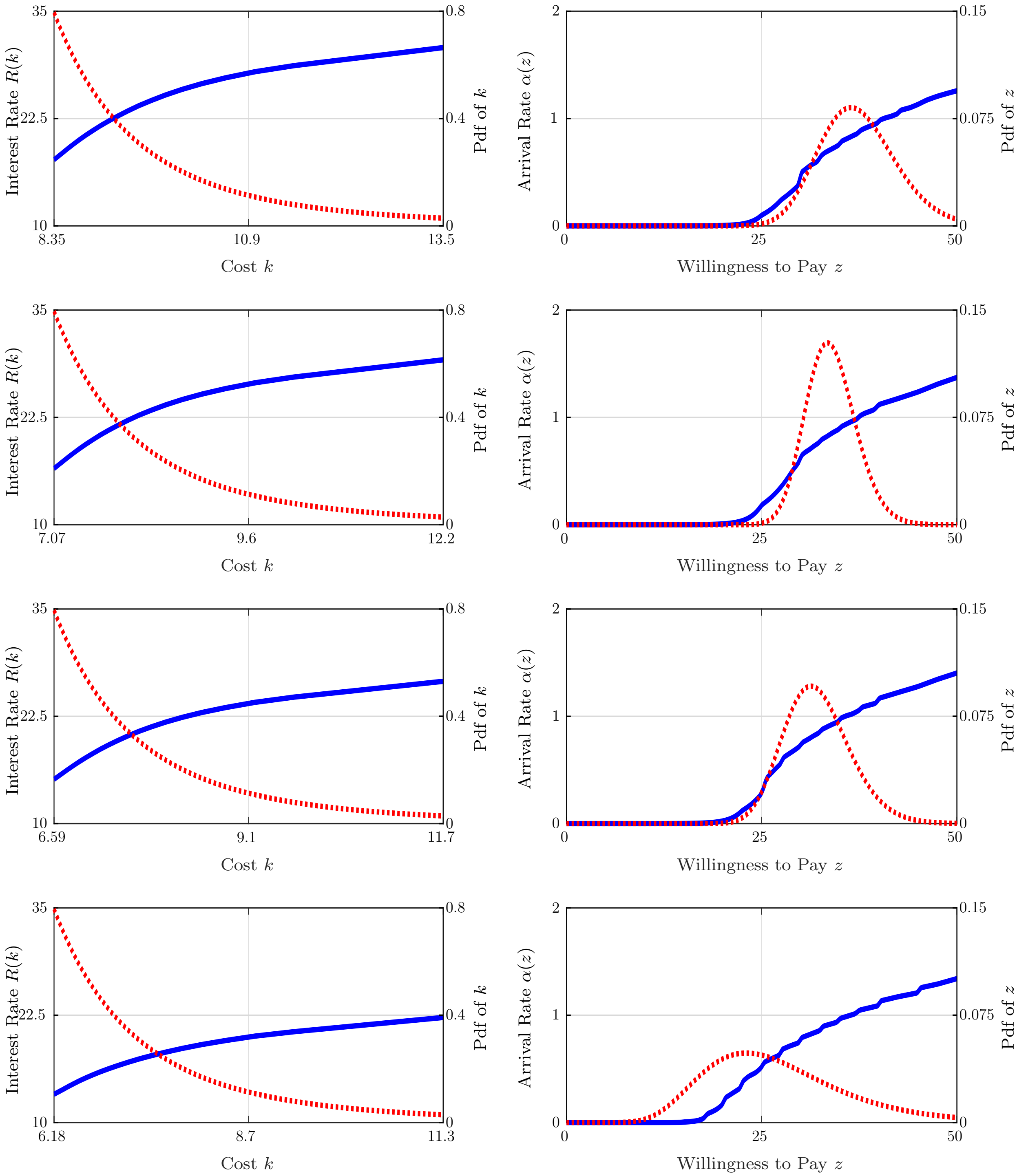

Figure 1: The left panels display lenders' optimal interest rate $R(k)$ (solid line, left axis) as a function of their cost k, as well as the density of lenders' cost k (dotted line, right axis). The right panels display borrowers' optimal arrival rate $\alpha(z)$ (solid line, left axis) as a function of their willingness to pay z, as well as the density of borrowers' willingness to pay z (dotted line, left axis). The first row refers to the sub-prime market, the second row to the near-prime market, the third row to the prime market, and the fourth row to the super-prime market.

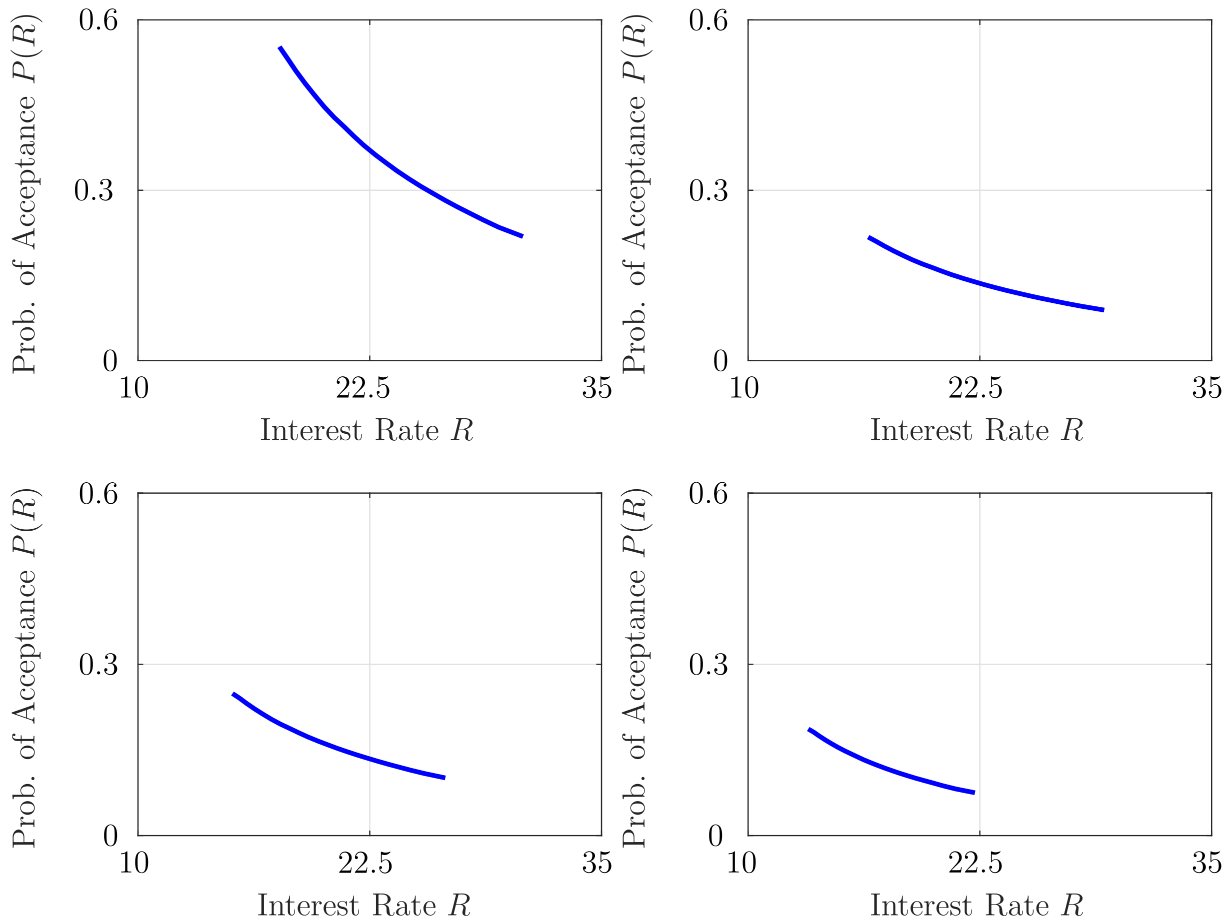

Figure 2: Probability $P(R)$ that borrowers accept an offer with interest R, for sub-prime borrowers (top-left panel), near-prime borrowers (top-right panel), prime borrowers (bottom-left panel), and super-prime borrowers (bottom-right panel).

The top rows of Table 5 report summary statistics of market outcomes—prices and quantities—as well as consumer surplus, lenders' profits, and aggregate welfare in each market. The calibrated model implies that consumer surplus, lenders' profits, and aggregate welfare, although they are all lowest in the super-prime market. The bottom two rows of Table 5 report the optimal number of offers and welfare in the constrained-efficient economy that we characterized in Section 4.3. As our theoretical analysis points out, the constrained-efficient allocation differs from the market allocation. Most notably, it requires a larger number of offers L_j in each market, on average, by 7 percent; the resulting welfare gains would be large, ranging from 21 percent in the sub-prime market to 30 percent in the super-prime market.

5.7 Comparative Statics

We further illustrate the working of our model through two comparative statics that vary the two parameters that are the main focus of our framework, namely the parameter β_{0j}

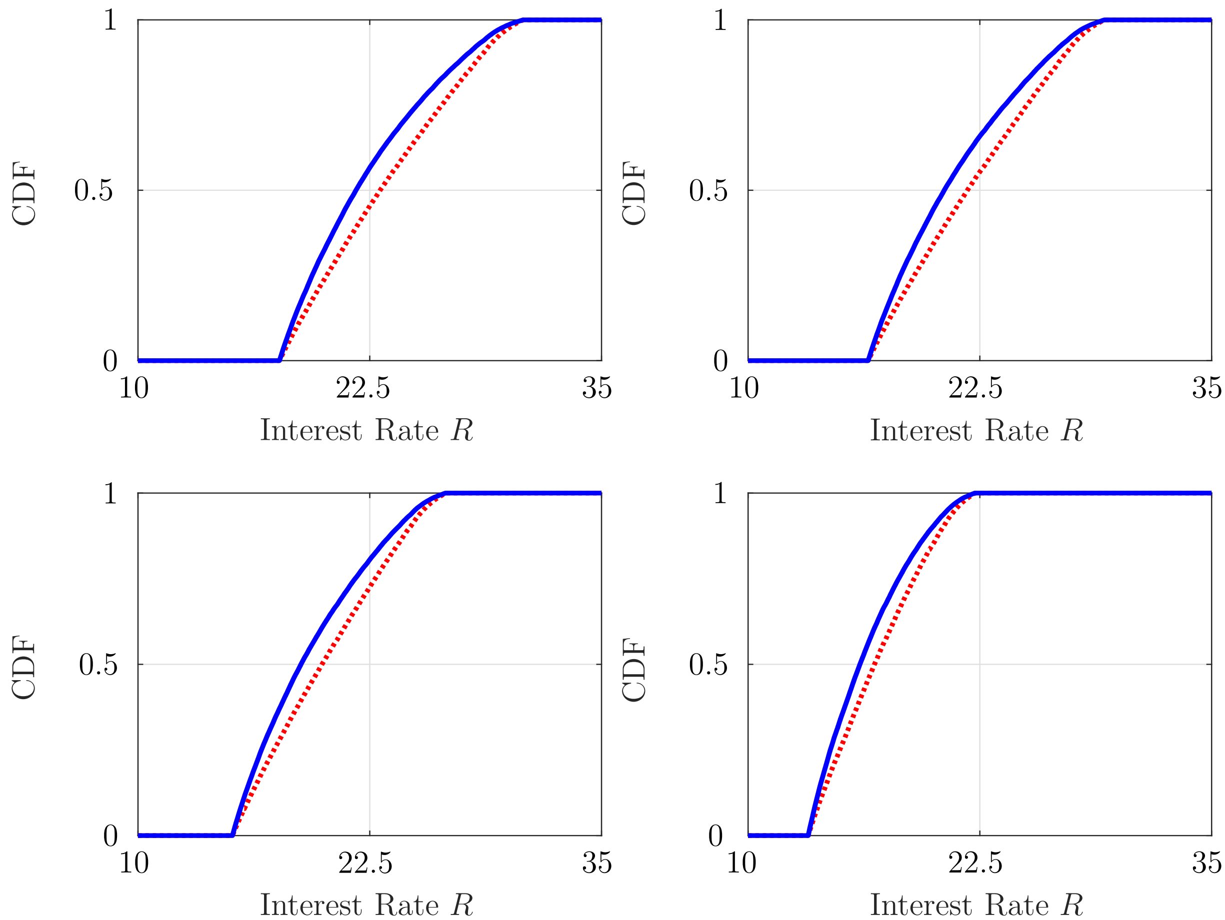

Figure 3: The solid line displays the cumulative distribution function $H_R(R)$ of accepted interest rates and the dotted line displays the cumulative distribution function $F_R(R)$ of offered rates, for sub-prime borrowers (top-left panel), near-prime borrowers (top-right panel), prime borrowers (bottom-left panel), and super-prime borrowers (bottom-right panel).

that affects the effort cost of examining offers, and the standard deviation σ_{a_j} of the product attribute a.

