Credit Constraints and Search Frictions in Consumer Credit Markets*

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Abstract

This paper documents consumer credit constraints in the market for automobiles and argues that they persist in part because of search frictions. Using rich microdata from several million auto loans extended by hundreds of financial providers, we isolate plausibly exogenous variation in interest rates due to institution-specific rule-of-thumb pricing rules. We show that these discontinuities a) lead to substantial interest rate dispersion among otherwise similar borrowers in the same MSA, b) distort car-buyer behavior, and c) are more consequential in areas we measure as having high search costs. Overall, our results provide an explanation for why both credit constraints and price dispersion persist in equilibrium in household finance.

Keywords: Household finance, credit constraints, price dispersion, search, auto loans

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Introduction

Households frequently finance their consumption with consumer credit products such as credit cards, student loans, and mortgages. Household borrowing has increased substantially over time, to the extent that aggregate household debt outstanding now exceeds aggregate corporate debt in the United States.[1] Despite this increase in credit use, ironically, some of the most important open questions in household finance center around whether consumption is constrained by access to credit, and if so, why credit constraints persist in equilibrium? This paper speaks to these two important questions by documenting credit constraints in auto lending markets that distort auto purchasing decisions. We then address the question of why constraints persist in equilibrium, arguing that consumers are unable to find optimal financing terms because searching for the optimal contract is costly.

When frictions in the market prevent consumers from borrowing from future income in quantities or prices that satisfy their Euler equation, consumers are said to be credit constrained. Generally speaking then, credit constraints could be defined as any reason why the Euler equation fails. More specifically, however, the literature has highlighted several examples of credit constraints that cause consumption to be distorted from first best levels. The first example are circumstances where borrowers are not allowed to borrow any amount from future income (e.g. the introduction of subprime loans to borrowers who previously were unable to get any type of mortgage). A second type of credit constraint, more common in the literature, are circumstances where borrowers would like to borrow larger amounts from future income but are constrained in the amount they are able to borrow. For example, Gross and Souleles (2002) document significant increases in consumer debt levels in response to credit card debt limit increases, interpreted as evidence that borrowers are able to borrow from future income but not in utility maximizing amounts.

Our auto loan setting highlights a third type of credit constraint. These are circumstances

[1]As of the first quarter of 2016, aggregate household debt outstanding was \$14.3 trillion, while the non-farm corporate sector had \$8.3 trillion debt outstanding (Federal Reserve Flow of Funds Table D.3).

where consumers cannot borrow at interest rates that allow them to borrow from future income in amounts that satisfy their demand. Though borrowers are not explicitly limited in the amount they can borrow, interest rates that are higher than the market-clearing risk-adjusted rate ultimately limit the dollar amount they can borrow, distorting consumption away from first best. Our empirical strategy features a setting where otherwise identical borrowers are exogenously offered substantially different interest rates. Assuming that borrowers with similar observables have similar auto consumption preferences, we argue that borrowers offered higher interest rates are credit constrained because higher offered interest rates limit the amount they are able to borrow, ultimately altering the type of car they purchase.[2] Throughout the remainder of the paper, then, our use of the term credit constraints refers to a set of borrowers that are psuedo-exogenously offered and accept higher interest rates as compared to interest rates that are offered to a set of otherwise similar borrowers.

We demonstrate the existence of credit constraints, how they distort consumption, and provide a rationale for their persistence using data on approximately 5.6 million auto loans extended by 326 different financial institutions in all 50 states. We document three main empirical facts. First, the segment of the auto lending market we study does not feature risk-based pricing; we observe large loan-rate and loan-term discontinuities at various institution-specific FICO thresholds. Second, consumer purchasing decisions are distorted by the resulting interest rate dispersion around these lending thresholds. Third, we show that constrained borrowers could find loans that would alleviate constraints but borrowers' propensity to search for loans with better terms is lower in areas likely to have higher search costs. Taken together, we argue that these three facts support a search frictions-based explanation for the persistence of credit constraints in the market for auto loans.

Our conclusions rely crucially on our ability to differentiate loan supply from loan demand. Our identification strategy exploits empirically identified discontinuities in offered

[2]The difference, then, between this and the other definitions of credit constraints, is that the credit constraints arise from a personal budget constraint that binds because offered interest rates are higher than the market-clearing risk-adjusted rate, instead of a borrowing cap imposed by an external institution.

loan terms around FICO thresholds across lending institutions. FICO thresholds appear to exist in 173 of the 326 lending institutions in our sample, and the location of the thresholds along the FICO spectrum varies across institutions. We document in first stage results that borrowers just to the right of FICO thresholds are offered longer loans at lower interest rates. On average, borrowers just to the right of an institution's FICO threshold originate loans with 1.47 percentage point lower interest rates for 1.4 longer months as compared to otherwise similar borrowers just to the left of a FICO threshold. Figures 1-2 provide instructive examples. The observed FICO thresholds differentiate the effects of changes in loan supply from demand under the assumption that changes in loan demand are not likely to be uniquely correlated with discrete, quasi-random FICO thresholds that vary across institutions even in the same MSA.

These documented credit supply thresholds give rise to compelling second stage results. Borrowers quasi-randomly offered easier credit spend $978.86 more on the cars they purchase. These borrowers also purchase cars that are more than 4.8 months newer, on average. Borrowers to the left of FICO thresholds are otherwise identical when applying for loans; they apply for similar loan amounts, with the same frequency, and report statistically identical ex-ante debt-to-income ratios. Ex-ante similarities on these observable dimensions suggest that borrowers on the wrong side of an arbitrary FICO threshold presumably would also like to purchase a more expensive and newer car, but are not offered credit terms that would allow them to afford the car.

Though the documentation of credit constraints of this type is still relatively novel to the literature, identifying frictions that contribute to the persistence of credit constraints is potentially more novel. In an otherwise frictionless world, borrowers similar in credit risk should obtain similar loan terms. Yet, we show that for constrained borrowers on the left side of lending thresholds, there exists within the same MSA loan terms that strictly dominate the constrained borrowers' loan terms. The magnitude of realized differences in loan terms is striking; differences in interest rates for similar borrowers average close to 200 basis points.

These results indicate that credit is indeed being offered at terms more favorable to a set of similar borrowers in the same city at the same time. The persistence of variation in loan terms around FICO thresholds indicates that frictions do exist such that, in equilibrium, otherwise similar borrowers are accepting loans on vastly different terms.

Our proposed search cost explanation for differences in equilibrium rates among similar borrowers is on account of the following evidence. We show that borrowers on the wrong side of FICO thresholds reject offered loans in patterns that are correlated with the number of financial institutions conceivably available to supply credit to borrowers. We measure borrowers propensity to search by calculating the fraction of borrowers that are offered loans and accept them, on either side of FICO thresholds, a term we define as the loan "take up" rate.[3] We then evaluate whether differences in borrowers search propensity is correlated with measures of search costs. Using the physical branch locations of every bank and credit union in the United States, we calculate the density of financial institutions within a 20 minute drive from each borrower. We find that differences in the difference of loan take-up rates around FICO thresholds are substantially larger for borrowers with the highest driving-time densities. That is, borrowers on the wrong side of a threshold are more likely to reject offered loans and search for a different loan if they live in a locale with more lending institutions close by. In contrast, differences in take up rates around lending thresholds are much smaller in areas with very few lending institutions. Borrowers that would presumably have to exert more effort to search for a loan with better terms are more likely to accept the terms they are offered. In a set of robustness checks, we verify that borrowers' ex-ante and ex-post observables are not correlated with our measure of search costs. Taken together, we interpret the evidence as suggesting that search costs represent a meaningful market friction that allows for the persistence of borrower credit constraints.

The empirical result that many borrowers in our sample could have found better loan

[3]As would be expected, borrowers on the wrong side of FICO thresholds, and thus offered worse terms, accept offered loans less frequently than their otherwise similar counterparts on the right side of FICO thresholds. Importantly, borrowers do not apply for loans at differential rates across the FICO thresholds.

terms at the same time in the same MSA is also consistent with explanations outside of search costs. The most natural alternative is a classic adverse selection hypothesis. Though borrowers might be similar on observables around FICO thresholds, borrowers on the borders of FICO thresholds might be different along soft information dimensions, leading institutions to ration credit. Two pieces of evidence suggest that soft information is not driving our results. First, borrowers on either side of FICO thresholds do not default on loans at statistically different rates. Second, we exploit a unique feature of the data that allows us to observe borrower FICO scores at loan origination and then again at time periods after origination. These data indicate that borrowers' FICO scores do not change by differential amounts through time around FICO thresholds. If borrowers on the wrong side of FICO thresholds were systematically worse along soft information dimensions, presumably this would ultimately be made manifest in declining FICO scores through time as borrowers missed payments on any credit obligation. Finally, in a very limited sample, we are able to directly observe the same borrower applying for multiple loans. The incidence of multiple loan applications is also correlated with the measure of driving distance from nearby lending institutions.

Related Literature

Two broad types of evidences on credit constraints are most common in the literature; increases in consumer spending in response to one-time liquidity shocks and changes in consumption patterns around exogenous changes in financing conditions. Papers documenting consumption increases in response to temporary liquidity shocks include Adams, Einav, and Levin (2009), Johnson, McClelland, Parker, and Souleles (2013), Mian and Sufi (2011a), Japepelli and Pistaferri (2010), and Agarwal, Liu, and Souleles (2007). Gross and Souleles (2002b) document changes in consumption on account of financing conditions by showing that consumer debt levels in response to declining interest rates were the largest among borrowers that carried debt levels near binding credit limits. A reduction in the supply of finance during the financial crisis also appears to have reduced spending among the most ex-ante leveraged borrowers (Mian, Rao, and Sufi (2013), Mian and Sufi (2014a), and Baker (2014)). Our paper adds to the financing-induced changes in consumption literature by documenting how car consumption decisions are influenced by quasi-random variation in offered interest rates, evidence that borrowers behave as though they are credit constrained via the interest rate channel.

