Monthly Payment Targeting and the Demand for Maturity*

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Abstract

In this paper, we provide evidence of mental accounting in the market for consumer installment debt and argue that increases in credit supply have been an important contributor in the recent rise in auto debt through a demand-for-maturity channel. Since the Great Recession, auto debt has grown faster than any other category of U.S. consumer credit and now eclipses credit cards in total debt outstanding. Simultaneously, auto-loan maturities have increased such that more than half of 2016 auto-loan originations had a term of over 65 months. We document three phenomena we jointly refer to as monthly payment targeting using data from millions of auto loans issued by hundreds of credit unions. First, using discontinuities in the contract terms offered by lenders with an instrumental-variables regression-discontinuity design to estimate demand elasticities, we find borrowers to be much more sensitive to maturity than to interest rate, consistent with existing work finding that payment size is more salient to borrowers than the total cost of a loan. Second, many consumers appear to employ segregated mental accounts, spending much of unanticipated monthly payment savings on larger loans as if having budgeted a set amount per month for a given category of spending. Third, consumers bunch at salient round-number monthly payment amounts, suggesting the use of monthly budgeting heuristics. The resulting strong preference for long-maturity loans, combined with increases in aggregate credit supply, explains around 15% of the growth in household debt since 2012.

Keywords: household leverage, installment debt, mental accounting, auto loans

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1 Introduction

While existing theories of household debt decisions are relatively silent on the role of monthly payment management, in this paper we ask how households make decisions about optimal leverage in practice. In a frictionless model of household finance, consumers make financing decisions that minimize the marginal utility-weighted present value of total borrowing costs, all else equal. However, minimizing installment payments instead could be optimal if borrowers are credit constrained, if cognition costs are large, or in the presence of commitment problems. We show that many consumers appear to target specific monthly payment amounts rather than minimizing total borrowing costs or satisfying debt-service coverage constraints. Such debt decisions that focus on monthly payment levels represent a departure from classical models of intertemporal consumption decisions but are consistent with recent work on mental accounting (e.g., Hastings and Shapiro, 2013).

Our setting consists of auto loan decisions made by over two million individual borrowers from 319 different lending institutions. We employ a robust regression-discontinuity (RD) design to isolate exogenous shifts in the supply of credit made available to borrowers. Over half of the lenders in our dataset offer interest rates and loan maturities that jump discontinuously at various FICO thresholds that differ across institutions. Given that borrowers' observable attributes are consistently smooth across these FICO thresholds, the thresholds represent quasi-random variation in the financing terms offered to otherwise similar borrowers and identify consumer preferences over loan characteristics.

We present four main empirical findings. First, estimated demand elasticities with respect to loan maturities are substantially larger than elasticities with respect to interest rates.[1] As we show, such preference for maturity is inconsistent with a consumer optimization function that minimizes the present value of total borrowing costs, which is more sensitive to a ten percent change in interest rates than a ten percent change in loan maturity. In contrast,

[1]See also evidence of this first fact in Attanasio, Goldberg, and Kyriasidou (2008) and Karlan and Zinman (2008) on borrowers' relative sensitivity of maturity and interest rate, as we discuss in Section 2.

a taste for maturity is consistent with consumer focus on the dollar amount of monthly payments, which is more sensitive to maturity than rate.

Second, we document that the majority of consumers in our sample smooth monthly payments when they are exogenously offered more favorable loan terms, adjusting their auto-debt levels instead of reallocating across all budget categories (consistent with results contradicting fungibility in Hastings and Shapiro, 2017). When provided better (worse) financing terms, borrowers increase (decrease) leverage, but only up to the level that keeps their monthly payments roughly the same. This behavior points to an optimization process where borrowers have set monthly payment amounts in mind when making debt decisions and budget expense categories using segmented mental accounts (as in Thaler, 1990).

Third, we show that borrowers' monthly payments bunch disproportionately at salient monthly payment amounts, especially \$200, \$300, and \$400 per month. Given the breadth of our data and the wide heterogeneity across borrowers (in income, assets, risk aversion, expectations, and debt-to-income constraints, etc.), these round-number payment levels likely represent budgeting heuristics rather than the result of an integrated utility maximization process or a lender underwriting process.