We present the results of these comparative statics for near-prime borrowers—that is, the group for which the model without measurement error matches the data most precisely, according to Table 4—but the outcomes for the other groups are similar.

Cost of Examinining Offers. Figure 4 compares outcomes of the model at the calibrated parameters (solid line) with those of the model when we decrease the parameters β_{0j} of the cost of effort by 30 percent (dotted line) while holding all other parameters at their calibrated values.

The top-left panel shows that the interest rate function $R(k)$ is lower than that in the baseline case, as all lenders uniformly decrease their interest rates. The decrease is larger for low-cost lenders than for high-cost lenders, because borrowers accept high-cost lenders' offers

Table 5: Market Outcomes and Welfare

	Sub-	Near-	Prime	Super-
Average Number of Offers per Borrower	1.51	3.78	3.22	3.00
Average Accepted Rate	22.42	21.20	19.35	16.44
Standard Deviation of Accepted Rates	3.49	3.41	3.07	2.31
Fraction of Borrowers	55.70	55.48	54.27	38.80
Consumer Surplus	5.10	4.18	4.31	3.76
Lender Profits	1.48	1.53	1.49	1.08
Welfare	6.58	5.71	5.80	4.84
Efficient Average Number of Offers per Borrower	1.62	4.07	3.47	3.23
Efficient Welfare	7.99	7.19	7.22	6.29

Notes: This table reports market outcomes and welfare in each market.

almost exclusively when borrowers consider one of these high offers only, and thus high-cost lenders do not need to lower their rates as much as low-cost lenders. The top-right panel explains why lenders' offered rates are lower: because the cost of effort is lower, borrowers increase their search effort.

The bottom-left panel shows that the probability $P(R)$ that borrowers accept an offer with a given interest rate R is higher than that of the baseline case for low values of R and lower for high values of R. The reason is that borrowers consider a larger number of offers, and thus their probability of accepting any offer increases, but they are relatively less likely to accept high-interest-rate offers. Demand becomes more elastic relative to that of the baseline case. Moreover, because lenders decrease their rates and borrowers accept offers with lower rates with a higher probability, the fraction of individuals with credit card debt increases relative to its value in the baseline case—from 55.5 percent to 68.8 percent.

The bottom-right panel of Figure 4 displays the distribution of offered rates (thick lines) and of accepted rates (thin lines). Both distributions obtained in the model with a lower β_{0j} (dotted lines) are first-order stochastically dominated by the corresponding distributions obtained in the model at the calibrated β_{0j} (solid lines). The reason is that low-cost lenders decrease their offered rates, because borrowers compare more offers if their effort to examine them is less costly. The average offered and accepted rates equal 20.45 and 19.03, respectively, and the standard deviation of offered and accepted rates equal 4.21 and 3.93, respectively, when the cost-of-effort parameter β_{0j} is 30 percent lower than its calibrated value. As the bottom plots shows, the lower cost of effort affects lower percentiles relatively more than higher percentiles.

Figure 4 also helps us understand why the calibrated model calls for relatively large effort costs: if they were smaller, the level of offered and of accepted interest rates would be lower, and the fraction of borrowers would be higher than those observed in the data.

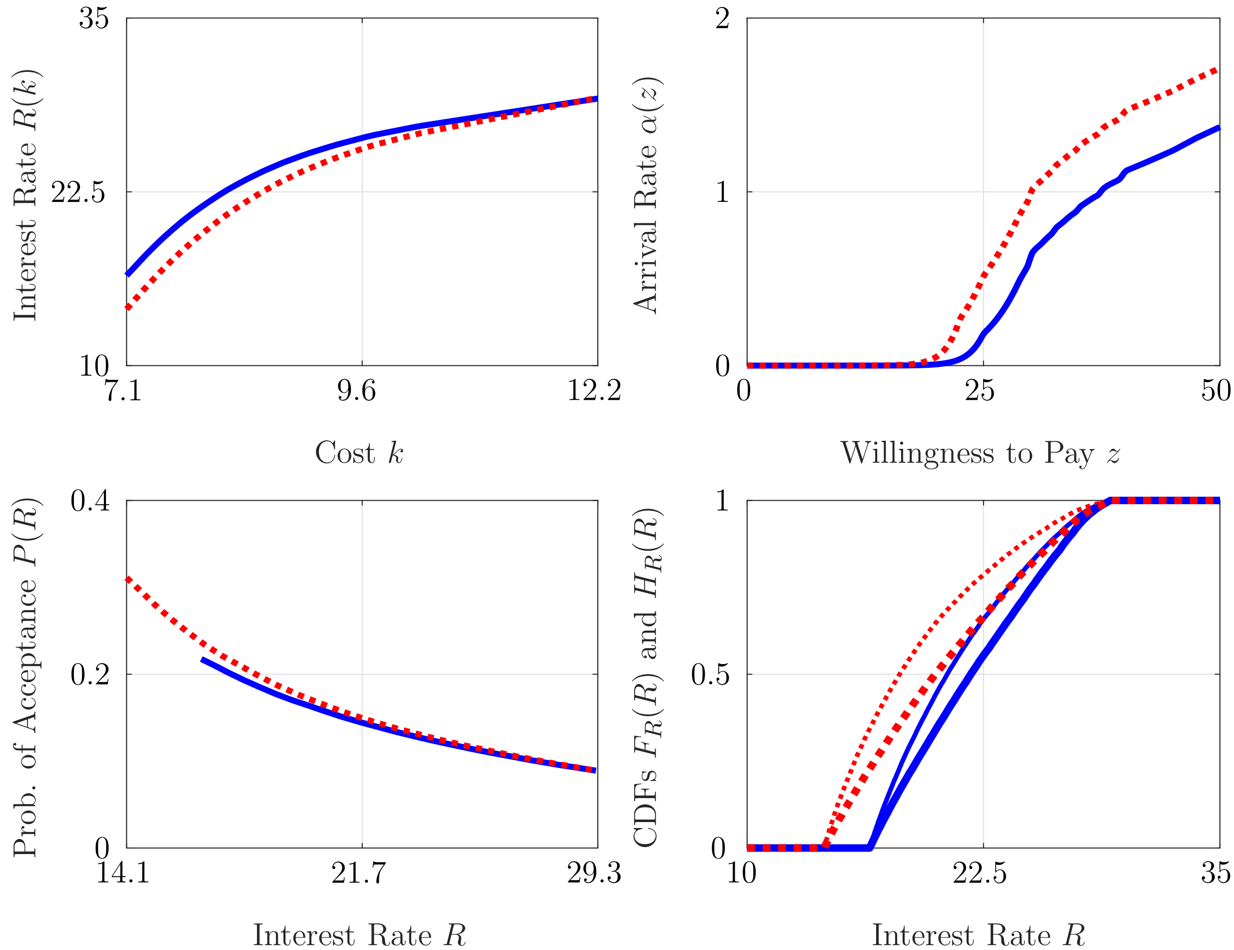

Figure 4: These panels display model outcomes at the calibrated parameters (solid line) and in the case when $\beta'_{0j} = 0.7\beta_{0j}$ (dotted line). The top-left panel displays lenders' optimal interest rate $R(k)$ as a a function of their cost k; the top-right panel displays borrowers' effective arrival rate $\alpha(z)$ as a function of their willingness to pay z; the bottom-left panel displays the probability $P(R)$ that borrowers accept an offer with interest rate R; and the bottom-right panel displays the distribution $F_R(R)$ of offered rates (thick lines) and the distribution $H_R(R)$ of accepted rates (thin lines).

Product Differentiation. Figure 5 compares outcomes of the model at the calibrated parameters (solid line) with those of the model with lower search costs (dotted line) and those of the model when we further increase the standard deviation σ_{a_j} of the product attribute a (dashed line), while holding all other parameters at their calibrated values. Because σ_{a_j} is calibrated to be small, we increase it by a factor of 30, which makes the value of the interquartile range of a similar to that of R observed in the data.

The top panels show interesting outcomes. Most notably, the top-left panel shows that the interest rate function $R(k)$ flattens when product differentiation is more important for borrowers. The reason is that a larger σ_{a_j} means that the interest rates affect consumers' choice across lenders relatively less, and thus all lenders charge similar rates.

The comparison between the dashed and the dotted lines in the top-right panel shows that a