This paper is among the first however to argue for search costs as an explanation for the persistence of credit constraints. Mulitple studies have shown that search costs explain price dispersion, but not in settings where price dispersion is associated with credit constraints. For example, Stango and Zinman (2015) document price dispersion in the U.S. credit card market, driven by variation in shopping intensity. Hortacsu and Syverson (2004) document large dispersion in the fees of very similar mutual funds that are driven by information/search frictions. Sorenson (2000) documents dispersion in prices of prescription drugs that are driven by search costs. However, as argued by Zinman (2014), compelling explanations in the literature for the existence and persistance of credit constraints remain few. The most notable exception is Adams, Einav, and Levin (2009), who document credit constraints in auto markets and provide evidence of adverse selection and moral hazard as the cause. Our proposed search cost explanation need not be mutually exclusive to an adverse selection explanation. Though we attempt to rule out adverse selection as an explanation for the specific set of results we observe, we consider search costs as friction number two, alongside adverse selection (Adams, Einav and Levin (2009)), on the list of empirically documented frictions contributing to credit constraints. Usury laws are another possible friction contributing to credit constraints. Though theory suggests that prices could and should perform their standard role in clearing credit markets, even for the riskiest of borrowers; in practice, usury laws impose a ceiling on rates that would be required to compensate lenders for the most extreme risk. The credit quality of borrowers in our sample likely fall outside the scope of a usury law explanation.

A Taxonomy of Credit Constraints

A discussion of credit constraints necessarily begins with the Permanent-Income Hypothesis (PIH) as the benchmark. In the frictionless world of the PIH, consumers borrow from future income in amounts and at interest rates that satisfy budget constraints, allowing for utility maximizing consumption. We motivate our taxonomy of credit constraints with the standard utility maximization problem. Consumers maximize expected lifetime utility by solving solving the optimization problem,

$$\max \sum_t \frac{u(c_t)}{(1+\delta)^t} \tag{1}$$

$$s.t. \sum_t \frac{c_t}{(1+r^*)^t} \leq \sum_t \frac{y_t}{(1+r^*)^t} + (1+r^*)A_t \tag{2}$$

where y_t is income, A_t represents total consumer assets, and r^* represents the market-clearing, risk adjusted cost of borrowing. Maximizing utility with respect to lifetime consumption yields the standard Euler equation,

$$u'(c_t) = \frac{1+r^*}{1+\delta} u'(c_{t+1}). \tag{3}$$

Having outlined the classic frictionless consumer optimzation problem, we are now able to consider three forms of credit constraints. In an extreme form of credit constraints, consumers are unable to access credit in any form. That is, they face an additional constraint that limits consumption to be less than the sum of current income and assets, as follows,

$$c_t \leq y_t + A_t \; \forall \; t. \tag{4}$$

In a less-extreme version of credit credit constraints, borrowers can access credit but only up to an exogenously defined limit. Under these conditions, consumption is constrained to be less than the sum of current income, total assets, and the pre-specified borrowing limit (B_t), as follows,

$$c_t \leq y_t + A_t + B_t \; \forall \; t. \tag{5}$$

In our setting credit constraints are characterized by a friction that affects the offered interest rate. Equation (3), the utility maximizing first-order condition, requires access to borrowing/saving technologies at the break-even rate of r^*. We define consumers to be credit constrained if they are unable to access credit at r^*. If actual rates are offered at the level $r > r^*$, then borrowers will not be able to borrow in the amount that satisfies the Euler equation. An offered $r > r^*$ thus constrains the amount of consumption via the interest rate channel in the budget constraint.

1 Data

We analyze the loan contract terms and auto purchasing decisions of 5.6 million individual borrowers in the United States from 326 retail lending institutions. The loan data are provided by a technology firm that provides data warehousing and analytics services to retail oriented lending institutions nationwide. Roughly two thirds of the lending institutions represented in the data set are credit unions ranging between \$100 million and \$4 billion in asset size. The remainder are finance companies of unknown total asset size. On a loan-weighted basis, 83.2% of the loans were originated by credit unions and the remaining 16.8% originated from finance companies. Loans originated by finance companies are generally of lower credit quality. Borrowers from all 50 states are represented in the data, but the five largest states in the data are Washington (770,334 loans), California (476,791 loans), Texas (420,090 loans), Florida (314,718 loans), and Utah (292,523 loans). The dataset contains information over three dimensions of a loan's life; loan applications, loan originations, and ex-post performance and monitoring. We have loan application data for approximately 2.2 million loans from 46 different institutions. The available loan application data report FICOs and DTIs at the time of application and whether the borrower was approved for a loan, denied, whether the borrower withdrew the application, or whether the loan was originated. For loans that were originated, the data include information on loan amounts, loan terms, auto purchase amounts, and whether the loan came through a direct or indirect origination channel.[4] Direct loans represent 87.5% of the loans in the sample. Finally, with regards to ex-post loan performance, lending institutions also report the number of days a borrower is delinquent. Table 1, panels A, B, and C present summary statistics on loan applications, loan originations, and measures of ex-post performance and monitoring, respectively. As reported in Panel A of Table 1, the median loan application size is $18,093 from borrowers with median FICO scores of 658 and DTI ratios of 27.3%. The percentage of loans approved is 45.7%, with 73.3% of the approved borrowers subsequently originating a loan. Throughout the paper we refer to the number of loans originated scaled by the number of applications approved as the loan "take-up" rate. We exploit variation in the loan take-up rate in Section 3.3.

Panel B of Table 1 reports summary statistics on loan originations, revealing several interesting patterns. The unconditional average loan size is $19,706 over the full sample. Loan terms average 65.3 months over the full sample, also increasing over the sample period. Interest rates average 5.03% in the sample and exhibit interesting cross-sectional variation. Interest rates in the upper quartile average 9.24% compared to lowest quartile averages of 2.3%. Panel C tabulates measures of ex-post loan performance. Defining default as a loan that is at least 90 days delinquent, default rates average 2.35%. In untabulated results, default rates for borrowers with sub-600 FICOs average 7.1%, compared to a default rate of 2.8% for borrowers with FICOs between 600 and 700, and 1.7% average default rates for over-700 FICO borrowers. Lending institutions periodically check the credit score of their borrowers subsequent to loan origination, creating a novel feature of our data. Panel C of Table 1 reports summary statistics for $\Delta FICO$, capturing changes in borrower FICO scores from the time of origination to the most recent FICO pull. The time between FICO pulls varies by institutions, but institutions that pull updated FICO scores do so at least once

[4] Direct loans are defined as loan originations that happen directly through the lending institution. Indirect loans occur when borrowers apply for a loan through an auto dealership and the dealership sends the loan application to various lending institutions.

a year. Thus, conditional on having an updated FICO score, the amount of time passed between the original FICO and the current FICO is equal to the loan age. Updated FICO scores indicate that borrowers with FICO scores above 700, on average, experienced a 1.9% reduction in FICO score since origination, whereas borrowers with FICO scores below 600, on average, realize a 5.4% increase in FICO score.

1.1 External Validity of the Data

The bulk of our auto loan data come from credit unions, prompting questions about the external validity of the data. Popular perception is that credit union usage is concentrated in an older demographic. Our data confirm this fact. Over 41% of borrowers in our sample were between 45 and 64 years old at loan origination. In contrast, census data indicates 34% of the general U.S. population are between the ages of 45-65. Borrowers in our sample are also less racially diverse than the general public. Over 73% of our sample is estimated to be white (as of 2015), as compared to a census reported 64.5% percent white (as of 2015) in the general population.[5] Borrowers in our data report median FICO scores at origination of 715 (Table 1, Panel B) over the full 2005-2016 sample period. The NY Fed Consumer Credit Panel (NYFed CCP), a representative 5% sample of U.S. borrowers, reports median FICO scores for originated auto loans to be 695 over the sample period.[6] Almost 70% of the loans in our sample were originated between 2012 and 2015, with median FICO scores of 714. In comparison, the NYFed CCP reports median FICO scores of 696 over the same period. In summary, our sample contains borrowers that are slightly older, less racially diverse, and of a higher average credit quality than national averages. These sample biases should not limit our ability to draw inference given that the biases in our sample likely tilt towards borrowers less likely to be credit constrained.

[5]Borrowers do not report race at the time of loan origination but most lenders in our sample estimate race ethnicity in an effort to comply with fair lending standards required by the Consumer Financial Protection Board (CFPB).

[6]The NY Fed consumer credit data report quarterly median FICO scores over our sample period. The reported 695 median FICO is actually the median of the quarterly medians that span our sample period.

A second data validity issue involves the distribution of loan originations through time. As reported previously, over 70% of loan originations in our sample occurred between 2012 and 2015, despite a sample period that runs from 2005-2016. The massive increase in loans through time reflects the increase in the client base of our data provider through time rather than auto credit origination in general. Auto loan originations in the general population have increased through time, from an aggregate outstanding balance of $725 M in Q1 2005 to just over $1 trillion in Q1 2016, but not at the rate reflected in our database. We view the non-representative time series of our data as less relevant to any inference we attempt to draw given that we rely on a cross-sectional RD approach for identification.

2 Identification

Lending institutions make auto lending decisions using a combination of hard and soft information on borrower credit quality. Hard information generally consists of quantifiable credit metrics such as FICO scores, debt-to-income ratios, and bankruptcy history, among others. Soft information, loosely defined as information related to the likelihood of a borrower's future willingness or ability to repay a loan that cannot be easily quantified, is, by definition, unobservable to the econometrician.[7] Any econometric analysis that specifies loan outcomes as the dependent variable is subject to the critique that equilibrium loan outcomes are influenced by unobservable soft information, thereby limiting the scope for inference. Our setting is no exception. While our dataset consists of millions of equilibrium lending outcomes, our ability to draw inference is hindered by the strong possibility that unobserved soft information played a critical role in observed loan terms. We address this critique, and other potential omitted variables, by exploiting observed discontinuities in offered loan terms across various rule-of-thumb FICO thresholds. Unlike the 620 rule of thumb setting exploited in Keys, et al. (2010) in the case of mortgage lending, no industry standard rule-of-thumb thresholds exist in auto lending (i.e., not all institutions adhere to a standard FICO cutoff

[7]See Petersen (2004) for a careful treatment of hard and soft information in financial markets.

of 620). While there exists no threshold common to all lenders, the existence of a given threshold at some point across the FICO spectrum is prevalent for most lenders in the data. Multiple lending institution executives revealed in separate conversations the fact that they offer higher interest rates and shorter loan terms as a function of a given FICO threshold.[8] Also in contrast to Keys, et al (2010), the rule of thumb FICO thresholds observed in our data have little to do with secondary markets given that many auto loans are retained by the lending institutions in our dataset. Rather than reflecting demand for securitization or loan salability, the rule of thumb thresholds reflect risk managers' assessments that borrowers on either side of the threshold represent meaningfully different credit risks.