Finally, we use our data to provide evidence of aggregate shifts in credit supply. Median loan maturities increased 10% in our sample from 60 months in 2013 to 66 months by 2015.[2] Given coincident *declines* in equilibrium interest rate spreads on auto loans, we argue that the observed maturity increases are the result of an outward shift in the aggregate supply of loan maturity. In back-of-the-envelope calculations, we estimate that an aggregate shift in the supply of maturity, coupled with high maturity borrowing elasticities, can explain

[2]We are not the first to sound an alarm about rising auto-loan maturities and their connection with monthly payment targeting. For example, a recent government report (OCC, 2015) warned, "Too much emphasis on monthly payment management and volatile collateral values can increase risk, and this often occurs gradually until the loan structures become imprudent. Signs of movement in this direction are evident, as lenders offer loans with larger balances, higher advance rates, and longer repayment terms... Extending loan terms is one way lenders are lowering payments, and this can increase risk to banks and borrowers. Industry data indicate that 60 percent of auto loans originated in the fourth quarter of 2014 had a term of 72 months or more... Extended terms are becoming the norm rather than the exception and need to be carefully managed." See also a recent report by the Consumer Financial Protection Bureau (Brevoort et al., 2017) using nationally representative data and documenting similar trends.

approximately 30% of the aggregate increase in outstanding auto debt. Given that the recent increase in auto debt can account for 50% of the increase in aggregate consumer debt, increased maturities account for about 15% of the growth in aggregate household debt from 2013–2015.

We interpret the phenomena we jointly observe (high maturity elasticities, monthly payment smoothness, bunching at salient monthly payment amounts, and increasing loan maturities) as most consistent with a form of mental accounting we refer to as monthly payment targeting. However, we also consider alternative explanations, the most plausible of which being that borrowers are month-to-month liquidity constrained (as in Attanasio et al., 2008). While we find strong support for this in our elasticity results, this cannot be the only explanation as it is unlikely that borrowers' monthly credit constraints bind exactly at monthly payment amounts of $200, $300, and $400. Moreover, we show that the borrowers who are least likely to be liquidity constrained (borrowers without any other debt and purchasing the most expensive cars in our sample) also bunch at salient monthly payment amounts, suggesting that that liquidity constraints are not the only explanation for monthly payment targeting. Across a wide variety of demographic groups, borrowers appear to bunch at salient payment amounts. Instead, these payment levels could represent self-imposed constraints for borrowers that are attempting to adhere to a monthly household budget.

While these findings have broader implications for our understanding of household capital budgeting, the market for auto loans is of independent interest given its ubiquity and the important role of cars in aggregate durable consumption. Over 86% of all car purchases are financed (Brevoort et al., 2017), and vehicles are the largest asset class on many low-wealth household balance sheets (Campbell, 2006). Auto loans recently have represented the fastest growing segment of consumer debt: between 2013 and 2015, outstanding auto, student-loan, and mortgage debt grew by 34%, 25%, and 4%, respectively. Auto debt is now the third largest category of consumer debt (behind mortgages and student loans), with over $1 trillion in outstanding balances and $400 billion in annual originations. Of particular relevance to our work is the recent trend in auto-loan maturities. Brevoort et al. (2017) document significant increases in the volume of auto loans originated with terms of more than six years and show that such loans are more likely to be larger, to borrowers with lower creditworthiness, and more likely to end up in default.

Our results are also relevant to efforts to understand shrouded marketing in consumer financial markets (e.g., Gabaix and Laibson, 2006; Gurun, Matvos, and Seru, 2016). Consumers who are fixated on monthly payment levels when making debt decisions are likely to ignore product attributes that are nevertheless consequential for future utility. Such myopia may lead to taking on debt contracts with higher present values and larger loan sizes. These two margins, coupled with longer maturity loans can lead to a mass of borrowers that are more likely to be underwater on their auto loans and repayment being more sensitive to economic shocks, risks that are opaque to borrowers targeting monthly payment levels.

The paper proceeds as follows. In Section 2, we describe how our conceptual framework fits in the context of various literatures in household finance. Section 3 introduces our borrower-level data on loan applications, offers, originations, and performance. We detail our empirical strategy for estimating demand elasticities in Section 4 and present our core empirical results. In Section 5, we discuss the merits of various interpretations of Section 4's results. Section 6 features a set of calculations to estimate the contribution of the maturity channel on total outstanding household debt, and Section 7 concludes.