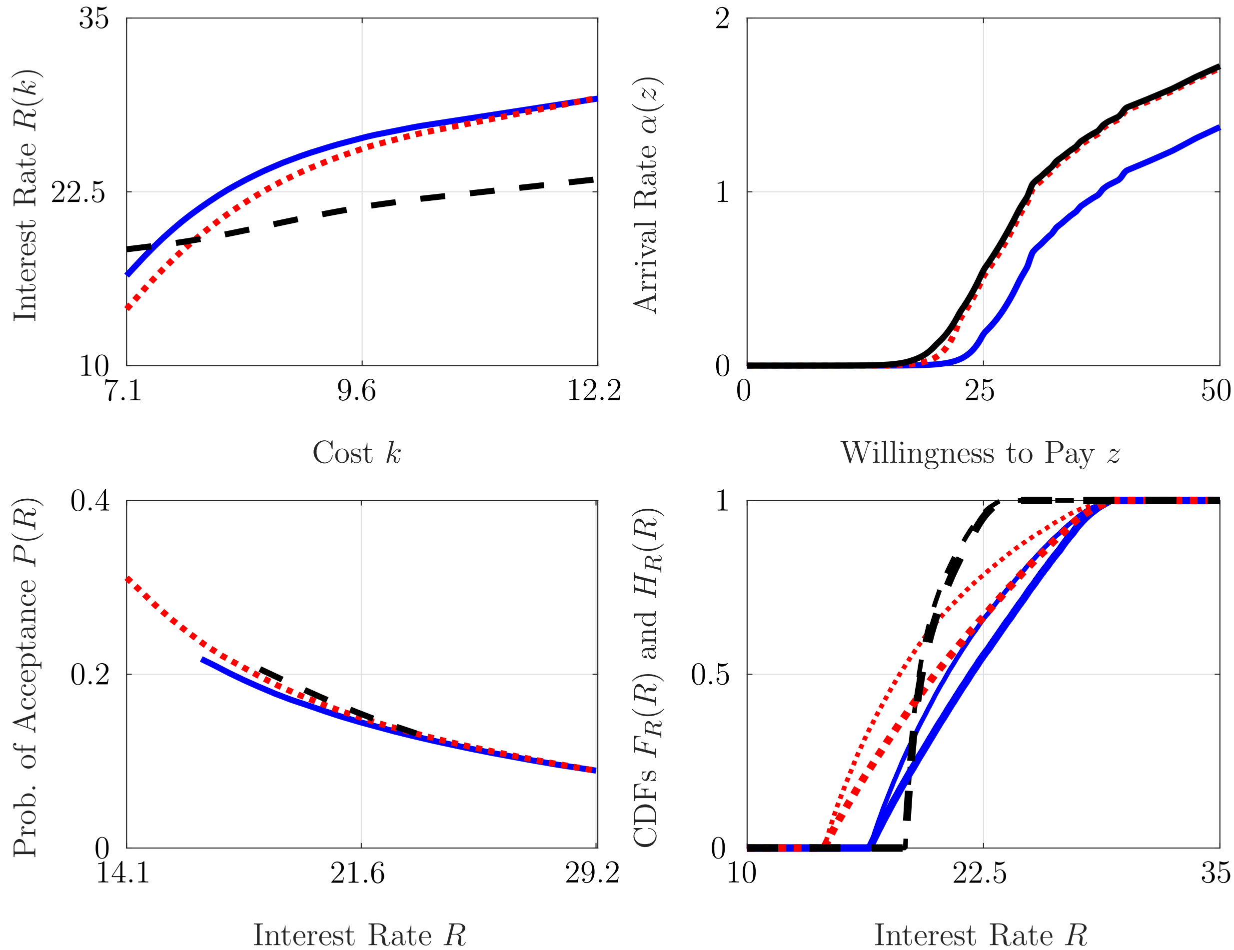

Figure 5: These panels display model outcomes at the calibrated parameters (solid line), in the case when $\beta'_{0j} = 0.7\beta_{0j}$ (dotted line), and in the case when $\beta'_{0j} = 0.7\beta_{0j}$ and $\sigma'_{a_j} = 30\sigma_{a_j}$ (dashed line) for near-prime borrowers. The top-left panel displays lenders' optimal interest rate $R(k)$ as a a function of their cost k; the top-right panel displays borrowers' effective arrival rate $\alpha(z)$ as a function of their willingness to pay z; the bottom-left panel displays the probability $P(R)$ that borrowers accept an offer with interest rate R; and the bottom-right panel displays the distribution $F_R(R)$ of offered rates (thick lines) and the distribution $H_R(R)$ of accepted rates (thin lines).

higher σ_{a_j} has a small effect on borrowers' search effort. This small change in effort is the result of opposite effects. Specifically, holding the distribution of offered rates fixed, the increase in the product-differentiation parameter induces borrowers to search more aggressively, because they are more likely to receive offers with product features a that they value more. However, the dispersion of offered interest rates decreases, which decreases borrowers' incentives to search. As a result of these offsetting effects, borrowers' effort to examine offers changes minimally.

The bottom-left panel displays the probability $P(R)$ that borrowers accept an offer with interest rate R. Because lenders offer similar interest rates when σ_{a_j} is higher, the acceptance probability of an individual offer with a given R increases relative to the case with identical costs of effort but a lower σ_{a_j}. Holding the distribution of offered rates fixed, this increase, cumulated over the range of R, would lead to a non-trivial increase in the fraction of individuals who borrow on credit cards, as we recount in Section 5.5.

The bottom-right panel displays the distribution of offered rates (thin lines) and of accepted rates (thick lines). Both distributions obtained in the model with a higher product differentiation and lower search costs (dashed lines) intersect the corresponding distributions obtained in the model at the calibrated values (solid lines), as well as those obtained with lower search costs only (dotted lines). This crossing is intuitive, because offered rates—and thus accepted rates as well—are less dispersed if the product attribute a matters more for consumers' choices. The average offer rate and the average accepted rate decrease from 22.12 and 21.20, respectively, in the baseline case at the calibrated parameters to 19.78 and 19.59, respectively, in the case with lower β_{0j} and higher σ_{a_j}. However, the most striking effects are on the standard deviation of offered and accepted rates, which decrease from 3.54 and 3.41, respectively, in the baseline case to 1.32 and 1.23, respectively, in the case with greater product differentiation and lower costs of effort.

Figure 5 also helps us understand why the calibrated model disfavors low costs of effort and large values of σ_{a_j}: if costs were low and σ_{a_j} were large, the dispersion of interest rates would be significantly lower than those observed in the data.

6 Policy Experiments

In this section, we use our model to study two policy experiments, motivated by recent regulatory interventions: 1) a cap on the interest rate—that is, a maximum rate R_{max}; 2) higher compliance costs for lenders, captured by higher fixed costs χ_j. The goal of both experiments is to study how borrowers' examination effort and lenders' offered rates respond, thereby affecting market outcomes and welfare.

6.1 Cap on Interest Rates

As we recount in the Introduction, several countries recently introduced price controls in markets for some consumer financial products, and are currently considering intervening in other markets as well. The goal of this section is to study the effects of a interest rate cap on the equilibrium of our model.

The theoretical literature points out that these caps may have unintended consequences, for two main reasons. First, caps reduce profit margins and thus may reduce the supply of credit, most notably to riskier borrowers who have higher default rates. Second, Fershtman and Fishman (1994) and Armstrong, Vickers, and Zhou (2009) show that, in markets with search frictions, price caps may have the unintended consequences of *increasing* the equilibrium prices that consumers pay. Specifically, they identify two opposing effects: 1) The direct effect of regulation is to reduce prices for uninformed consumers who, before the regulation, were paying high prices; and 2) the indirect effect is to reduce price dispersion, which reduces consumers' incentives to acquire information about prices, thereby increasing suppliers' market power and, thus, prices. Armstrong, Vickers, and Zhou (2009) further show that if consumers are heterogenous in their costs of acquiring information, the introduction of a price cap has an ambiguous effect on the equilibrium price paid by consumers, thereby leading to the possibility that equilibrium prices may increase. Hence, the relative magnitude of these contrasting effects is an empirical/quantitative question. Our calibrated model allows us to determine which of these opposing effect dominates, and thus whether price caps are beneficial to consumers.

To understand these issues, we set a common cap at $R_{max} = 25$ percent. This cap does not bind in the super-prime market, but it does in all other markets: Table 2 shows that it corresponds approximately to the 65th, 75th, and 95th percentiles of the distributions of accepted interest rates in the subprime, near-prime, and prime market, respectively.

We study this counterfactual case in general equilibrium; that is, we require that lenders' free-entry condition (13) holds. Thus, some lenders may exit the market, in which case we decrease the aggregate arrival rate of offers to a new value L'_j proportionally. Formally, the new arrival rate equals $L'_j = \Lambda_j G(\hat{k}')$, where $\hat{k}'$ is the marginal cost of the marginal lender—i.e., the lender that satisfies the free-entry condition (13)—in the counterfactual case (the marginal cost of the marginal lender in the baseline case equals $\hat{k}$).

Figure 6 compares outcomes of the model at the calibrated parameters (solid line) with those of the model with $R_{max} = 25$ percent, while holding all other parameters at their calibrated values, for the near-prime market.[21] The top-left panel shows interesting outcomes. First, the highest-cost lenders exit the market, even though the cap is above their marginal cost. Specifically, frictions are such that even if these lenders were to decrease their interest rates substantially, their market share would not increase enough to allow them to cover their fixed costs; hence, they exit. Second, all surviving lenders charge lower interest rates, because the function $R(k)$ lies strictly below that of the baseline case. In particular, the lender with marginal cost $\hat{k}'$ finds it worthwhile to drop its rate to satisfy the constraint, rather than exit. Similarly, all other lenders with lower marginal costs charge slightly below their higher-cost competitors.

The top-right panel shows how borrowers' effective arrival rate of offers adjusts, displaying

[21] In particular, we keep the standard deviations σ_{a_j} of the product attribute a constant. We should point out that: 1) reducing these standard deviations does not affect our main counterfactual results, as these standard deviations are very small relative to the standard deviation of R_j; 2) In the counterfactuals of Appendix D, which considers the case in which R and a are correlated, the standard deviations of the product attribute endogenously adjust when R is capped.

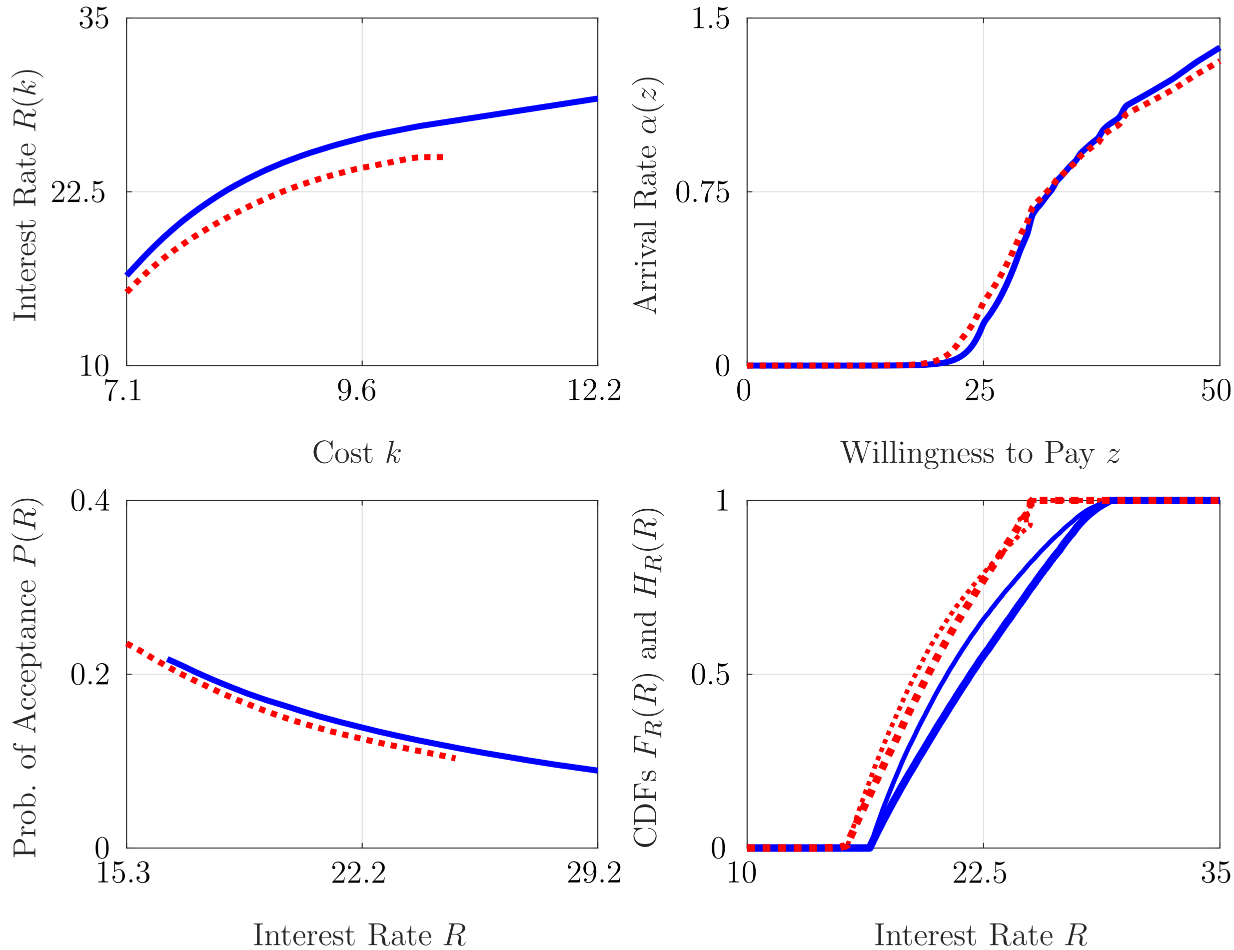

Figure 6: These panels display outcomes in near-prime market at the calibrated parameters (solid line) and in the case when interest rates are capped at 25 percent (dotted line). The top-left panel displays lenders' optimal interest rate $R(k)$ as a a function of their cost k; the top-right panel displays borrowers' optimal arrival rate $\alpha(z)$ as a function of their willingness to pay z; the bottom-left panel displays the probability $P(R)$ that borrowers accept an offer with interest rate R; and the bottom-right panel displays the distribution $F_R(R)$ of offered rates (thick lines) and the distribution $H_R(R)$ of accepted rates (thin lines).