To illustrate the effect of FICO thresholds on equilibrium interest rates, Figure 1 presents interest rate plots for 3 different institutions. The figures plot point estimates and confidence intervals arising from a mutivariate regression where realized interest rates are regressed on a set of indicator variables for 5-point FICO bins. The 5-point FICO bins begin at a FICO score of 501 where the first bin includes FICO scores in the 501-505 range, the second bin includes 506-510 FICOS, etc., up through FICO scores of 800. The estimated coefficients on the FICO bins represent the average interest rate on loans contained in the bin, relative to the estimated constant. Panel A of Figure 1, estimated on one institution in our data with approximately[9] 12,000 borrowers, illustrates the large breaks in average interest rates for borrowers with FICO scores around FICO cutoffs at 600, 660, and 700. The breaks in interest rates at the FICO cutoffs are large (representing jumps of over 2%). Average interest rates for borrowers in the 595-599 FICO bin are .025 higher than the average interest rate for borrowers in the 600-604 FICO bin and differences in average interest rates between the two bins are statistically significant at the .001 level. Panels B and C illustrate similar rule-of-thumb FICO breaks for unique institutions with approximately 6,000 and 25,000 loans, respectively. One important observation arising from the anecdotal plots is the fact that the

[8]As an example, one executive pointed to a FICO score of 610 as the explicit cutoff that determines the loan terms offered perspective borrowers. Applicants below a FICO score of 610 were offered higher rates and loan terms below 60 months in contrast to applicants with FICO scores above 610.

[9]The exact number of borrowers is unreported to protect institutional anonymity.

breaks occur at different FICO scores across different institutions. This is supportive of the fact that the rule-of-thumb breaks are not driven by secondary market considerations, but are reflective of idiosyncratic risk management policies across institutions.

Interest rates are not the only loan policy that is influenced by rule of thumb thresholds. Loan terms are also discontinuous across FICO thresholds. In Figure 2 we plot point estimates and standard error bands for a set of loan term, 5-point FICO bin regressions. The institution represented in Panel A, with approximately 162,000 loans in the portfolio, has loans in its portfolio with longer terms for borrowers just to the right of the 630 FICO threshold. Panels B and C illustrate similar loan term discontinuities around different rule-of-thumb FICO thresholds for institutions originating approximately 42,000 and 36,000 loans, respectively. The plots presented in Figures 1 and 2 are illustrative of rule-of-thumb thresholds that exist at different institutions throughout our sample.

In order to standardize our analysis to include every institution that employs rule of thumb thresholds, we empirically identify the existence of discontinuities at each institution (if they exist at all) in our sample through the following criteria. We first estimate the interest rate-FICO bin regressions within each institution in our sample and harvest the coefficients from each FICO bin. Within each institution, in order to establish the existence of a meaningful interest rate discontinuity we require that interest rate differences across consecutive bins be larger than 50 basis points and be estimated with p-values that are less than 0.1%. We further refine the set of discontinuities by requiring that an identified discontinuity cannot lie within 20 FICO points of another identified discontinuity within the same institution. Implementing this screen limits any potential contamination that could occur if borrowers simultaneously fall into a treated sample at one observed threshold but serve as a control in a sample with a different threshold. We examine each potential threshold visually to ensure that the identified discontinuities are well behaved around the candidate thresholds. Finally, in an effort to maximize the statistical power in our RD design, we require that each candidate threshold contain 100,000 loans within the span of

38 FICO points around the candidate threshold. The 38 FICO points represent 19 points on either side of a threshold that do not bump up against a different threshold that could exist within 20 FICO points. Implementing each of these restrictions ultimately results in large and meaningful discontinuities in interest rates and loan terms at FICO scores of 600, 640, and 700 across 173 institutions and 489,993 loans.[10] Table 2 reports a battery of summary statistics for the lending thresholds sample. A comparison of the full sample summary statistics (Table 1) with the threshold-specific sample (Table 2) reveals that the threshold sample is similar to the full sample along observables.

As mentioned in Section 1, loans can be originated through direct applications with a lending institution or through an indirect auto dealership channel. One concern with indirect loans is the possibility that dealerships are aware of the existence of rule-of-thumb thresholds at the institutions where they most frequently send loans. As a result, borrowers from an indirect loan application on the favorable side of a rule-of-thumb threshold are likely not random as compared to borrowers on the wrong side of a threshold. For this reason we exclude all indirect loan applications throughout our entire analysis. The sample criteria requiring 100,000 loans within 38 FICO points of a threshold is met after removing all indirect loan applications.

2.1 First Stage: Validating the RDD Approach

In order to formalize the existence of, and to estimate the size of discontinuities at the proposed FICO thresholds of 600, 640, and 700 we present a series of diagnostics designed to test whether our data meet the requirements of a RD analysis. RD design relies on two key assumptions. First, the RD approach assumes that the probability of borrower treatment with respect to loan terms is discontinuous at FICO thresholds of 600, 640, and 700. Second, and perhaps more importantly, valid RD requires that any borrower attribute (observed or

[10]Relaxing the requirement of 100,000 loans within 38 FICO points around the threshold results in a larger set of identified thresholds. The two most populated thresholds outside of our selected three thresholds are at 680 and 660 which contain approximately 90,000 and 80,000 loans, respectively.

unobserved) that could influence loan outcomes be continuous across the rule of thumb FICO thresholds. Referred to most frequently in the literature as the smoothness condition, this assumption requires that borrowers on either side of a FICO threshold are otherwise similar, such that borrowing outcomes on either side of a threshold would be continuous, absent the treatment induced by policy differences enacted at the threshold. We begin our analysis by presenting a series of plots. Figure 3A plots interest rates on the vertical axis against borrower FICO scores along the horizontal axis, where FICO scores are restricted between 581 and 619. Each dot in the plot represents the average interest rate for borrowers with a given FICO score within the 581-619 range. The plots demonstrate smoothness in interest rates with respect to FICO scores until the FICO 600 threshold, at which point interest rates jump in discontinuous fashion. We repeat the plot using similar 38 point FICO ranges for the 640 and 700 FICO thresholds in panels B and C of the same figure. These plots confirm the existence of large interest rate discontinuities at these thresholds. The magnitude of the discontinuities are smaller at higher FICO thresholds, as might be expected.

In Figure 4 we plot the value of other borrower characteristics around these FICO thresholds in order to evaluate the smoothness condition. Importantly, these plots are constructed with loan application data in order to ensure that borrowers are similar at FICO thresholds along characteristics at the time of application. Panel A plots borrower debt-to-income ratios against FICO scores while Panel B plots application loan amounts. Panels C and D plot applicant age and gender. These plots indicate smoothness in ex-ante borrower characteristics around FICO thresholds. Borrowers on either side of FICO thresholds do not appear meaningfully different in terms of their debt capacity, their willingness to borrow, or along demographics. Finally, Panel E plots the number of applicants within each FICO bin. The plot indicates no statistically significant jump in the number of applications around the thresholds.[11] Smoothness in the propensity to apply for loans around FICO thresholds is

[11] We note one unusual spike in applications at FICO 600 but the spike does not constitute a violation of parallel trends because application frequencies appear constant through the full distribution of FICO scores. A violation in the smoothness condition for a valid RD would require a consistent shift in the level of applications for all FICO scores to the right of the threshold.

especially important as it illustrates that borrowers are likely not aware of the existence of the FICO thresholds when they apply. We formalize the results inferred by the plots by estimating a battery of RD regressions, specified as follows:

$$y_{cit} = \delta_c + \delta_t + \beta \mathbb{I}_{normfico_{cit} \geq 0} + \gamma normfico_{cit} + \psi normfico_{cit} \times \mathbb{I}_{normficocit \geq 0} + \varepsilon_{cit} \qquad (6)$$

where y_{cit} is the outcome for loan i originating from lending institution c in quarter t and $\mathbb{I}_{normficocit \geq 0}$ is in indicator variable equal to one if the normalized FICO score ($normfico_{cit}$) is above the threshold. Our baseline regression specification pools each of the three discontinuities into one dataset and thus one discontinuity by normalizing the data around each threshold. As in the plots, our estimate bandwidths are specified at 19 FICO points on either side of the threshold. Our baseline specification controls for polynomials of order 2, though our estimates are strongly robust to any higher order polynomial specification. Our estimates further control for lending-institution fixed effects and quarter-of-origination fixed effects. Standard errors are clustered at the FICO level.

Table 3 presents results. Interest rates to the right of the FICO cutoff are estimated to be 1.47 percentage points lower than borrowers just to the left (column (1)). Loan terms to the right of the cutoff are 1.38 months longer than otherwise similar borrowers to the left (column (2)). Table 4 reports more formal tests of the smoothness condition using the loan application data, available for a subset of lending institutions. The estimates indicate no statistical difference in requested loan amounts for borrowers on either side of the threshold (column (1)). In column (2) we present estimates of differences in debt-to-income ratios around the thresholds. Ex-ante debt-to-income ratios of borrowers on either side of the thresholds are statistically indistinguishable. Finally, the number of borrowers applying for loans on either side of the threshold is also not statistically different (column (3)).

2.2 Second Stage: Do Credit Constraints Alter Consumption Decisions?

In this section we evaluate whether borrowers behave as though they are credit constrained. While credit constraints are difficult to directly observe, we can infer their existence by evaluating the auto purchasing decisions of borrowers on either side of the documented FICO thresholds. Given the empirical result that, ex-ante, borrowers are similar around FICO thresholds, we start with the null hypothesis that borrowers around FICO thresholds would also have similar demand for cars, conditional on obtaining the same set of financing terms. Exploiting a useful feature of the data, namely our ability to observe the exact amount that each borrower spent on a car, we test whether borrowers spend differently around the observed FICO thresholds. Figure 5 plots car purchase amounts around the normalized FICO threshold. Purchase amounts are smooth leading up to the FICO threshold and then jump discontinuously at the threshold. Using the same RD design as previously employed, we formally test for statistical differences in purchase amounts. As before, we control for lending institution and quarter-of-origination fixed effects, polynomials of order 2, and a bandwidth of 19 around the normalized FICO threshold. Table 5, column (1) presents the results. Borrowers quasi-randomly offered more favorable terms spend \$978.86 more on the cars they purchase, on average. Column (2) presents results with loan amounts as the dependent variable. Realized loan size increases \$1,479.67 around the threshold, on average. The fact that loan sizes increase by larger amounts around the threshold than purchase amounts indicates that, ex-post, borrowers on the right side of the cutoff are allowed higher loan-to-value ratios. This result is confirmed in column (3) of Table 5, which indicates that ex-post LTV ratios are slightly higher, 2.7 percentage points on average, for borrowers to the right of FICO thresholds.