2 Conceptual Framework and Related Literature

Conditional on financing consumption with a fixed amount of debt, in an extended version of classical models of intertemporal utility maximization that feature a rational and unconstrained borrower choosing from a menu of loan contracts, consumers would minimize the present value of total loan costs subject to a lifetime-wealth budget constraint.[3]

[3]For ease of exposition, we will work with a simplified setting that abstracts away from the intricacies of a model featuring both durable and non-durable consumption. See Berger and Vavra (2015) for a

Consider the standard model of an infinite-horizon agent choosing optimal consumption and asset paths $\{c_t,\, A_t\}_{t=0}^{\infty}$ in discrete time with no uncertainty. The consumers problem is then

$$\max_{\{c_t,\, A_t\}} \sum_t \beta^t \left[u(c_t) + \lambda_t(A_{t-1}(1+r) + y_t - c_t - A_t)\right] \tag{1}$$

where β is the discount factor, $u(\cdot)$ is the flow utility function, λ_t is the marginal utility of wealth, A_t and y_t are, respectively, net asset holdings (which could be negative in the case of debt) and after-tax income at time t. Debt and savings earn the same rate of return in this standard setup, with all debt being short term and interest and principal due one period ahead (although debt can be rolled over subject to a transversality condition).

To account for a portfolio of more realistic longer-run debt contracts as in Pissarides (1978), Attanasio et al. (2008) allow rate of return $r^i_{t,t+k}$ of a non-amortizing asset i to depend on both the maturity k and its outstanding balance A^i_t. Adapting this concept to our baseline model in (1), the first-order condition for A^i_t is the equalization of (suitably discounted) marginal utilities of wealth across periods:

$$\lambda_t = \beta^k \left(1 + r^i_{t,t+k} + \frac{\partial r^i_{t,t+k}}{\partial A^i_t} A^i_t\right) \lambda_{t+k} \tag{2}$$

where the term $\partial r^i_{t,t+k}/\partial A^i_t$ allows for the dependence of the interest rate on asset i on its level (including whether the position was savings or debt). Borrowing constraints may prevent the consumer from achieving condition (2). If credit limits are binding, marginal utility of wealth may be too high this period as constrained borrowing prevents sufficiently high consumption today to drive down λ_t such that (2) holds.

In extending this framework to consider optimal consumer choice amongst a menu of consumer debt contracts, let ℓ index the set of available consumer loans of a fixed loan size D characterized by their interest rate r_ℓ and maturity T_ℓ.[4] The household's lifetime wealth

comprehensive treatment of this margin.

[4]For illustrative purposes, we do not endogenize D here and instead focus on the extensive margin of loan choice (take up of a given contract conditional on approval). Note, however, that our empirical results will feature both extensive- and intensive-margin demand elasticities, and we will rely on the same intuition here for both dimensions.

constraint then becomes

$$\max_{\{c_t, S_t, D, \ell\}} \sum_t \beta^t \left[u(c_t) + \lambda_t B_t^\ell \right] \tag{3}$$

where the budget constraint B_t^ℓ depends on the chosen loan and is defined as

$$\begin{aligned} B_t^\ell \equiv S_{t-1}(1 + r_S) + y_t - c_t - S_t + D \cdot 1(t_0^D = t) \\ - m(D, r_\ell, T_\ell) \cdot 1(t_0^D \leq t \leq t_0^D + T_\ell). \end{aligned} \tag{4}$$

As before, y_t and c_t are income and consumption, respectively. To differentiate between savings and debt, we denote savings $S_t \geq 0$ with a one-period rate of return r_S. The amount of debt $D \geq 0$ is originated at time t_0^D such that at the origination date, the household receives D to spend or save. For all time periods t starting with the origination date and extending until the date $t_0^D + T_\ell$ when the loan characterized by contract ℓ matures, the household must make fixed, amortizing loan payments m that depend only on the amount of debt and the loan's interest rate r_ℓ and maturity T_ℓ.[5]

The key observation from the budget-constraint specification in (4) is that in the absence of credit constraints and for a fixed loan size D, the household's optimal loan-contract choice ℓ^* is related to the present value of per-period (e.g., monthly) payments. Formally, the first-order condition for ℓ yields

$$\ell^* = \arg\min_\ell \sum_{t=0}^{T_\ell} \beta^t \lambda_t m(D, r_\ell, T_\ell), \tag{5}$$

showing that an unconstrained consumer choosing to take out a fixed amount of debt D will only consider the present value of the marginal utility lost from the required payment stream.[6]