the indirect and direct effects that Fershtman and Fishman (1994) and Armstrong, Vickers, and Zhou (2009) emphasize. Specifically, because some lenders exit the market, on average, borrowers receive seven-percent-fewer offers than in the baseline case. Nevertheless, low-valuation borrowers slightly increase their effort to more than offset the lower arrival rate of offers, and thus the average effective number of offers $\alpha(z)$ that they examine is higher than in the baseline. The reason is that the cap reduces the level of interest rates relative to the baseline case, thereby increasing the expected payoff from a credit card loan for these lower-valuation borrowers. However, high-valuation borrowers respond differently than low-valuation borrowers, in that the average number of offers $\alpha(z)$ that they consider is lower than in the baseline: these borrowers already had positive gains from trade in the baseline

Table 6: Market Outcomes and Welfare with a Price Cap

	Sub-	Near-	Prime	Super-
Average Number of Offers per Borrower	0.87	0.93	0.99	1.00
Average Accepted Rate	0.88	0.90	0.98	1.00
Standard Deviation of Accepted Rates	0.70	0.81	0.94	1.00
Fraction of Borrowers	0.97	1.01	1.01	1.00
Consumer Surplus	1.11	1.18	1.05	1.00
Lender Profits	0.47	0.62	0.92	1.00
Welfare	0.97	1.03	1.01	1.00

Notes: This table reports market outcomes and welfare in each market, as ratios of those of the baseline case.

case, but the cap reduces the dispersion of interest rates across lenders and thus reduces the benefits of examining multiple offers.

The bottom-left panel displays that the probability $P(R)$ that borrowers accept an offer with a given interest rate R decreases relative to that of the baseline case. The reason is that the cap reduces lenders' rates, and thus borrowers are less likely to accept an offer with a given R and are more likely to accept offers with lower interest rates. The average acceptance probability across lenders increases and demand is more elastic relative to the baseline case. Moreover, the fraction of individuals with credit card debt increases minimally to 55.97 percent from 55.47 percent in the baseline case. The reason is that the higher examination effort of borrowers with a relatively lower lower z leads them to consider and to accept more offers than in the baseline case. This increase more than offsets the decrease due to borrowers with a relatively high z, who examine fewer offers and thus are less likely to accept an offer relative to the baseline. Thus, marginal borrowers (i.e., those with a low valuation z) display a stronger response to the cap than infra-marginal borrowers (i.e., those with a high valuation z).

The bottom right panel of Figure 6 displays the distribution of offered rates (thick lines) and of accepted rates (thin lines). Both distributions in the case of an interest rate ceiling (dotted lines) are first-order stochastically dominated by the corresponding distributions of the baseline case with no ceiling (solid lines). The average offered and accepted rates equal 19.86 and 19.16, respectively, and the standard deviations of offered and accepted rates equal 2.87 and 2.77, respectively. These values are lower than those of the baseline, suggesting that the price cap increases the surplus of those who borrow.

Table 6 reports summary statistics of market outcomes, as well as consumer surplus, lenders' profits, and welfare for each group of borrowers when interest rates are capped, as ratios of those of the baseline case. The cap induces a large redistribution of surplus from lenders to borrowers, but small aggregate welfare effects. Specifically, consumer surplus increases in all markets affected by the cap, with larger increases in markets in which lender pricing is more constrained: the increase in consumer surplus equals 11 percent in the subprime market, 18 percent in the near-prime market, and five percent in the prime market (it is zero in the super-prime market because the cap is not binding); weighting markets by the share of borrowers in each of them, the aggregate increase in consumer surplus equals 6.2 percent. Correspondingly, aggregate lender profits decline by 21 percent—i.e., they decline by 53 percent in the subprime market, by 38 percent in the near-prime market, and by eight percent in the prime market. As a result, aggregate welfare is almost unchanged—i.e., it declines by less than one percent on aggregate, because it decreases in the sub-prime market by three percent, whereas it increases by two percent in the near-prime and by one percent in the prime markets. Appendix D shows that these welfare results are quite similar in the case in which the attribute a is correlated with the interest rate R, since nevertheless the data seem to reject that the unobserved attribute, whether correlated with R or not, has a large variance.

The results reported in Table 6 are broadly consistent with the empirical findings of Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), who report an increase in consumer surplus and a decrease in lender profits after the 2009 Credit Card Act banned overlimit fees on credit cards. More generally, the aggregate welfare reported Table 6 assigns equal weights to consumer surplus and to lender profits. Of course, any larger weight assigned to consumer surplus relative to that assigned to lender profits increases the assessments of the benefits of the interest rate cap.

6.2 Higher Compliance Costs

A second set of regulations that have been introduced since the Financial Crisis has broadly increased lenders' compliance costs. While many of these regulations may have potential benefits, such as greater financial stability and/or fewer abusive lending practices, through the lenses of our model, higher compliance costs can be interpreted as an increase in lenders' fixed costs χ_j. Hence, we wish to understand the effect of these cost-increasing regulations on borrower outcomes.

The increase in the fixed costs shares with our previous counterfactual regarding the introduction of an interest rate cap the feature that highest-costs lenders will exit the market; thus, this counterfactual with larger fixed costs allows us to understand how much the results displayed in Figure 6 obtain because of the exit of these highest-cost lenders. Moreover, Janssen and Moraga-González (2004) show that a decrease in the number of active sellers could increase examination effort because fewer sellers may decrease price dispersion, possibly leading to higher average prices.[22] Thus, our model is well suited to understand these effects.

[22] Similarly, Armstrong and Chen (2009) show that a decrease in the number of sellers could increase welfare in a search model with inattentive consumers.

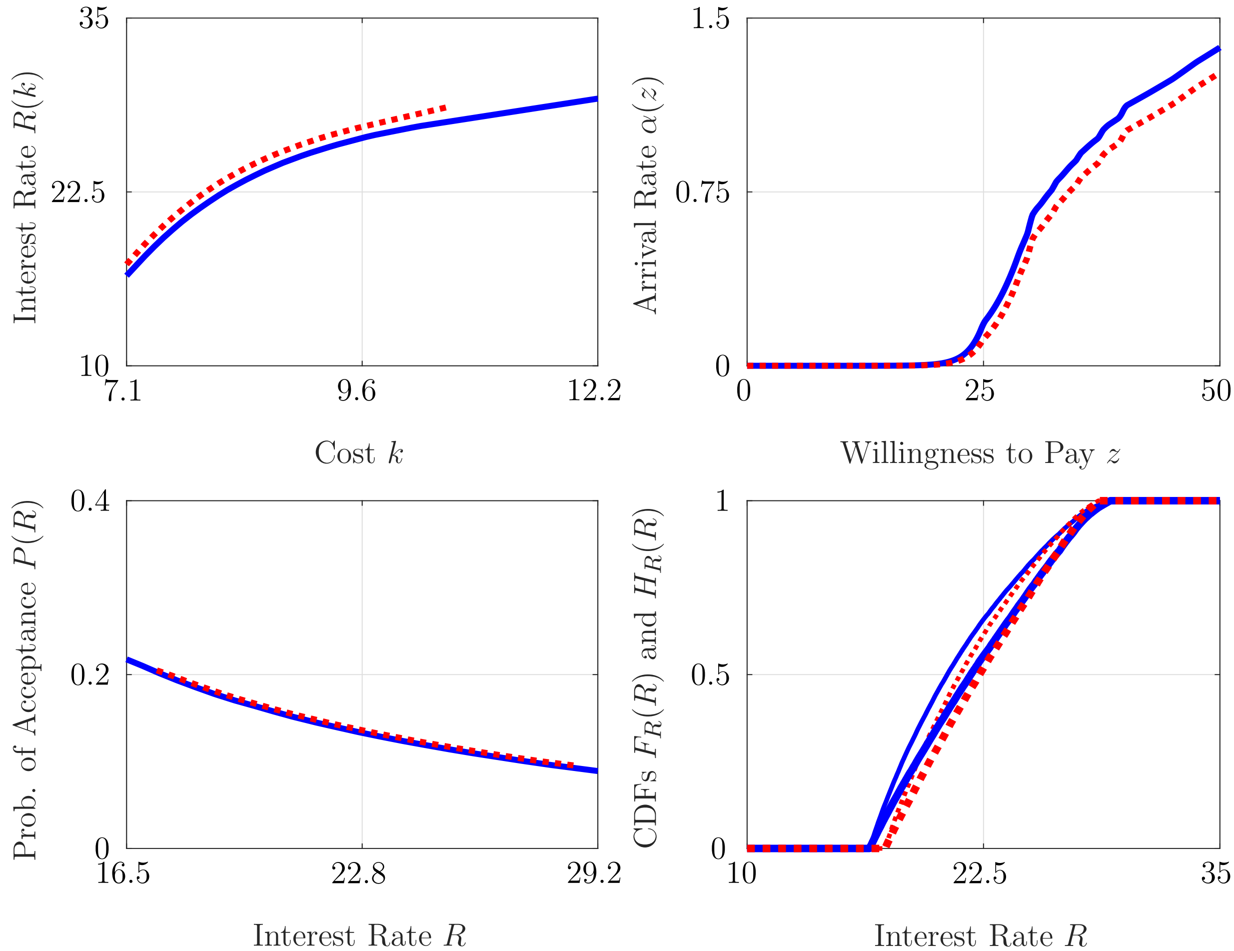

Figure 7: These panels display outcomes in near-prime market at the calibrated parameters (solid line) and in the case when the fixed cost $\chi' = 1.138\chi$ (dotted line). The top-left panel displays lenders' optimal interest rate $R(k)$ as a a function of their cost k; the top-right panel displays borrowers' effective arrival rate $\alpha(z)$ as a function of their willingness to pay z; the bottom-left panel displays the probability $P(R)$ that borrowers accept an offer with interest rate R; and the bottom-right panel displays the distribution $F_R(R)$ of offered rates (thick lines) and the distribution $H_R(R)$ of accepted rates (thin lines).

To facilitate the comparison with our price-cap experiment of Figure 6, we increase the fixed cost χ so that the marginal lender has marginal cost equal to $\hat{k}'$—i.e., the marginal cost of the lender that satisfies the free entry (13) condition in the case of the price cap $\bar{R} = 25$. In practice, the new fixed cost χ' is 13.8-percent larger than that of the baseline case in the near-prime market (it is 20-percent and 2.2-percent larger in the sub-prime and prime market, respectively, whereas it does not change in the super-prime market because the cap did not bind in that market). We further decrease the aggregate arrival rate of offers to a new value L'_j correspondingly; that is, the new arrival rate equals $L'_j = \Lambda_j G(\hat{k}')$.