Detailed data on loan amounts and loan terms allow us to calculate the implied monthly payment of borrowers on either side of the thresholds. In column (4) of Table 5 we test whether ex-post monthly payments are different around the thresholds. On average, larger loan amounts swamp the effects of longer terms, resulting in \$9.67 a month higher loan payments for borrowers to the right of the threshold. Higher ex-post LTV ratios and slightly higher monthly payments, which imply higher ex-post DTI ratios, warrant further consideration. One concern with these results is the possibility that borrowers on either side of the FICO thresholds are different ex-ante in their ability to service debt – a violation of the smoothness conditions required for valid RD. We interpret these results differently. Given that ex-ante DTI ratios in the loan application data are continuous around the thresholds, we interpret these results as further evidence of the easing of credit terms for borrowers on the right side of FICO thresholds. That is, ex-post, borrowers on the right side of thresholds are offered lower rates, longer terms, and allowed higher ex-post LTV and DTI ratios.

Otherwise similar borrowers spending different amounts on the cars they purchase as a result of the financing terms they are offered is potentially evidence in favor of the existence of credit constraints via the interest rate channel. An alternative explanation is the possibility that dealers somehow exploit borrowers' ability to service larger debt amounts by charging more for the exact same car that otherwise similar borrowers on the wrong side of FICO thresholds purchase.[12] We address this possibility by controlling for year-make-model fixed effects in our RD regressions.[13] Table 6, column (1) reports results when controlling only for make-model fixed effects. Borrowers to the right of FICO thresholds continue to spend \$887 more on cars, even in the presence of make-model fixed effects. In column (2) we include year-make-model fixed effects and find no statistical differences in the car purchase price. In column (3) we present results with vehicle age as the dependent variable and find that, controlling for make-model fixed effects, borrowers with easier access to credit purchase 4.8 month newer cars, on average.

The evidence presented in Tables 5 and 6, indicate that financing terms influence auto purchasing decisions. Borrowers offered easier credit spend more on cars and originate larger

[12]Note that although we constrain our sample to include only direct loan applications, borrowers still frequently purchase from dealerships with direct loans.

[13]Year-make-model fixed effects are made possible by vehicle VINS provided in our data set.

loans. Further still, results with make-model and year-make-model fixed effects suggest that borrowers offered easier credit terms choose to purchase slightly newer cars at slightly higher prices, but that borrowers pay the exact same amounts for the exact same car. The lack of a difference in car pricing outcomes with year-make-model fixed effects is also evidence that there is no private information or selection around buyers' savvy or skill in car buying decisions. Differences in pricing outcomes among otherwise similar borrowers is determined solely by financing terms.

2.3 Evaluating Alternative Explanations: Adverse Selection

In this section we analyze the possibility that borrowers to the left of thresholds are not offered credit on similar terms as borrowers to the right because of information asymmetries. Adams, Einav, and Levin (2009) attribute credit constraints in the auto market to adverse selection. Adverse selection could explain the persistence of credit constraints in our setting as well, in the following, classic adverse selection way. Although ex-ante, borrowers around thresholds apply for loans with equal propensity, differences in ex-post take up rates could reflect private information held by borrowers, rationally internalized by lenders. Knowing they are of poor quality along soft dimensions, borrowers on the left side of thresholds rationally recognize that the terms they are offered by lenders are not optimal but also realize they are likely the best terms they will be offered given their unfavorable soft attributes. Lending institutions also recognize that borrowers that choose to accept the unfavorable terms are indeed lemons, as anticipated, and so the arbitrary thresholds serve their purpose in creating an equilibrium that separates high quality borrowers from low quality borrowers, with the appropriate pricing differences offered to each borrower type.

We test for the possibility that adverse selection drives the observed equilibrium in our data by comparing ex-post borrower performance around the FICO thresholds. We formulate three specific tests. First, we specify as a dependent variable in our RD setting the number of days a borrower is delinquent. Again, we use the standard bandwidth, polynomial order, and fixed effects, and present results in column (1) of Table 7. Estimates indicate that borrowers on either side of the threshold do not exhibit statistical differences in delinquency. Our second test is to form a binary indicator of loan default, defined as borrowers' delinquent in excess of 90 days, a standard default metric in evaluating loan performance. Estimates using the institution-reported charge off (column (2)) and our measure of default (column (3)) also indicate no differences in default rates around the thresholds.

A novel feature of our dataset allows for a third test of adverse selection as an explanation for our observed results. As a means of monitoring borrowers, many lending institutions in our dataset pull credit scores on borrowers after loan origination. Ex-post credit score pulls occur as frequently as every six months, and, in a few cases, as infrequently as once post-origination. The most common convention for the subset of institutions that pull credit ex-post is to pull credit scores once a year. Ex-post credit scores allow us to calculate changes in credit scores over time. Adverse soft information, though unobserved at the time of loan origination, should impact credit scores through time if borrowers are unable to perform on their credit obligations. Using the sub-sample of institutions that pull credit ex-post, we calculate the difference between credit scores at origination and the most recently observable credit score, and specify this variable, change in credit, as the dependent variable in our RD framework. Results presented in column (4) of Table 7 show no statistical differences in credit score changes for borrowers around the threshold.

Taken together, the evidence on borrower delinquency, defaults, and ex-post changes in credit scores indicate that borrowers to the left of FICO thresholds do not represent meaningfully different credit risks as compared to otherwise similar borrowers to the right of thresholds. While adverse selection is likely at play in some form for lending decisions across the full spectrum of borrowers, adverse selection does not appear to be a primary determinant of the acute differences in lending behavior around the observed FICO thresholds.

3 Credit Constraints and Search Costs

3.1 Why Credit Constraints Persist? Motivating a Search Cost Hypothesis

Results presented thus far demonstrate that discontinuities in offered loan terms result in a form of credit constraints that alter consumption decisions. The persitance of interest-rate induced credit constraints in equilibrium is a puzzle, however. In frictionless markets, borrowers of similar risk should be offered similar rates. Indeed, Zinman (2014) argues, "for all of the advances in risk-based pricing, mechanism design, nonlinear contracting etc., prices are still quite far from clearing consumer credit markets." We propose search costs as an explanation for persistence in credit constraints. Our hypothesis is motivated by recent work in household finance suggesting that borrowers are reluctant to shop for loans. For example, Hall and Woodward (2012) document that mortgage borrowers overpay for mortgage origination services due to a reluctance to shop for mortgages. Likewise, Zinman & Stango (2015) document price dispersion in the credit card market that varies with borrower shopping intensity. In this section we explore whether a search cost explanation for persistence in credit constraints has support in the data.

Theories of search costs suggest that when search costs are high, agents find it too costly to solicit the full distribution of offered prices. As a result, equilibrium prices reflect the distribution of offered prices and the random draw that agents get from the offered price distribution. For example, consider a financial institution that offers an interest rate on auto loans that is high relative to competitors, conditional on borrower quality. If search is costly, consumers that arrive randomly to solicit a loan are more likely to accept the offered rate, despite the existence of better available rates. Lenders can expect to make loans in the presence of search costs despite not offering the lowest rates among their competitors because of the possibility that a randomly arriving customer will not exert the effort required to find better rates (see Sorensen (1999) for a model). Lowering of search costs, or an increase in the gains to search will result in lower price dispersion as consumers increase their propensity to search, thus tracing out a more complete distribution of available prices. In a similar spirit, if consumer search costs are reduced, lenders will be forced to offer more competitive rates knowing that consumers are more likely to search out competitors rates.

One natural prediction of search cost models is that price dispersion will exist in equilibrium. Borrowers will not always originate a loan with the best available loan terms because it is costly for borrowers to search out the optimal loan. In the following sections we test these ideas in the data, in two ways. First, we document whether price dispersion exists for borrowers on the wrong side of lending thresholds, i.e., whether constrained borrowers could have found better loans. Second, we evaluate whether borrowers' propensity to search for better loan terms is correlated with measures of search costs.

3.2 Are loans with better terms available to constrained borrowers?

To assess whether constrained borrowers, borrowers on the left side of FICO thresholds, could have found a loan with more favorable terms, we calculate the difference from the lowest available rate (DLAR) for borrowers with FICO scores just to the left of observed FICO thresholds. To construct the DLAR, we first bucket borrowers by MSA and with FICO scores between 595-599, 635-639, and 695-699, respectively. We further refine the match to require that borrowers in the same MSA and 5 point FICO bucket purchased cars within a \$1,000 price range. The \$1,000 auto purchase bins are non-overlapping, beginning from \$2,000 to \$2,999, up to a maximum purchase amount of \$100,000. We further pool borrowers into 5% debt-to-income bins. To control for time variation in interest rates, matched borrowers require that all auto purchases occurred within 2 quarters of each other. Table 8 tabulates summary statistics of DLARs for constrained borrowers. The average (median) DLAR for borrowers with FICO scores from 595 to 599, 635-639, and 695-699 is 3.36% (2.98%), 2.5% (2%), and 1.6% (1.3%), respectively. That is, for borrowers with FICO scores between 595 and 599, the difference between the constrained borrower interest rate and the lowest available rate obtained by a matched peer was 3.36%, on average. The standard deviation of DLAR across these cells is 2.5%, 2.1%, and 1.4% with an average number of borrowers in the cell of 2.46, 2.99, and 3.99, respectively. Kernel densities for DLARs to the left of the 600, 640, and 700 thresholds are shown in Figure 6.