Figure 7 compares outcomes of the model at the calibrated parameters (solid line) with those of the model with a higher fixed cost χ' for the near-prime market, displaying interesting

Table 7: Market Outcomes and Welfare with Higher Compliance Costs

	Sub-	Near-	Prime	Super-
Average Number of Offers per Borrower	0.87	0.93	0.99	1.00
Average Accepted Rate	1.00	1.03	1.00	1.00
Standard Deviation of Accepted Rates	0.83	0.91	0.99	1.00
Fraction of Borrowers	0.89	0.91	0.99	1.00
Consumer Surplus	0.86	0.85	0.98	1.00
Lender Profits	0.39	0.62	0.95	1.00
Welfare	0.75	0.79	0.97	1.00

Notes: This table reports market outcomes and welfare in each market, as ratios of those of the baseline case.

patterns. Notably, the exit of high-cost lenders reduces interest rate dispersion (top-left panel), but it does not reduce the level of interest rates, as surviving lenders increased their rates due to lower competition. Hence, borrowers consider fewer offers than in the baseline case (top-right panel) for two reasons: 1) they receive fewer offers—i.e., $L'_j = 3.50$ when compliance costs are higher versus $L_j = 3.79$ in the baseline case;[23] and 2) they choose not to exert much effort because price dispersion is lower, and thus the benefits of considering multiple offers are lower. The bottom-left panel shows that the probability $P(R)$ that borrowers accept an offer with a given interest rate R increases relative to the baseline case, because high and low offers are no longer available. However, the average acceptance probability across lenders decreases relative to the baseline case—i.e., 0.145 versus 0.147. Similarly, the fraction of borrowers declines to 0.50 from 0.55 in the baseline.

The bottom-right panel of Figure 7 shows that the distributions of offered rates (thick lines) and of accepted rates (thin lines) in a market with a higher fixed cost χ' (dotted line) intersect the corresponding distributions obtained in the baseline case (solid lines), as lenders no longer offer the lowest and the highest rates. The average offered and accepted rates are higher than those of the baseline (22.47 and 21.76 versus 22.12 and 21.20, respectively), whereas the standard deviations of offered and accepted rates are lower (3.20 and 3.11 versus 3.54 and 3.41, respectively).

Table 7 reports summary statistics of market outcomes, as well as consumer surplus, lenders' profits, and aggregate welfare for each group of borrowers when fixed costs are higher, as ratios of those of the baseline case. Higher fixed costs reduce lender profits, as the price cap did, but they also decrease consumer surplus, with large negative welfare effects. Specifically, consumer surplus decreases in all markets in which the cap is binding: the decrease in consumer surplus equals 14 percent in the subprime market, 15 percent in the near-prime market, and

[23] L'_j in this counterfactual case is identical by construction to that of the counterfactual case of caps on interest rates.

two percent in the prime market (it is zero in the super-prime market because the fixed cost is the same as in the baseline case). The aggregate decrease in consumer surplus equals six percent once we weight markets by their share of borrowers. Similarly, aggregate lender profits decline by 23 percent—they decline by 61 percent in the subprime market, by 38 percent in the near-prime market, and by five percent in the prime market. As a result, aggregate welfare declines by ten percent on aggregate—it declines by 25 percent in the sub-prime market, by 21 percent in the near-prime market and by three percent in the prime market. Appendix D shows that these results carry through in the case in which the unobserved attribute a is correlated with the interest rate R.

7 Conclusions

This paper develops a framework that captures the observed large number of credit card offers that individuals receive and the high level and large dispersion of the interest rates that individuals pay on their credit cards. We focus on two main reasons: endogenous (low) effort of examining offers and product differentiation. We calibrate the model using data on the U.S. credit card market, fitting them well. Our analysis implies that low effort of examining offers mostly accounts for the observed patterns on the data, whereas product differentiation plays a smaller role. We further use the calibrated model to perform policy experiments. Most notably, we find that interest rate caps generate quite large gains in consumer surplus, because they decrease lenders' market power.

We should point out that these results obtain in a model with some limitations, and thus future research could enhance it in several ways. As we recount in Section 3, our cross-sectional data impose some limitations on what our model can identify in the data, and richer data on borrowers and lenders would allow us to further enrich our current framework. Specifically, extreme multidimensional heterogeneity is difficult to identify with our data. Many structural search models share this limitation due to similar data constraints, and one contribution of this paper is to adapt and to enrich these models to incorporate two key features—i.e., consumer limited examination effort and product differentiation—that may rationalize the large number of credit card offers and the large dispersion of interest rates that we observe in the data.

For these main reasons, we view this paper as a first step in quantifying the role of effort for examining and evaluating offers in search markets. The quantitative analysis clarifies the data requirements to calibrate/estimate such a model and how the parameters are identified, and the calibration delivers a sense of the magnitudes involved, allowing us to assess which forces dominate. Nonetheless, we hope that the future availability of richer data will allow us to incorporate additional features of retail financial markets.

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APPENDIX

A Additional Empirical Results

In this Appendix, we report additional empirical results that complement those of Section 3. Specifically, we perform some robustness checks that construct the empirical distribution of interest rates by weighting observations using the revolving balance of each credit card account. This weighting strengthens the evidence that a pervasive feature of the credit card market is that borrowers pay very different interest rates on their credit card debt.

Table A1 presents these results. Its construction is similar that of Table 1, with some differences that we now explain. Column (1) replicates column (1) of Table 1, thus reporting selected percentiles of the raw data over the entire sample period January 2006-December 2008. Column (2) weighs each observation used in column (1) by its revolving balance in the corresponding month; hence, the distribution does not include interest rates of accounts whose balances are paid in full. For all borrower groups, the percentiles of the distributions reported in column (1) and in column (2) are very similar.

Column (3) replicates column (3) of Table 1, thus restricting the data to January 2007 and excluding introductory "teaser" rates (i.e., low initial rates that reset to higher rates after an initial offer period). Column (4) weighs each observation used in column (3) by the average revolving balance calculated over all available months in the panel period January 2006-December 2008. Again, for all borrower groups, the distributions reported in column (3) and in column (4) display very similar levels and overall dispersions of interest rates.

Column (5) replicates the regressions and the corresponding percentiles of the interest rates distributions of column (6) of Table 1, thus restricting the sample to cards with a revolving balance in January 2007. The regressions reported in column (6) of Table A1 weigh each observation used in the regressions of column (5) by the average revolving balance calculated over all available months in the panel period January 2006-December 2008. The coefficient estimates are similar between column (5) and column (6), most notably that of the FICO score. Moreover, based on these weighted regressions, we construct the residual interest rates using equation (2). The percentiles reported in the bottom part of column (6) further weigh these residual interest rates by their average revolving balance over the sample period—i.e., both the coefficient estimates and the distribution of residuals weigh each observation by the amount of the average revolving balance. For all borrower groups, the percentiles of the distributions reported in column (5) and in column (6) are strikingly similar.

Table A1: Interest Rates Weighted by Revolving Balance, by Borrower Group

Subprime Borrowers	(1)	(2)	(3)	(4)	(5)	(6)
FICO Score					-0.018	-0.022
					(0.006)	(0.008)
Reward Card					0.405	0.069
					(0.674)	(0.535)
Credit Limit					-0.158	-0.124
					(0.125)	(0.116)
Credit Balance					0.174	0.219
					(0.140)	(0.108)
R^2					0.013	0.037
Observations	27,024	27,024	877	877	766	766
10th Percentile	11.90	9.90	14.24	12.99	14.39	13.22
25th Percentile	16.15	15.90	17.24	16.24	17.58	16.43
50th Percentile	20.65	21.40	21.74	22.90	21.93	22.05
75th Percentile	27.49	28.24	27.99	29.23	27.80	27.75
90th Percentile	29.99	29.99	30.24	30.24	30.16	30.27
Near-prime Borrowers						
FICO Score					-0.052	-0.076
					(0.013)	(0.014)
Reward Card					0.562	-0.253
					(0.565)	(0.504)
Credit Limit					-0.255	-0.173
					(0.078)	(0.061)
Credit Balance					0.225	0.053
					(0.100)	(0.072)
R^2					0.043	0.090
Observations	27,059	27,059	900	900	661	661
10th Percentile	10.49	9.90	12.99	12.25	13.20	13.73
25th Percentile	14.90	14.24	15.94	15.81	16.55	16.99
50th Percentile	18.24	18.24	19.24	19.24	20.20	20.96
75th Percentile	23.15	24.24	23.30	25.40	25.72	25.67
90th Percentile	28.99	29.74	29.24	29.99	29.16	29.81
Prime Borrowers						
FICO Score					-0.052	-0.054
					(0.015)	(0.015)
Reward Card					-0.240	-0.614
					(0.520)	(0.503)
Credit Limit					-0.065	-0.100
					(0.049)	(0.045)
Credit Balance					0.013	0.078
					(0.059)	(0.047)
R^2					0.029	0.033
Observations	31,115	31,115	953	953	604	604
10th Percentile	9.90	9.90	11.99	11.24	11.55	11.63
25th Percentile	12.99	12.99	14.31	14.24	14.81	14.73
50th Percentile	16.74	16.99	18.24	18.24	17.90	18.00
75th Percentile	19.99	20.34	20.34	21.24	21.90	21.84
90th Percentile	25.99	28.99	28.15	28.99	28.65	28.88
Super-prime Borrowers						
FICO Score					-0.024	-0.039
					(0.010)	(0.011)
Reward Card					0.346	-0.226
					(0.471)	(0.498)
Credit Limit					0.028	0.030
					(0.031)	(0.029)
Credit Balance					-0.040	0.008
					(0.051)	(0.040)
R^2					0.012	0.028
Observations	56,880	56,880	1,645	1,645	546	546
10th Percentile	9.90	7.99	11.24	10.09	10.79	10.53
25th Percentile	12.99	11.74	14.15	13.49	13.82	13.07
50th Percentile	15.98	15.24	16.99	17.15	16.84	16.63
75th Percentile	18.24	18.74	18.24	19.99	19.54	19.76
90th Percentile	20.24	24.24	20.31	24.24	23.98	24.67

Notes: This table reports coefficient estimates of equation (1) and the corresponding percentiles of the distribution of centered interest rates as in equation (2). Columns (2), (4), and (6) report percentiles of the distribution weighted by revolving balance.

B Auxiliary Results: Distribution of Offers

We pointed out in Section 5.2 that survey respondents may report all offers that they receive, not only those that they would consider if they were not surveyed. We now derive the distribution of the number of offers and the distribution of the difference between the offers with the smallest and the largest interest rates under the assumption that respondents report all offers that they receive.

The expected number of offers for a borrower who receives $n \geq 2$ offers is

$$\mathbf{E}[n|n \geq 2] \quad = \quad \frac{L\left(1-e^{-L}\right)}{1-e^{-L}-Le^{-L}}.$$

Denote the probability distribution of the difference between the highest and the lowest interest rate of a borrower who receives $n \geq 2$ offers by $D(x)$. Denote the probability distribution of the difference between the highest and the lowest interest rate of a borrower who receives exactly n offers by $D_n(x)$ and note that

$$D(x) \quad = \quad \frac{1}{1-e^{-L}-Le^{-L}} \sum_{n=2}^{\infty} \frac{e^{-L}L^n}{n!} D_n(x).$$

Consider a borrower who receives n offers. Denote the lowest offer by R_L and note that its distribution follows $\bar{F}_n(R_L) = 1-(1-F(R_L))^n$. Each of the other $n-1$ offers are distributed iid according to $\hat{F}(R|R_L) = \frac{F(R)-F(R_L)}{1-F(R_L)}$, for $R \geq R_L$. The highest among these $n-1$ offers is distributed according to $\hat{F}(R_H|R_L)^{n-1}$. As a result

$$\begin{aligned} D_n(x) &= \int_{\underline{R}}^{\overline{R}} \left(\frac{F(R_L+x)-F(R_L)}{1-F(R_L)}\right)^{n-1} d\bar{F}_n(R_L) \\ &= \int_{\underline{R}}^{\overline{R}} n\left(F(R_L+x)-F(R_L)\right)^{n-1} F'(R_L)dR_L. \end{aligned}$$

Combining the above, we obtain

$$\begin{aligned} D(x) &= \frac{1}{1-e^{-L}-Le^{-L}} \sum_{n=2}^{\infty} \frac{e^{-L}L^n}{n!} \int_{\underline{R}}^{\overline{R}} n\left(F(R_L+x)-F(R_L)\right)^{n-1} F'(R_L)dR_L \\ &= \frac{1}{1-e^{-L}-Le^{-L}} \int_{\underline{R}}^{\overline{R}} \sum_{n=2}^{\infty} \frac{e^{-L}L^n}{(n-1)!} \left(F(R_L+x)-F(R_L)\right)^{n-1} F'(R_L)dR_L \\ &= \frac{Le^{-L}}{1-e^{-L}-Le^{-L}} \int_{\underline{R}}^{\overline{R}} \left(e^{L(F_R(R_L+x)-F_R(R_L))}-1\right) F'_R(R_L)dR_L. \end{aligned}$$

C Proofs

Proof of Proposition 2. We first show that the cost distribution for a low n first-order stochastically dominates that for a high n (thereby proving that $v_{z,n}$ is increasing in n) and that the derivative of the cost distribution for a high n first-order stochastically dominates that for a low n (thereby proving strictly decreasing differences)

$$\begin{aligned} \frac{d\bar{F}_{c,n}(c)}{dn} &= -\big(1-F_c(c)\big)^n \log\big(1-F_c(c)\big) > 0, \\ \frac{d^2\bar{F}_{c,n}(c)}{dn^2} &= -\big(1-F_c(c)\big)^n \Big(\log\big(1-F_c(c)\big)\Big)^2 < 0. \end{aligned}$$

Therefore, $v_{z,n+1} > v_{z,n}$ and $v_{z,n+2} - v_{z,n+1} < v_{z,n+1} - v_{z,n}$ for all n.

Differentiating equation (5) with respect to e (and noting that $v_{z,0} = 0$)

$$\begin{aligned} V_z'(e) &= \sum_{n=1}^{\infty} \Big(-\frac{e^{-eL}(eL)^n}{n!} v_{z,n} + \frac{e^{-eL}(eL)^{n-1}}{(n-1)!} v_{z,n}\Big) L \\ &= \Big(-\sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} v_{z,n} + \sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} v_{z,n+1}\Big) L \\ &= \sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} \big(v_{z,n+1} - v_{z,n}\big) L > 0. \end{aligned}$$

As a result, the borrower's expected value of offers is strictly increasing in their examination effort, and equation (8) characterizes the optimal choice of effort.

Furthermore, the expected value of loan offers is strictly concave in examination effort:

$$\begin{aligned} V_z''(e) &= \sum_{n=1}^{\infty} \left(-\frac{e^{-eL}(eL)^n}{n!} + \frac{e^{-eL}(eL)^{n-1}}{(n-1)!}\right) (v_{z,n+1} - v_{z,n})\, L^2 \\ &= \sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} \left(v_{z,n+2} - v_{z,n+1} - (v_{z,n+1} - v_{z,n})\right) L^2 < 0 \end{aligned}$$

Therefore, equation (6) has a unique solution $e(z)$, which yields the optimal examination effort for a type-z borrower.

Finally, notice that

$$\begin{aligned} \frac{\partial v_{z,n}}{\partial z} &= b\,(1-\rho) \int_{-\infty}^{z} d\bar{F}_{c,n}(c) = b\,(1-\rho)\,(1-(1-F_c(z))^n) > 0, \\ \Rightarrow \frac{\partial V_z(e)}{\partial z} &= \sum_{n=1}^{\infty} \frac{e^{-eL}(eL)^n}{n!} b\,(1-\rho)\,(1-(1-F_c(z))^n) > 0. \end{aligned}$$

Thus, higher-marginal-utility borrowers exert more examination effort, because they gain more from an increase in the effective arrival rate of offers.

We now calculate the distribution of accepted offers. Denote the probability that a type-z borrower gets a loan by Q_z and the probability that he gets a loan with interest rate less than R by $Q_z(R)$. Note that a type-z borrower gets a loan if he receives at least one offer with cost below z. Therefore

$$\begin{aligned} Q_z &= 1 - e^{-e(z)LF_c(z)} \\ &= 1 - e^{-e(z)L\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)}, \\ Q_z(R) &= 1 - e^{-e(z)L\int_{\underline{R}}^{R} F_a(z-x)dF_R(x)}. \end{aligned}$$

Denote the probability that a borrower gets a loan by Q and the probability that he gets a loan with interest rate less than R by $Q(R)$:

$$\begin{aligned} Q &= \sum_{z\in Z} Q_z \\ &= 1 - \sum_{z\in Z} e^{-e(z)L\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)}, \\ Q(R) &= 1 - \sum_{z\in Z} e^{-e(z)L\int_{\underline{R}}^{R} F_a(z-x)dF_R(x)}. \end{aligned}$$

The distribution of accepted interest rates $H_R(R)$ gives the proportion of borrowers who get a loan with interest rate less than R among the borrowers who get a loan:

$$\begin{aligned} H_R(R) &= \frac{Q(R)}{Q} \\ &= \frac{1 - \sum_{z\in Z} e^{-e(z)L\int_{\underline{R}}^{R} F_a(z-x)dF_R(x)}}{1 - \sum_{z\in Z} e^{-e(z)L\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)}}. \end{aligned}$$

The density of the accepted-rate distribution is

$$H_R'(R) = \frac{1}{Q}\sum_{z\in Z} e^{-e(z)L\int_{\underline{R}}^{R} F_a(z-x)dF_R(x)} e(z)LF_a(z-R)F_R'(R).$$

This completes the proof of proposition 2. ■

Proof of Lemma 3. Denote the probability that a type-z borrower accepts a loan offer with total cost c by $P_c(c,z)$. If $c \le z$, the borrower accepts the offer if it is the lowest-cost offer received, which occurs with probability $\big(1 - F_c(c)\big)^n$ when the borrower examines n additional offers. If $c > z$, the borrower does not accept that offer. Therefore

$$\begin{aligned}
P_c(c,z) &= \sum_{n=0}^{\infty} \frac{e^{-\alpha(z)}\alpha(z)^n}{n!}\big(1-F_c(c)\big)^n \\
&= e^{-\alpha(z)F_c(c)} \\
&= e^{-\alpha(z)\int_{\underline{R}}^{\overline{R}} F_a(c-x)dF_R(x)}, \quad \text{if } \; c \le z, \qquad \text{(C1)} \\
P_c(c,z) &= 0, \qquad \text{if } \; c > z. \qquad \text{(C2)}
\end{aligned}$$

Denote by $P_R(R,z)$ the probability that a type-z borrower accepts a loan offer with interest rate R. A borrower with valuation z accepts this offer if its cost (including the idiosyncratic attribute) is less than z and if all other offers that he examines have higher costs. Integrating over the potential values of the idiosyncratic utility draw yields

$$\begin{aligned}
P_R(R,z) &= \int_{-\infty}^{\infty} P_c(R+a,z)dF_a(a) \\
&= \int_{-\infty}^{z-R} e^{-\alpha(z)\int_{\underline{R}}^{\overline{R}} F_a(R+a-x)dF_R(x)} dF_a(a). \qquad \text{(C3)}
\end{aligned}$$

A borrower of type z accepts a loan offer with interest rate R if he examines the offer (probability $e(z)$) and the offer is better than any other offer that he examines (probability $P_R(R,z)$). Therefore, the probability that a randomly drawn borrower accepts a loan with interest rate R equals

$$\begin{aligned}
P(R) &= \sum_{z\in Z} s_z e(z) P_R(R,z) \\
&= \sum_{z\in Z} s_z e(z) \int_{-\infty}^{z-R} e^{-\alpha(z)\int_{\underline{R}}^{\overline{R}} F_a(R+a-x)dF_R(x)} dF_a(a),
\end{aligned}$$

which yields equation (11).

Because $F_a(\cdot)$ is smooth, $P(R)$ is continuous and differentiable in R. Differentiating $P(R)$ with respect to R yields

$$\begin{aligned}
P'(R) = & -\sum_{z\in Z} s_z e(z) \Bigg(\int_{-\infty}^{z-R} e^{-\alpha(z)\int_{\underline{R}}^{\overline{R}} F_a(R+a-x)dF_R(x)} \left(\alpha(z) \int_{\underline{R}}^{\overline{R}} F_a'(R+a-x)dF_R(x) \right) dF_a(a) \\
& + e^{-\alpha(z)\int_{\underline{R}}^{\overline{R}} F_a(z-x)dF_R(x)} F_a'(z-R) \Bigg) < 0.
\end{aligned}$$

Hence, the probability that borrowers accept a loan is strictly decreasing in the interest rate R. This completes the proof of lemma 3. ■

Proof of Proposition 4. The optimal interest rate for a type-k lender solves

$$\pi_k'(R) = b(1-\rho)P(R) + b\left(R(1-\rho)-k\right)P'(R) = 0.$$

Note that $\pi_k(R) < 0$ for $R < \frac{k}{1-\rho}$, $\pi_k\left(\frac{k}{1-\rho}\right) = 0, \pi_k'\left(\frac{k}{1-\rho}\right) = b\left(1-\rho\right)P\left(\frac{k}{1-\rho}\right) > 0$ and $\lim_{R\to\infty}\pi_k(R) = 0$. Therefore, some $\tilde{R} > \frac{k}{1-\rho}$ exists such that $\pi_k'(\tilde{R}) = 0$, and thus the optimal choice $R(k)$ exists. In the case of multiple roots, the lender chooses the solution that yields higher profits. Finally, because $\pi_k(R)$ is continuously differentiable in k, $R(k)$ is continuous and differentiable in k.

The cross-partial derivative of profits with respect to lender type and interest rate is positive:

$$\begin{aligned}
\frac{\partial \pi_k(R)}{\partial k} &= -bP(R),\\
\frac{\partial^2 \pi_k(R)}{\partial k \partial R} &= -bP'(R) > 0,
\end{aligned}$$

which implies $R'(k) > 0$.

Because the optimal interest rate is strictly increasing in the lender's cost k, we have $F_R\big(R(k)\big) = G(k)$ for $k \in [\underline{k}, \overline{k}]$. Hence,

$$F_R(x) = G\big(R^{-1}(x)\big).$$

Using this feature, we can rewrite equation (11) as follows:

$$P\big(R(k)\big) = \sum_{z\in Z} s_z e(z)\int_{-\infty}^{z-R(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(k)+a-R(x)\right)dG(x)} dF_a(a). \tag{C4}$$

Equation (C4) defines the probability that borrowers accept the loan of the cost-k lender when all lenders make their equilibrium choice. This probability does not directly depend on the interest rate distribution, because it incorporates the result that the offered interest rate is strictly decreasing in a lender cost k.