The summary statistics tabulated in Table 8 indicate that borrowers to the left of lending thresholds had significantly better interest rates available to them. Earlier results indicated that ex-post default rates and subsequent changes in FICO scores are indistinguishable around FICO thresholds, indicating that adverse selection is not the primary cause for differences in offered rates around thresholds. Indeed, the summary statistics appear to be consistent with the hypothesis that one potential reason credit constraints persist is because borrowers are not able, or are unwilling, to exert the effort required to find loans that would allow them to consume the amount of car they would demand, finance permitting.

3.3 Creating measures of loan search

Having shown that constrained borrowers could have found loans with better terms, in this section we evaluate more directly whether borrowers' propensity to search is correlated with search costs. This analysis requires the construction of two measures; a measure of search propensity and a measure of search costs. We measure search propensity as the fraction of borrowers that reject an offered loan. Presumably borrowers that applied for, and then reject an offered loan, reject the loan in favor of searching for a different loan. Using loan application data, we calculate and define the loan "take-up" rate as the number of originated loans in a 5 point FICO bin scaled by the number of offered loans in the same 5-point bin. While borrowers could reject loans for different reasons, of course, including the decision not to originate any loan, we view differences in the decision to reject an offered loan around lending thresholds as a reasonable proxy for differences in borrowers' propensity to engage in further loan search. Using reported FICO scores at the time of loan application, we estimate differences in take up rates around FICO thresholds.

Having defined our measure of search propensity, we now describe one potential measure of search costs. We identify the physical location of every bank branch and credit union branch in the United States. We then create a measure of driving-time density for an individual borrower by summing the number of physical branch locations within a 20 minute drive of the borrower, similar to the approach employed by Degryse and Ongena (2005). The calculation of actual driving times relies on posted speed limits along driving routes, and abstracts from traffic conditions. Aside from traffic conditions, a second assumption required in our analysis is that driving routes calculated as of the writing of this paper existed at the time a loan was originated. Naturally, we calculate driving distances and trip durations for only those institutions which existed at the time of loan origination.

Interesting summary statistics categorize the nature of our driving time and distance analysis. The median borrower in our applications dataset lives within a 20 minute drive of 63 lending institutions. Borrowers in the 25th percentile of driving distance live a 20 minute drive from 20 institutions, as compared to 148 institutions for borrowers in the 75th percentile. In the applications dataset, just under 4% of applicants in our sample live in an area with 1 or fewer lending institutions within a 20 minute drive. In contrast, 65.8% of applicants live within a 20 minute drive of at least 100 different lending institutions (see Argyle, Nadauld, and Palmer 2016b for a more thorough analysis of credit deserts in the U.S.).[14]

The driving-time density measure is designed to capture the effort, proxied by physical distance, for each borrower to search out a lending institution that is within a reasonable distance from their home. If search costs influence the propensity to search, differences in loan take up rates around FICO thresholds should be higher in areas with higher driving-time density, for the following reason. If a borrower lives in an area with higher driving-time density, borrowers in that area to the left of FICO thresholds, i.e. those offered unfavorable loan terms, would be more likely to reject the unfavorable loan terms in favor of searching

[14] We discuss the issue of digital search in section 3.5.

for better terms elsewhere. Importantly, our empirical specification measures *differences* in loan take up rates around FICO thresholds. We then compare differences in loan take-up rates for borrowers in high versus low driving-time density areas.

Using our standard RD framework, we specify loan take-up rates as the dependent variable and estimate differences in the take-up rate around FICO thresholds. We estimate the RD regressions separately for borrowers in the top and bottom half of search cost and report results in Table 9. As reported in column 2, take-up rates for borrowers to the left of FICO thresholds are 14.2 percent lower than take-up rates for borrowers to the right of FICO thresholds in the high search cost areas, i.e. those areas with LOW driving-time density. In contrast, differences in take-up rates around FICO thresholds are 19.6 percent in the low search cost areas (Column 3). These results indicate that borrowers in high search cost areas are more likely to accept loan terms that are less favorable than they might otherwise obtain, given the cost associated with finding better terms is presumably high.

One obvious concern with measuring search costs with driving-time density is that driving-time density may not uniquely measure borrower search costs. Driving-time density, as constructed, might also measure competition among lenders. In an effort to differentiate between search costs and lending competition, economic concepts that are inherently similar, we construct empirical measures of lending competition within MSAs. We calculate the share of originated mortgage loans by HMDA lenders within a given MSA, a commonly accepted measure of lending competition, and use the origination shares to construct an MSA-level Herfindal index. In an effort to differentiate between search costs and competition we divide loans into LOW and HIGH competition halves based on our constructed Herfindahl index. We then sort within a competition half along search costs and perform our take-up regression on each of the four regressions in the double sort. Table 10 tabulates the results. For LOW competition MSAs, lower search cost loans report differences in take-up rates around lending thresholds of 0.193. In comparison, HIGH search cost loans in the same competition bin are associated with take-up rate differences of 0.12. Looking at the HIGH competition bin, we find similar results with lower search costs (higher search costs) resulting in a takeup differential of 0.478(0.272). This result is consistent with higher search costs limiting borrower's propensity to search for a better loan when offered unfavorable terms on account of being on the wrong side of lending thresholds. Estimates of differences in take-up rates are qualitatively similar across competition bins. These results indicate that, although competition likely plays an important role in equilibrium outcomes, we are capturing something orthogonal to competition with the lending density measure.

3.4 Direct Evidence of Loan Search

In this section, we present a more direct measure of loan search by calculating the average number of applications per vehicle purchase. We evaluate whether the propensity of an individual borrower to search for an auto loan, as measured by the number of filed loan applications per borrower, varies with our proxy for search costs. Using our loan application data, we attempt to measure how many unique applications were filed by a borrower prior to purchasing a car. We assume that loan applications originating from the same longitude-latitude-applicant birthdate are from the same individual and that loan applications occuring within 90 days of each other are for the same vehicle. We divide borrowers into search cost quartile, using the driving-time density as a proxy. Table 11 reports that applicants in high search cost areas (column 1) apply for 1.08 loans/vehicle purchase, on average. In contrast, applicants in low search cost areas (column 2) apply for 1.101 loans/vehicle purchase, on average. These averages are statistically significantly different from each other at the 1% level. In untabulated results, borrowers in areas with fewer than 2 lending institutions within a 20 minute drive apply for 1.06 loans per purchase, compared to 1.10 for borrowers with at least 100 instutions within 20 minutes. We also note that an unreported regression confirms a positive and strongly significant relationship between loan applications per purchase and lending institutions within a 20 minute drive. These results are consistent with the hypothesis that borrowers facing high search costs search less and accept worse rates than borrowers facing relatively low search costs.

3.5 Digital Search

Many consumers now search for loans on the internet, potentially rendering lending density and driving distances moot in measuring search costs. Technology trade journals, and common sense, point towards an increase in internet loan originations over our sample period. We view our results with respect to lending density and driving times as even more noteworthy given the increased propensity for borrowers to search for loans online. One potential explanation for the ability of physical search measures to explain variation in loan search propensity is the fact that our sample is skewed towards older borrowers. Another possibility is that, although borrowers can be easily pre-approved on the internet, the actual closing of loans (signing documents, transfer of title, etc.) still most frequently occurs at physical locations. Though our data include only direct loan applications, borrowers most frequently close these loans at the physical location of the lending institution or at car dealerships.

3.6 Exclusivity of Credit Unions

One of the important results in this paper is the empirical fact that, for constrained borrowers, lower interest rates were frequently available in the same geography at the time a loan was originated. One critique of this result is that because many of the loans in our sample were originated by credit unions, it is not immediately obvious that a given borrower could have joined the credit union offering the lower rate. This is because credit unions frequently have membership requirements dictated by members' common bond. As an example, if the lowest available interest rate that we assume could have been offered a constrained borrower was offered by a firefighters credit union, then borrower search costs would not only involve the effort required to find the low rate, but also the effort required to become a firefighter. Our primary estimation sample is comprised entirely of credit union's whose primary membership requirement is geography. This fact is not surprising given that our sample requirements include the need for institutions to have a sufficient number of loans around thresholds. Smaller, niche credit unions do not have enough members to meet these sample requirements. Every borrower in our MSA-based matched portfolios is eligible to become a member at any of the credit unions included in the estimation sample by virtue of living in the same MSA as the credit unions involved in the creation of the matched portfolios. We also note that the finance companies in our sample have no membership requirements.

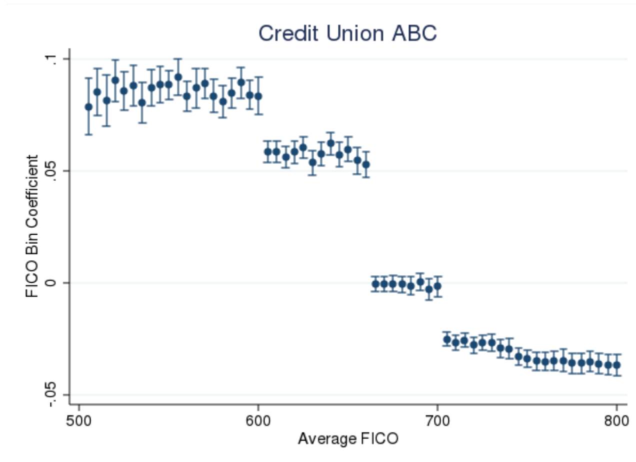
4 Conclusion

Mounting evidence indicates that credit constraints are a key issue in household finance and that the supply of finance does indeed influence consumer purchasing decisions. In this paper, we made two main points. First, we presented evidence that borrowers in auto credit markets behave as though they are credit constrained via an interest rate channel. The quasi-random assignment of better loan terms to one borrower results in the purchase of a more-expensive and newer car compared with the purchasing decisions of otherwise similar borrowers offered inferior loan terms. We rule out alternative explanations for the statistically significant response of relaxing a car buyer's credit constraints using data on ex-ante loan application behavior and ex-post loan performance.