The profits of a type-k lender who follows the strategy of a type-$\tilde{k}$ lender are

$$\pi_k\big(R(\tilde{k})\big) = b\Big(R(\tilde{k})(1-\rho)-k\Big)\sum_{z\in Z} s_z e(z)\int_{-\infty}^{z-R(\tilde{k})} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(\tilde{k})+a-R(x)\right)dG(x)} dF_a(a).$$

Differentiating profits with respect to $\tilde{k}$, we obtain

$$\begin{aligned}\frac{\partial \pi_k(R(\tilde{k}))}{\partial \tilde{k}} &= bR'(\tilde{k})(1-\rho)\sum_{z\in Z} s_z e(z)\int_{-\infty}^{z-R(\tilde{k})} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(\tilde{k})+a-R(x)\right)dG(x)} dF_a(a)\\ &\quad -b\left(R(\tilde{k})(1-\rho)-k\right)\sum_{z\in Z} s_z e(z)\left(\int_{-\infty}^{z-R(\tilde{k})} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(\tilde{k})+a-R(x)\right)dG(x)}\right.\\ &\quad \left(\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a'\left(R(\tilde{k})+a-R(x)\right)R'(\tilde{k})dG(x)\right)dF_a(a)\\ &\quad \left. +R'(\tilde{k})e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(z-R(x))dG(x)} F_a'\left(z-R(\tilde{k})\right)\right).\end{aligned}$$

This derivative equals zero when $\tilde{k}=k$. Therefore

$$\begin{aligned}&(1-\rho)\sum_{z\in Z} s_z e(z)\int_{-\infty}^{z-R(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(k)+a-R(x)\right)dG(x)} dF_a(a)\\ &= \left(R(k)(1-\rho)-k\right)\sum_{z\in Z} s_z e(z)\left(\int_{-\infty}^{z-R(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(R(k)+a-R(x)\right)dG(x)}\left(\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a'\big(R(k)+a\right.\right.\\ &\left.\left. -R(x)\big)dG(x)\right)dF_a(a)+e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a\left(z-R(x)\right)dG(x)} F_a'\big(z-R(k)\big)\right),\end{aligned}$$

which yields equation (12) that defines the interest rate schedule $R(k)$. This completes the proof of proposition 4. ∎

Proof of Proposition 5. A lender's expected profits are strictly decreasing in his cost k, because a lender can always mimic the action of a higher-cost lender and make strictly higher profits.

Denote the highest-cost lender that enters the market by $\hat{k}$, where $\hat{k}\leq\overline{k}$, and note that the measure of lenders that enter the market is $L=\Lambda\Gamma(\hat{k})$. Denote the profits of the highest-cost lender by $\underline{\pi}_{\hat{k}}$:

$$\underline{\pi}_{\hat{k}}(R(\hat{k})) = b\Big(R(\hat{k})(1-\rho)-\hat{k}\Big)P(R(\hat{k})),$$

where

$$P(R(\hat{k})) = \sum_{z\in Z} s_z e(z)\int_{-\infty}^{z-R(\hat{k})} e^{-e(z)\Lambda\Gamma(\hat{k})\int_{\underline{k}}^{\hat{k}} F_a\left(R(\hat{k})+a-R(x)\right)d\frac{\Gamma(x)}{\Gamma(\hat{k})}} dF_a(a).$$

This equation makes explicit the dependence of L and $G(\cdot)$ on $\hat{k}$.

The profits of the highest-cost lender are decreasing in his type:

$$\frac{d\pi_{\hat{k}}}{d\hat{k}} = \frac{\partial \pi_{\hat{k}}}{\partial R} R'(\hat{k}) - bP\big(R(\hat{k})\big) + b\Big(R(\hat{k})\big(1-\rho\big) - \hat{k}\Big) \frac{\partial P(R(\hat{k}))}{\partial L} \Lambda \Gamma'(\hat{k}),$$

which is negative because the first term equals zero by the envelope theorem, the second term reflects the cost increase, and the third term reflects that an increase in $\hat{k}$ increases the measure of lenders in the market, which reduces the probability that borrowers accept a loan offer. Therefore, given $e(\cdot)$, a unique $\hat{k}$ exists that characterizes lenders' cutoff cost $\hat{k}$.

The cutoff $\hat{k}$ is determined by equating the profits of the highest-cost lender with the entry cost χ, as equation (13) shows. ■

Proof of Proposition 6. Differentiating equation (14) with respect to e and equating to zero for every z, we obtain

$$\frac{\partial \mathcal{W}_z\big(e^*(z), \hat{k}^*\big)}{\partial e} = \frac{\partial q\big(e^*(z), L^*\big)}{\partial e}.$$

We use equation (16) to rearrange the above equation, obtaining equation (17). The solution is unique for reasons similar to the decentralized case.

Differentiating equation (14) with respect to $\hat{k}$ and equating to zero, we obtain equation (18). Notice that

$$\begin{aligned}
\frac{\partial \mathcal{W}_z(e^*(z), \hat{k}^*)}{\partial \hat{k}} &= \sum_{n=0}^{\infty} \Big[\frac{e^{-e^*(z)L^*}\big(e^*(z)L^*\big)^n}{n!} \mathcal{W}'_{z,n}(\hat{k}^*) \\
&\quad + \mathcal{W}_{z,n}(\hat{k}^*) \Big(\frac{e^{-e^*(z)L^*}\big(e^*(z)L^*\big)^{n-1} e^*(z) \Lambda \Gamma'(\hat{k}^*)}{(n-1)!} \\
&\quad - \frac{e^{-e^*(z)L^*} e^*(z) \Lambda \Gamma'(\hat{k}^*) \big(e^*(z)L^*\big)^n}{n!} \Big) \Big] \\
&= \sum_{n=0}^{\infty} \frac{e^{-e^*(z)L^*}\big(e^*(z)L^*\big)^n}{n!} \Big(\mathcal{W}'_{z,n}(\hat{k}^*) + e^*(z) \Lambda \Gamma'(\hat{k}^*) \Big(\mathcal{W}_{z,n+1}(\hat{k}^*) - \mathcal{W}_{z,n}(\hat{k}^*) \Big) \Big).
\end{aligned}$$

Furthermore

$$\mathcal{W}'_{z,n}(\hat{k}^*) = b(1-\rho) \int_{-\infty}^{z} (z-w) d\Big(\frac{\partial \bar{F}_{w,n}(w)}{\partial \hat{k}} \Big).$$

Combining the last two equations yields equation (19). ■

D Correlation between R and a

In this Appendix, we extend the baseline model to consider the case in which the attribute of a credit card is, in equilibrium, positively correlated with its interest rate R, which might, in principle, account for some of the interest rate dispersion that we observe in the data. We derive the equilibrium conditions for this extension of the model. We then calibrate it to investigate how the extended model with correlation between attribute a and the interest rate fits the data. Finally, we study the welfare effects of price caps and of higher compliance cost in this extended model at its calibrated parameters.

D.1 Assumptions and Equilibrium Conditions

The matching process between borrowers and lenders is the same as in the baseline model. The cost of a loan now consists of three components: the interest rate R, the idiosyncratic component of the attribute a (distributed according to the zero-mean exogenous distribution $F_a(\cdot)$) and a deterministic component $\tau(k)$, which depends on the lender's type and acts as a mean-shifter the overall attribute realization. The total cost of a loan is $c = R - \tau(k) + a$. We assume that $\tau(k)$ is a smooth function with $0 < \tau'(k) < 1$.

The additional feature of this extension, $\tau(k)$, captures the possibility that a lender with a higher funding cost might offer some additional desirable features that we do not observe in our data, leading to higher acceptance rate than in the baseline model.

Let $R(k)$ denote the optimal strategy of a type-k lender. The cost of a loan, then, depends on the draw of two independent random variables: the lender type k from distribution $G(\cdot)$, which determines $R(k)$ and $\tau(k)$, and the draw of the attribute a from distribution $F_a(\cdot)$. Hence, c is distributed according to

$$F_c(c) \quad = \quad \int_{\underline{k}}^{\overline{k}} F_a\big(c - R(x) + \tau(x)\big) dG(x). \tag{D1}$$

Using the amended definition for the cost distribution, the results regarding borrowers' choice are essentially identical to the baseline model. They are summarized in the following proposition (we omit all proofs, because all derivations are identical to those of the baseline case).

Proposition 7 *Given $G(\cdot)$, $R(k)$ and L, optimal effort $e(z)$ is characterized by the following* *equations:*

$$
\begin{aligned}
\sum_{n=0}^{\infty} \frac{e^{-eL}(eL)^n}{n!} \left(v_{z,n+1} - v_{z,n}\right) L &= \frac{\partial q(e,L)}{\partial e}, \\
v_{z,n} &= b \int_{-\infty}^{z} (z-c)\, d\bar{F}_{c,n}(c), \\
\bar{F}_{c,n}(c) &= 1 - (1 - F_c(c))^n .
\end{aligned}
$$

Turning to the side of the lenders, the probability that a loan of cost c is accepted by a type-z borrower is defined similarly to the baseline case:

$$
\begin{aligned}
P_c(c,z) &= e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(c-R(x)+\tau(x))dG(x)} && \text{if} \quad c \le z, \\
P_c(c,z) &= 0 && \text{if} \quad c > z.
\end{aligned}
$$

A loan from a type-k lender with interest rate R is accepted by a type-z borrower with probability:

$$
P_{k,R}(R,z) = \int_{-\infty}^{z-R+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(R-\tau(k)+a-R(x)+\tau(x))dG(x)} dF_a(a).
$$

A loan from a type-k lender with interest rate R is accepted with probability:

$$
P_k(R) = \sum_{z\in Z} s_z e(z) \int_{-\infty}^{z-R+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(R-\tau(k)+a-R(x)+\tau(x))dG(x)} dF_a(a),
$$

where $P_k'(R) < 0$ for the same reasons as in the baseline model.

Notice that, in contrast to the baseline model, a lender's probability of giving a loan depends on his type k directly (i.e. over and above his interest rate choice R) because k determines the value of the mean-shifter. More precisely, the probability of a loan *increases* in k:

$$
\begin{aligned}
\frac{\partial P_k(R)}{\partial k} = \; & \sum_{z\in Z} s_z e(z) \Bigg(\int_{-\infty}^{z-R+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(R-\tau(k)+a-R(x)+\tau(x))dG(x)} \Big(\alpha(z) * \\
& \int_{\underline{k}}^{\overline{k}} F_a'(R-\tau(k)+a-R(x)+\tau(x))\tau'(k)dG(x) \Big) dF_a(a) + \\
& \tau'(k) e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(z-R(x)+\tau(x))dG(x)} F_a'(z-R+\tau(k)) \Bigg) > 0,
\end{aligned}
$$

which is intuitive since higher-k lenders have higher mean-shifters. Furthermore:

$$\frac{\partial P_k(R)}{\partial k} = -\tau'(k)P_k'(R).$$

The expected profits of a lender of type k who offers interest rate R are:

$$\pi_k(R) = bP_k(R)\left(R(1-\rho)-k\right),$$

The optimal choice $R(k)$ is characterized, as before, by:

$$\pi_k'(R) = bP_k'(R)\big(R(1-\rho)-k\big) + bP_k(R)(1-\rho) = 0.$$

Note that equilibrium profits are declining in k:

$$\begin{aligned}\frac{\pi_k(R(k))}{\partial k} &= b\frac{\partial P_k(R(k))}{\partial k}\big(R(k)(1-\rho)-k\big) - bP_k(R(k)) \\ &= -\Big(\tau'(k)bP_k'(R)\big(R(k)(1-\rho)-k\big) + bP_k(R(k))\Big) < 0.\end{aligned}$$

Hence, lender entry follows a cutoff rule, as in the baseline model.

The cross-partial derivative of profits with respect to R and k is:

$$\frac{\partial \pi_k'(R)}{\partial k} = \frac{\partial P_k'(R)}{\partial k}\big(R(1-\rho)-k\big) + \frac{\partial P_k(R)}{\partial k}(1-\rho) - P_k'(R).$$

The second and third terms are positive. It is not possible to sign the first term:

$$\begin{aligned}\frac{\partial P_k'(R)}{\partial k} = {}& \tau'(k)\sum_{z\in Z} s_z e(z)\Bigg(\int_{-\infty}^{z-R+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(R-\tau(k)+a-R(x)+\tau(x))dG(x)}\Big(-\big(\alpha(z)* \\ & \int_{\underline{k}}^{\overline{k}} F_a'(R-\tau(k)+a-R(x)+\tau(x))dG(x)\big)^2 + \\ & \alpha(z)\int_{\underline{k}}^{\overline{k}} F_a''(R-\tau(k)+a-R(x)+\tau(x))dG(x)\Big)dF_a(a) - \\ & e^{-\alpha(z)\int_{\underline{k}}^{\overline{k}} F_a(z-R(x)+\tau(x))dG(x)} F_a''(z-R+\tau(k))\Bigg).\end{aligned}$$

We will, from now on, assume that the cross-partial is positive and numerically confirm that this assumption holds for our parameter values.