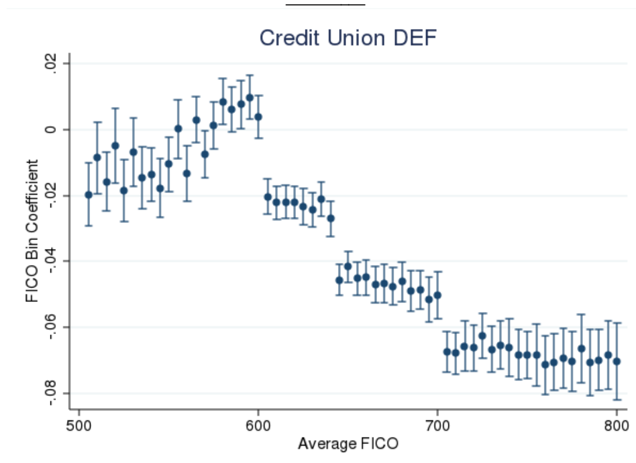
Second, we proposed search costs as a potential explanation for the persistence of both credit constraints and equilibrium price dispersion in the auto loans market. Because the arbitrary pricing schedules vary across lending institutions within the same MSA, borrowers on the wrong side of quasi-random pricing thresholds at one institution would likely find themselves on the favorable side of a pricing threshold at a different institution. Absent search frictions, borrowers would never accept dominated loan terms. In stark contrast, we find that for constrained borrowers in our sample, a lower interest rate loan was originated by an equally creditworthy borrower purchasing a similarly priced car on a similar date, suggesting that borrowers are either unwilling or unable to search for more favorable loan terms. Measuring the costliness of acquiring information about loan terms using the driving-time density of borrowers to the nearest lending institutions, we show that in areas with higher search costs, borrowers are more likely to accept inferior loan terms, constraining their access to efficient credit markets.

Even with a vast financial sector (including secondary markets for many forms of consumer debt), households are still constrained by their access to credit. While this result is well-known from prior empirical work, we provide an answer to an unresolved follow-up question in household finance—why such constraints continue to persist. Even with the possibility of shopping for interest rates online, searching for consumer credit products remains an opaque, local, and costly process for many borrowers. This relationship between costly search and distortionary credit market imperfections extends our understanding of equilibrium price dispersion to credit markets and could justify both the provision of pricing information as a public good and extra regulatory attention on so-called banking deserts.

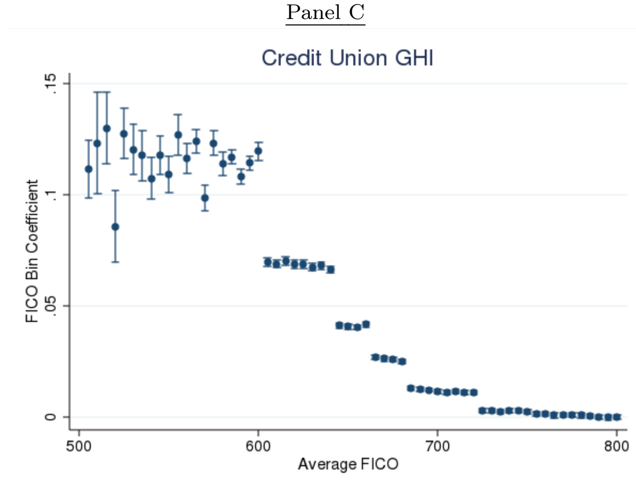
Figure 1: FICO-Based Lending Policies - Interest Rates



Panel B

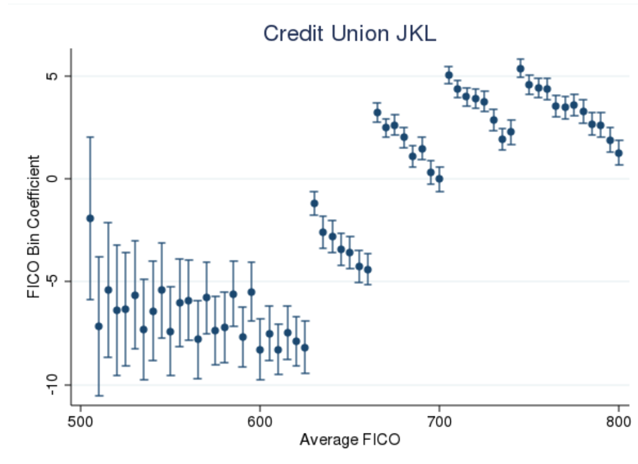


Panel C

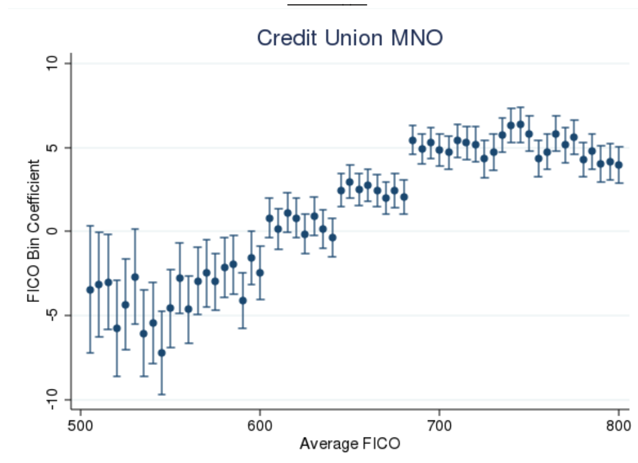


Notes: Loan rates are regressed onto dummies that represent 5-point FICO bins as outlined in section 2. Panels A-C depict the coefficient estimates for three different individual institutions.

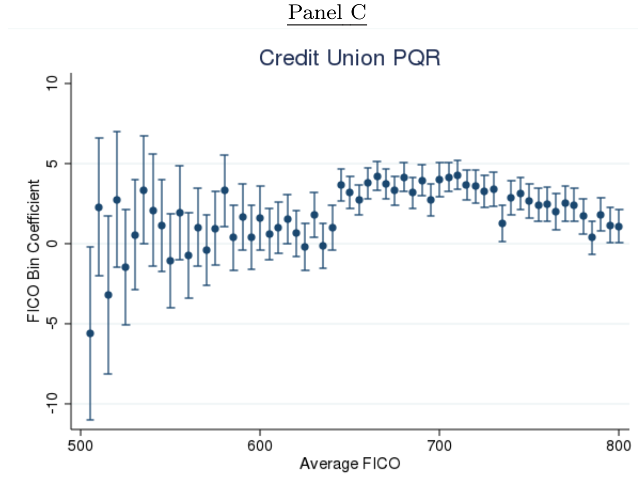
Figure 2: FICO-Based Lending Policies - Terms



Panel B

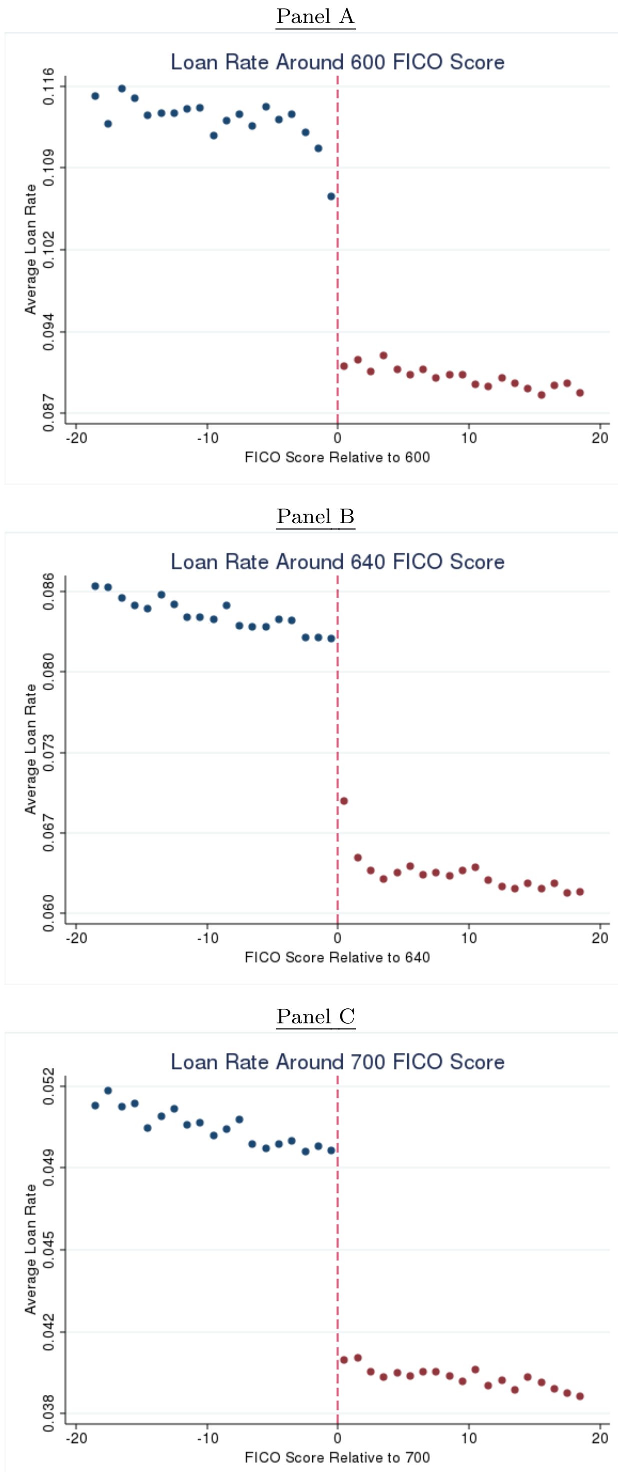


Panel C



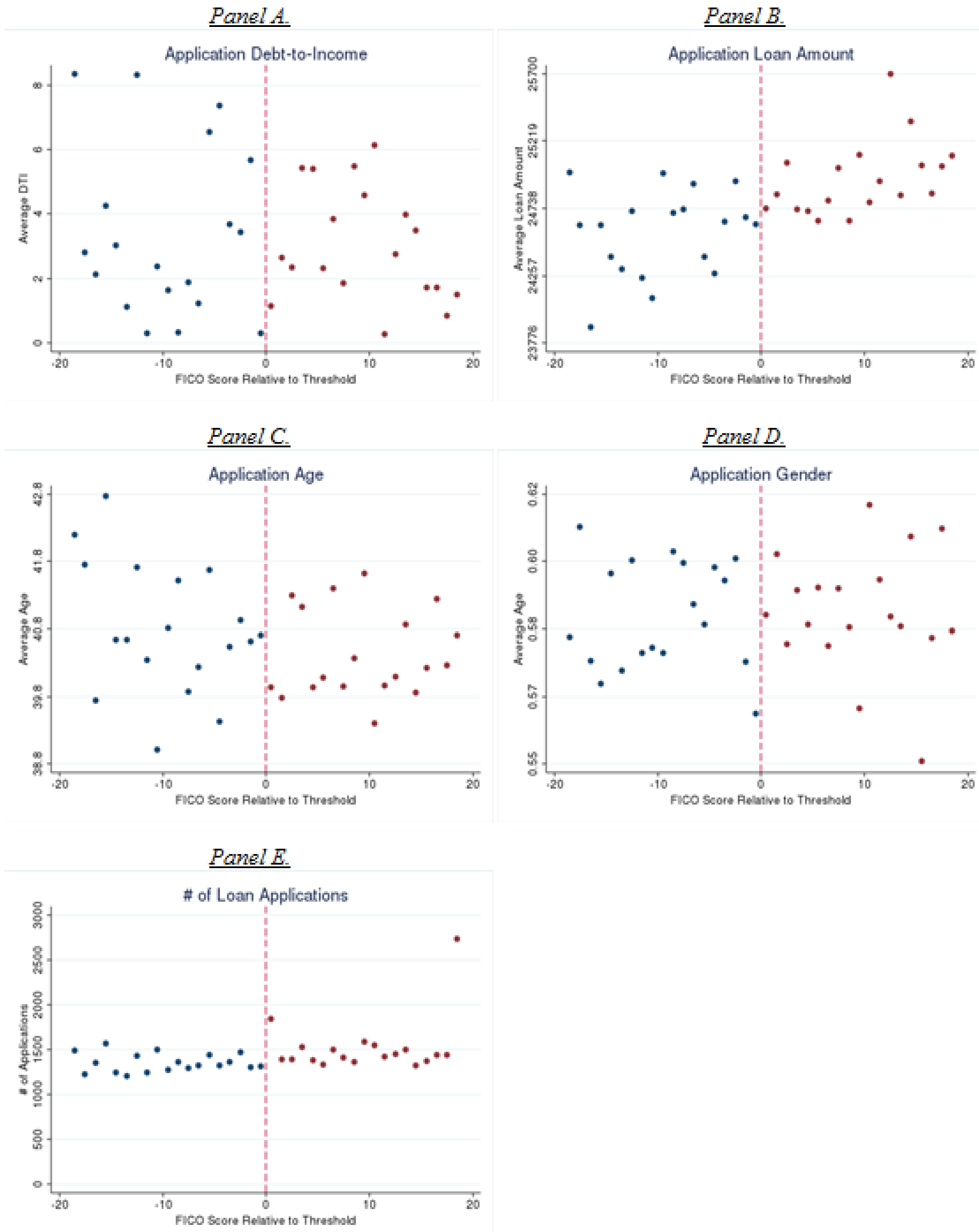
Notes: Loan terms are regressed onto dummies that represent 5-point FICO bins as outlined in section 2. Panels A-C depict the coefficient estimates for three different individual institutions.

Figure 3: FICO-Based Lending Policies - Interest Rates



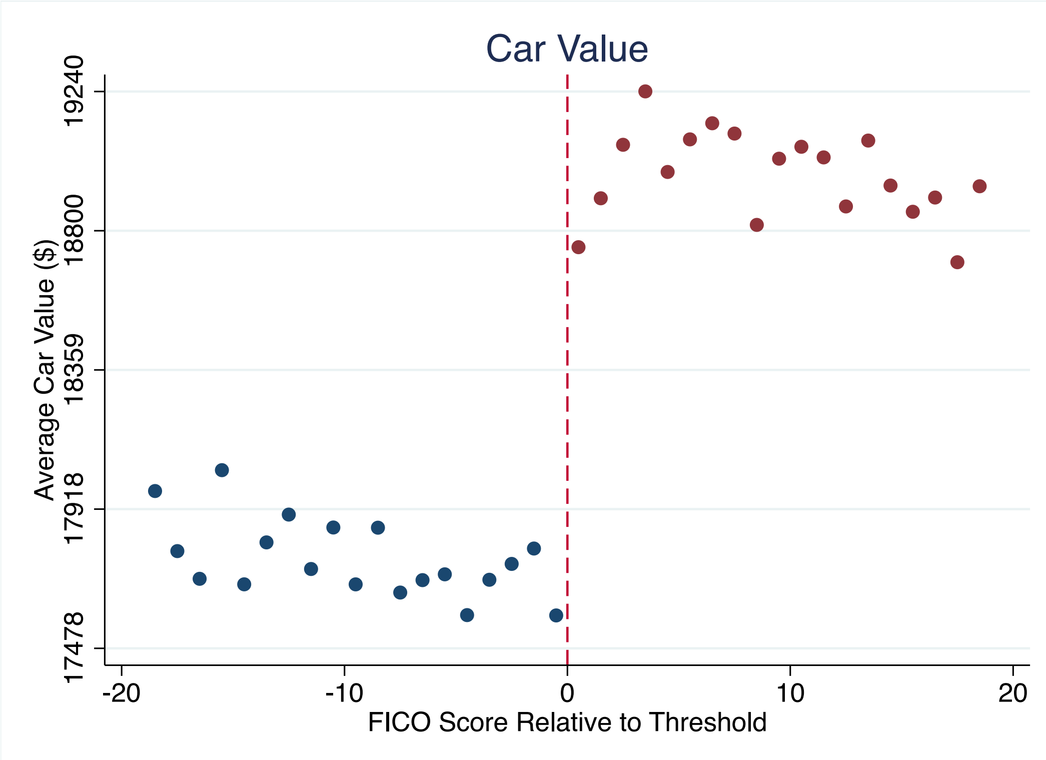
Notes: Figures plot interest rates on the vertical axis against borrower FICO scores along the horizontal axis. Panel A restricts FICO scores between 581 and 619. Each dot in the plot represents the average interest rate for borrowers with a given FICO score within the 581-619 range. We repeat the plot using similar 38 point FICO ranges for the 640 and 700 FICO thresholds in panels B and C.

Figure 4: Smoothness



Notes: Figure plots the value of other ex ante borrower characteristics around FICO thresholds shown in Figure 3 in order to evaluate the smoothness condition. Panel A plots borrower debt-to-income ratios against FICO scores. Panel B plots application loan amounts. Panels C and D plot applicant age and gender. Panel E plots the number of applicants within each FICO bin.

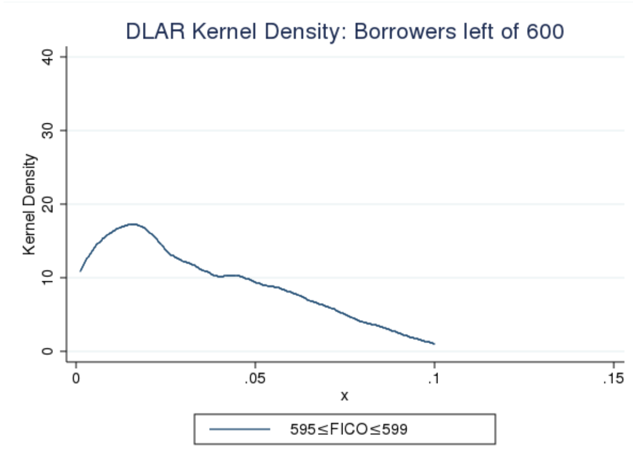
Figure 5: Second Stage



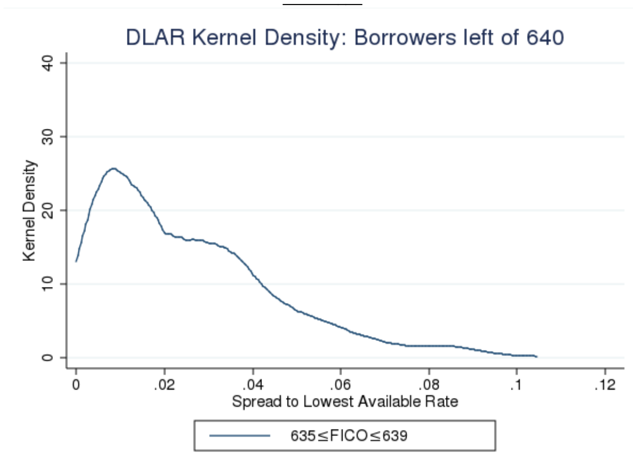
Notes: Figure reports point estimates from regressions described in Table 5.

Figure 6

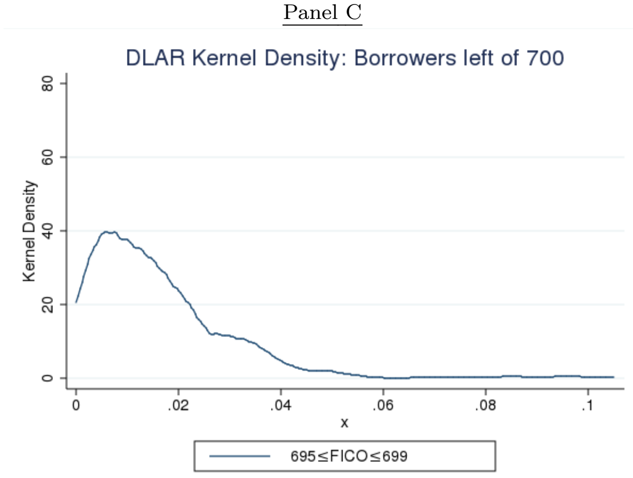
Panel A



Panel B



Panel C



Notes: Figure reports the kernel densities of the Distance from Lowest Available Rate (DLAR) for borrowers with FICO scores just to the left of a threshold that borrowered from institutions with lending thresholds of 600, 640, and 700, respectively.