Under our assumption, higher-cost lenders choose higher interest rates: $R'(k) > 0$. We characterize the optimal interest rate choice and entry by the lenders in the next proposition, following the same steps as in the baseline model.

Proposition 8 *Lenders' choices are characterized as follows:*

1. *Given borrowers' effort* $e(\cdot)$ *the optimal interest rate choice by lenders* $R(\cdot)$ *solves*

$$\sum_{z\in Z} s_z e(z) \int_{-\infty}^{z-R(k)+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\hat{k}} F_a(R(k)-\tau(k)+a-R(x)+\tau(x))dG(x)} dF_a(a)$$
$$= \left(R(k) - \frac{k}{1-\rho}\right) \sum_{z\in Z} s_z e(z) \left(\int_{-\infty}^{z-R(k)+\tau(k)} e^{-\alpha(z)\int_{\underline{k}}^{\hat{k}} F_a(R(k)-\tau(k)+a-R(x)+\tau(x))dG(x)} * \right.$$
$$\left(\alpha(z)\int_{\underline{k}}^{\hat{k}} F_a'(R(k)-\tau(k)+a-R(x)+\tau(x))dG(x)\right) dF_a(a) + \tag{D2}$$
$$\left. e^{-\alpha(z)\int_{\underline{k}}^{\hat{k}} F_a(z-R(x)+\tau(x))dG(x)} F_a'\left(z-R(k)+\tau(k)\right) \right).$$

2. *The marginal lender type who enters the market* $\hat{k}$ *is defined by*

$$b\left(R(\hat{k})(1-\rho)-\hat{k}\right) \sum_{z\in Z} s_z e(z) \int_{-\infty}^{z-R(\hat{k})+\tau(\hat{k})} e^{-e(z)\Lambda\Gamma(\hat{k})\int_{\underline{k}}^{\hat{k}} F_a\left(R(\hat{k})-\tau(\hat{k})+a-R(\hat{k})+\tau(\hat{k})\right)d\frac{\Gamma(x)}{\Gamma(\hat{k})}} dF_a(a) = \chi.$$

D.2 Calibration

We calibrate the model by making the same functional form-assumptions that we made in the baseline case of no correlation. In addition, we specify the function $\tau(k)$ to equal $\gamma(k-E(k))$, where $E(k) = \int_{k_{min}}^{\hat{k}} kdG(k)$ is the average cost.

We perform three calibrations for three separate values of γ: 1) $\gamma = 0.8$, which implies that the variance of the term $\tau(k)$ is large; 2) $\gamma = 0.4$, which implies that the variance of $\tau(k)$ is intermediate; and 3) $\gamma = 0.2$, which implies that the variance of $\tau(k)$ is small. Of course, the baseline calibration of Section 5 corresponds to the case with $\gamma = 0$.

Table D1 reports the parameters of these three cases and Table D2 reports how each case fits the data. These tables show the following: 1) The case with $\gamma = 0.8$ fits the data considerably worse than all other cases, including the baseline case with $\gamma = 0$. 2) The best fit of the data obtains with $\gamma = 0.4$, which corresponds to a moderate variance of $\tau(k)$. 3) The values of the other parameters—most notably, those of the cost-of-effort parameters β_{0j}—obtained in the best-fit case with $\gamma = 0.4$ are very similar to those obtained in the baseline case with $\gamma = 0$, thereby leading to similar implications to those of the baseline case.

Tables D3 and D4 report market outcomes and welfare for the counterfactual analyses in which we cap interest rates at $R_{max} = 25$ percent and in which we increase higher compliance costs, respectively, using the parameters in Panel B of Table D1 with $\gamma = 0.4$. These

Table D1: Calibrated Parameters, Correlation between R and a

Panel B: Large Variance			
μ_{z_1}	3.700	σ_{z_1}	0.123
μ_{z_2}	3.630	σ_{z_2}	0.088
μ_{z_3}	3.344	σ_{z_3}	0.126
μ_{z_4}	3.147	σ_{z_4}	0.344
ξ	3.836	$\hat{k}$	9.393
L_1	1.533	L_2	3.902
L_3	3.182	L_4	3.029
ρ_1	0.062	ρ_2	0.055
ρ_3	0.055	ρ_4	0.050
σ_{a_1}	0.110	σ_{a_2}	0.126
σ_{a_3}	0.136	σ_{a_4}	0.147
β_{01}	9.121	β_{02}	38.176
β_{03}	29.915	β_{04}	30.282
β_1	1.647	γ	0.800

Panel B: Medium Variance			
μ_{z_1}	3.616	σ_{z_1}	0.121
μ_{z_2}	3.524	σ_{z_2}	0.088
μ_{z_3}	3.461	σ_{z_3}	0.113
μ_{z_4}	3.205	σ_{z_4}	0.342
ξ	3.761	$\hat{k}$	9.970
L_1	1.525	L_2	3.765
L_3	3.211	L_4	3.035
ρ_1	0.042	ρ_2	0.024
ρ_3	0.018	ρ_4	0.014
σ_{a_1}	0.112	σ_{a_2}	0.130
σ_{a_3}	0.131	σ_{a_4}	0.135
β_{01}	8.844	β_{02}	35.759
β_{03}	27.627	β_{04}	27.261
β_1	1.638	γ	0.400

Panel B: Small Variance			
μ_{z_1}	3.607	σ_{z_1}	0.116
μ_{z_2}	3.519	σ_{z_2}	0.089
μ_{z_3}	3.458	σ_{z_3}	0.122
μ_{z_4}	3.208	σ_{z_4}	0.353
ξ	3.805	$\hat{k}$	9.903
L_1	1.518	L_2	3.806
L_3	3.253	L_4	3.067
ρ_1	0.035	ρ_2	0.021
ρ_3	0.017	ρ_4	0.011
σ_{a_1}	0.112	σ_{a_2}	0.130
σ_{a_3}	0.132	σ_{a_4}	0.155
β_{01}	8.844	β_{02}	35.124
β_{03}	27.548	β_{04}	27.481
β_1	1.619	γ	0.200

counterfactual analyses correspond to those of Section 6, with the only differences being that they use the parameters reported in Panel B of Table D1 rather than those reported in Panel A of Table 3.

Tables D3 and D4 confirm the robustness of our results of Section 6 that the price cap has positive effects on consumer surplus and negative effects on lenders' profits, whereas higher compliance costs have negative (and large) effects on consumers and on lenders. More specifically, Table D3 shows that, on aggregate, a price cap increases consumer surplus by 1.7 percent, decreases lender profits by 27.4 percent, resulting in a 3.3-percent welfare decrease. Table D4 shows that higher compliance costs decrease consumer surplus by 14.3 percent, decrease aggregate profits by 31.8 percent, resulting in a 17.3-percent welfare decrease.

Table D2: Model Fit, Correlation between R and a

	Data	Model $\gamma = 0.8$	Model $\gamma = 0.4$	Model $\gamma = 0.2$
10th Percentile Accepted Rate, Sub-prime Borrowers	14.39	20.24	18.52	18.41
25th Percentile Accepted Rate, Sub-prime Borrowers	17.58	21.35	19.60	19.51
50th Percentile Accepted Rate, Sub-prime Borrowers	21.93	23.64	21.87	21.86
75th Percentile Accepted Rate, Sub-prime Borrowers	27.80	26.73	25.15	25.19
90th Percentile Accepted Rate, Sub-prime Borrowers	30.16	29.41	28.06	27.97
10th Percentile Accepted Rate, Near-prime Borrowers	13.20	19.57	17.08	17.03
25th Percentile Accepted Rate, Near-prime Borrowers	16.55	20.65	18.16	18.12
50th Percentile Accepted Rate, Near-prime Borrowers	20.20	22.86	20.49	20.47
75th Percentile Accepted Rate, Near-prime Borrowers	25.72	25.90	24.01	23.86
90th Percentile Accepted Rate, Near-prime Borrowers	29.16	28.53	26.92	26.63
10th Percentile Accepted Rate, Prime Borrowers	11.56	13.75	15.60	15.53
25th Percentile Accepted Rate, Prime Borrowers	14.81	13.95	16.56	16.48
50th Percentile Accepted Rate, Prime Borrowers	17.93	14.57	18.66	18.53
75th Percentile Accepted Rate, Prime Borrowers	21.90	15.68	21.74	21.52
90th Percentile Accepted Rate, Prime Borrowers	28.68	16.85	24.47	24.07
10th Percentile Accepted Rate, Super-prime Borrowers	10.79	13.39	13.67	13.66
25th Percentile Accepted Rate, Super-prime Borrowers	13.82	13.60	14.49	14.45
50th Percentile Accepted Rate, Super-prime Borrowers	16.84	14.28	16.17	16.15
75th Percentile Accepted Rate, Super-prime Borrowers	19.54	15.43	18.57	18.53
90th Percentile Accepted Rate, Super-prime Borrowers	23.98	16.62	20.91	20.74
Fraction Receiving 2+ Offers (%)	75.00	74.65	74.54	74.86
Median Number of Offers Received, Conditional on 2+ Offers	3.00	3.00	3.00	3.00
Average Number of Offers Received, Conditional on 2+ Offers	4.00	3.49	3.48	3.50
10th Percentile Distribution of Differences in Offered Rates	0.00	0.72	1.54	1.55
30th Percentile Distribution of Differences in Offered Rates	2.25	1.80	3.88	3.85
50th Percentile Distribution of Differences in Offered Rates	4.34	2.75	5.71	5.65
70th Percentile Distribution of Differences in Offered Rates	7.25	3.65	7.59	7.46
90th Percentile Distribution of Differences in Offered Rates	9.25	7.94	9.84	9.59
Fraction with Credit Card Debt, Sub-Prime Borrowers	54.56	56.41	55.38	55.13
Fraction with Credit Card Debt, Near-Prime Borrowers	55.33	56.68	55.16	55.77
Fraction with Credit Card Debt, Prime Borrowers	54.00	51.05	54.26	54.69
Fraction with Credit Card Debt, Super-prime Borrowers	36.02	34.22	35.62	35.86
Charge-Off Rate	4.01	5.52	2.38	2.02
Average Funding Cost	7.02	6.03	6.07	6.05
Criterion Function		436.44	127.82	132.56

Table D3: Market Outcomes and Welfare with a Price Cap, Correlation between R and a

	Sub-	Near-	Prime	Super-
Average Number of Offers per Borrower	0.75	0.87	0.94	1.00
Average Accepted Rate	0.89	0.89	0.95	1.00
Standard Deviation of Accepted Rates	0.62	0.73	0.86	1.00
Fraction of Borrowers	0.85	0.97	0.99	1.00
Consumer Surplus	0.94	1.16	1.07	1.00
Lender Profits	0.41	0.42	0.74	1.00
Welfare	0.85	1.02	1.01	1.00

Notes: This table reports market outcomes and welfare in each market when interest rates are capped at $R_{max} = 25$ percent and R is correlated with the attribute a.

Table D4: Market Outcomes and Welfare with Higher Compliance Costs, Correlation between R and a

	Sub-	Near-	Prime	Super-
Average Number of Offers per Borrower	0.75	0.87	0.94	1.00
Average Accepted Rate	1.04	1.05	1.02	1.00
Standard Deviation of Accepted Rates	0.67	0.84	0.94	1.00
Fraction of Borrowers	0.74	0.84	0.94	1.00
Consumer Surplus	0.65	0.74	0.90	1.00
Lender Profits	0.25	0.45	0.67	1.00
Welfare	0.59	0.69	0.86	1.00

Notes: This table reports market outcomes and welfare in each market when compliance costs are higher and R is correlated with the attribute a.