Table 1: Summary Statistics

	Count	Mean	Std. Dev.	Percentile 25th	50th	75th
	Panel A. Loan Applications					
Loan Term	1,949,743	61.3	24.7	48.0	63.0	72.0
Loan Amount ($)	2,223,920	19,722	12,310	10,000	18,093	27,239
Loan Rate	1,984,681	0.057	.033	.033	.045	.072
Debt-to-Income	1,536,660	.285	.198	.164	.285	.399
FICO	1,549,749	650	105	600	658	717
	Panel B. Originated Loans					
Loan Rate	5,608,509	0.050	0.030	0.030	0.042	0.062
Loan Amount	5,608,509	19,706	11,214	11,490	17,737	25,745
Loan Term	5,608,509	65.3	20.7	60.0	63.0	72.0
FICO	5,033,536	712	72.9	665	715	769
Debt-to-Income	2,693,907	0.248	0.358	0.000	0.247	0.370
Collateral Value	5,608,509	20,766	11,051	12,900	18,763	26,484
Monthly Payment	5,608,509	340	162	225	314	426
	Panel C. Ex-Post Loan Performance Measures					
FICO(current)	3,865,046	704	82.9	653	712	770
Δ FICO	3,804,527	-0.011	0.088	-0.046	-0.003	0.030
Days Delinquent	3,820,969	37.1	927	0	0	0
Charged off	5,608,509	0.020	0.141	0	0	0
Default	5,608,509	0.024	0.151	0	0	0

Note: Panel A contains loan application statistics. Panel B contains loan origination information, and panel C contains ex-post loan performance measures. “Loan Term” is the term (in months) of the loan. “Loan Rate” is the annual interest rate of the loan. “Debt-to-Income” is the ratio of debt to income. “FICO” is the FICO score at origination. “Collateral Value” is the value of the car at origination. “Monthly Payment” is the monthly payment made by the borrower in order to service the loan. “FICO(current)” is the FICO score as of the date the data was pulled. $\Delta FICO$ is the change in FICO score since origination as a fraction of the FICO at origination. “Days Delinquent” is the number of days that a borrower has missed one or more monthly payments. “Charged off” is a dummy equal to 1 if the loan has been written off the books of the lending institution. “Default” is a dummy equal to 1 if a borrower has been delinquent for at least 90 days.

Table 2: Summary Statistics of Sample with Identified Discontinuities (Estimation Sample)

				Percentile		
	Count	Mean	Std. Dev.	25th	50th	75th
	Panel A. Loan Applications					
Loan Term	42,568	70.6	16.3	61.0	72.0	84.0
Loan Amount ($)	73,516	24,923	11,924	16,000	23,474	32,294
Loan Rate	38,236	0.052	0.054	0.038	0.042	0.060
Debt-to-Income	51,257	3.22	74.50	0.16	0.27	0.38
FICO	54,715	663	42.1	623	683	700
	Panel B. Originated Loans					
Loan Rate	489,315	0.067	0.031	0.043	0.060	0.085
Loan Amount	489,315	18,018	10,709	10,149	16,018	23,691
Loan Term	489,315	63.7	21.5	50	61	72
FICO	489,315	655	37.5	627	649	692
Debt-to-Income	278,160	0.252	0.309	0.014	0.257	0.374
Collateral Value	489,315	18,524	10,074	11,425	16,675	23,625
Monthly Payment	489,315	328	154	219	303	408
	Panel C. Ex-Post Loan Performance Measures					
FICO(current)	369,679	649	69.2	610	654	695
Δ FICO	369,679	-0.011	0.093	-0.054	0.000	0.044
Days Delinquent	336,961	46.8	289	0	0	0
Charged off	489,315	0.034	0.181	0	0	0
Default	489,315	0.033	0.178	0	0	0

Note: Panel A contains loan application statistics. Panel B contains loan origination information, and panel C contains ex-post loan performance measures. "Loan Term" is the term (in months) of the loan. "Loan Rate" is the annual interest rate of the loan. "Debt-to-Income" is the ratio of debt to income. "FICO" is the FICO score at origination. "Collateral Value" is the value of the car at origination. "Monthly Payment" is the monthly payment made by the borrower in order to service the loan. "FICO(current)" is the FICO score as of the date the data was pulled. $\Delta FICO$ is the change in FICO score since origination as a fraction of the FICO at origination. "Days Delinquent" is the number of days that a borrower has missed a one or more monthly payments. "Charged off" is a dummy equal to 1 if the loan has been written off the books of the lending institution. "Default" is a dummy equal to 1 if a borrower has been delinquent for at least 90 days.

Table 3: First Stage Regression

	(1) Loan Rate	(2) Loan Term
Coefficient	-0.0147***	1.3782***
	[-29.74]	[5.12]
Institution FE	YES	YES
Quarter FE	YES	YES
N	489315	489315

Notes: Table reports regression estimates from Equation (6), which pool each of the three discontinuities shown in Figure 3 into one dataset and thus one discontinuity by normalizing the data around each threshold. As in the figure, our estimate bandwidths are specified at 19 FICO points on either side of the threshold. Our baseline specification controls for polynomials of order 2, though our estimates are strongly robust to any higher order polynomial specification. Our estimates further control for lending institution fixed effects and quarter-of-origination fixed effects. Standard errors are clustered at the FICO level.T-statistics reported in brackets.

Table 4: Loan Application Regression

	(1) Loan Amount	(2) Debt-to-Income	(3) Number of Loan Applications
Coefficient	-110.090	-2.685	176.212
	[-0.56]	[-1.09]	[1.22]
Institution FE	YES	YES	YES
Quarter FE	YES	YES	YES
N	54,715	51,256	39

Notes: Table reports regression results for the subset of institutions for which we have detailed loan application data. Regressions are similar to the specification used in Table 3. T-statistics reported in brackets.

Table 5: Second Stage

	(1) Car Value	(2) Loan Amount	(3) LTV	(4) Monthly Payment
Coefficient	978.857***	1,479.674***	0.027***	9.670***
	[11.86]	[13.63]	[5.03]	[6.28]
Institution FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Make-Model FE	NO	NO	NO	NO
Year-Make-Model FE	NO	NO	NO	NO
N	489,315	489,315	489,315	489,315

Notes: Table uses a RD design. Regressions control for lending institution and quarter-of-origination fixed effects, polynomials of order 2, and a bandwidth of 19 around the normalized FICO threshold. T-statistics reported in brackets.

Table 6: Second Stage Robustness to Heterogeneity

	(1) Car Value	(2) Car Value	(3) Car Age
Coefficient	887.69***	84.623	-.4001***
	[10.84]	[1.56]	[-20.86]
Institution FE	YES	YES	YES
Quarter FE	YES	YES	YES
Make-Model FE	YES	NO	YES
Year-Make-Model FE	NO	YES	NO
N	448,017	448,017	448,017

Notes: Table employs a regression model similar to Table 5. In addition, these regressions control for year-make-model fixed effects in the RD regressions. T-statistics reported in brackets.

Table 7: Ex-Post Outcomes

	(1)	(2)	(3)	(4)
	Days Delinquent	Charge Off	Default	ΔFICO
Coefficient	-3.76	-.00079	-.00195	.00035
	[-1.12]	[-.636]	[-1.17]	[.18]
Institution FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
N	336,961	489,315	489,315	369,679

Notes: Column (1) uses the number of days a borrower is delinquent as the dependent variable in the RD setting. The regressions use the standard bandwidth, polynomial order, and fixed effects. Column (2) uses the institution-reported charge off measure. Column (3) uses a binary indicator of loan default, defined as borrowers' delinquent in excess of 90 days, a standard default metric in evaluating loan performance. Column (4) uses the change in the borrowers' ex-post credit score for the sub-sample of institutions that report credit scores after loan origination. T-statistics reported in brackets.

Table 8: Difference Between Lowest Available Rate (DLAR) Summary Statistics

FICO Range	# of Cells	Mean # Borrowers in Cell	Mean	Std. Dev.	Percentile 25th	Percentile 50th	Percentile 75th
$595 \leq FICO \leq 599$	124	2.46	.0336	.0254	.01	.0298	.05
$635 \leq FICO \leq 639$	1006	2.99	.025	.021	.01	.02	.037
$695 \leq FICO \leq 699$	671	3.92	.016	.014	.006	.013	.021

Notes: Table reports summary statistics on the DLARs of borrowers just left of lending thresholds. Borrowers within the same MSA are assigned to a 5 point non-overlapping FICO buckets. We further refine the match to require that borrowers in the same MSA and 5 point FICO buckets purchased cars within a \$1,000 range. The \$1,000 auto purchase bins are also non-overlapping, beginning from \$2,000 to \$2,999, up to a maximum purchase amount of \$100,000. We further pool borrowers into 5% debt-to-income bins. Finally, to control for time variation in interest rates, matched portfolios require that all auto purchases occurred within 2 quarters of each other. Within each of the matched bins, we then calculate the average difference between the lowest interest rate in the portfolio and each individual loan in the portfolio. Summary statistics are reported for only those cells that contain at least 2 borrowers.

Table 9: Effect of Search Cost Proxies on Loan Offer Take-up

	(1)	(2)	(3)
	0.172	.142	0.196
	[7.06]	[3.98]	[6.54]
Institution FE	YES	YES	YES
Quarter FE	YES	YES	YES
N	48679	24,446	24,233
Sample	Full	Driving-time Density - LOW	Driving-time Density - HIGH

Notes: Table shows results for RD regressions of loan take-up (conditional on being offered a loan) on different measures of search costs separately for the highest search cost quintile and lowest search cost quintile. Using our standard RD framework, we specify loan take up rates as the dependent variable and estimate differences in the take up rate around FICO thresholds. Loan take up rates are defined as the percentage of applicants that accept an offered loan. T-statistics reported in brackets.

Table 10: Search Costs- Double Sorts

		Competition LOW	Competition HIGH
Driving Density (20m)	LOW	0.12 [2.36]	0.272 [1.97]
	HIGH	0.193 [3.69]	0.478 [4.79]

Notes: We calculate the share of originated mortgage loans by HMDA lenders within a given MSA, a commonly accepted measure of lending competition, and use the origination shares to construct an MSA-level Herfindahl index. In an effort to differentiate between search costs and competition, we divide loans into low and high competition halves based on our our constructed Herfindahl index. We then sort within a competition half along search costs. We then perform our take up regression on each of the four subsets in the double sort. Loan take up rates are defined as the percentage of applicants that accept an offered loan. All regressions include Institution and quarter fixed effects. T-statistics reported in brackets.

Table 11: # of Loan Applications/Vehicle Purchase

	(1)	(2)	Diff
Mean	1.08	1.10	-.015
Standard Deviation	.499	.546	[14.12]
Institution FE	YES	YES	
Quarter FE	YES	YES	
N	487,560	482,137	
Sample	Driving-time Density - LOW	Driving-time Density - HIGH	

Notes: Table shows average applications per vehicle purchase. Standard deviation reported in brackets. Difference in means is also calculated. T-stat in brackets.