[5] In particular, in the case of standard (fixed-rate, self-amortizing) consumer loans (see Appendix for derivation),

$$m(D, r, T) = \frac{Dr(1 + r)^T}{(1 + r)^T - 1}.$$

[6] Note that absent any weighting by the marginal utility of wealth λ_t in a given period, any unconstrained borrower should finance any consumption expenditure in cash. In practice, however, many households hold savings balances earning a lower rate than simultaneously held credit balances (Fulford, 2015). Equation (5) offers one explanation for this phenomenon—households may issue debt despite also holding excess cash whenever the shadow value of liquidity (which can be spent on current consumption) is non-negligible.

In the appendix, we show that the present value of total loan payments is more sensitive to changes in interest rates than to changes in loan maturity. This baseline framework would thus predict that demand for a given contract would be more sensitive to its interest rate than its maturity.

In practice, three aspects of observed consumer behavior are inconsistent with this prediction, which we jointly refer to as monthly payment targeting. First, borrowers seem to focus on minimizing the level of monthly payments m rather than the present value of their stream, consistent with liquidity constraints, present-bias, or mental accounting. Second, borrowers spend any unexpected savings in monthly payments on larger loans and pricier cars, consistent with credit constraints and mental accounting. Third, consumers use round-number budgeting heuristics to allocate spending across consumption categories, consistent with cognitive costs. Monthly payment targeting has a different set of implications for borrowers' sensitivity to loan contract terms. Also in the appendix, we show that for a standard auto loan contract, monthly payment amounts are more sensitive to changes in loan maturity than interest rates. As a result, consumers can more effectively target a desired monthly payment by adjusting loan sizes in response to maturity choice than by being elastic to interest rate changes. In a monthly payment targeting framework as opposed to the classical framework above, demand would therefore be more sensitive to exogenous variation in maturities than rates.

2.1 Related Literature

The first empirical observation of monthly payment targeting, that demand is more sensitive to monthly payment levels than a loan's present value, is consistent with previous work that payment size matters and that maturity elasticities are higher than implied by a frictionless model. For example, experimental work in marketing by Shu (2013) documents the phenomenon of "NPV neglect" in installment loans, which she finds pervasive across education groups. In the mortgage context, Fuster and Willen (2017) find that consumer default is more sensitive to payment size than principal balance, a now standard feature in models of mortgage modification or optimal mortgage contract design (e.g., Eberly and Krishnamurthy, 2014).

Karlan and Zinman (2008) and Attanasio, Goldberg, and Kyriazidou (2008) both interpret high maturity elasticities as evidence of liquidity constraints elevating the importance of payment size.[7] In our setup, borrowing constraints such as credit limits (e.g., $D \leq \bar{D}$ for some credit limit $\bar{D}$) or payment-to-income constraints (e.g., $m/y \leq \bar{d}$ for some maximum allowable debt-service ratio $\bar{d}$) could prevent the borrower from borrowing from the future sufficient to satisfy the first order conditions. Optimizing with respect to such credit constraints would leave λ_t too high relative to its relationship with some λ_{t+k} in the future from the unconstrained model as in Pissarides (1978). Even without borrowing constraints, given penalties for missed payments (late fees, interest charges, and credit-record effects), households with risky income or self-control spending problems (e.g. Gathergood, 2012) may self-impose a constraint similar to a $\bar{d}$ bound on indebtedness. Likewise, if discount rates are particularly high (or if discounting is hyperbolic as in Laibson, 1997), the present value of the loan will be increasingly sensitive to the level of monthly payments.

Liquidity management more generally could influence debt decisions towards monthly payment considerations, even if liquidity constraints are not binding. Targeting low monthly payments could be an optimal decision if consumers find investment opportunities with rates of return in excess of borrowing costs. Alternatively, optimal debt allocation strategies could call for the lowest possible payment on auto loans (ignoring lifetime interest expenses) if such a strategy frees up liquidity to pay down higher rate-bearing debt obligations.[8] A buffer-stock model of household finance could also feature consumers willing to incur a higher interest

[7] Also related is work on endogenous maturity choice. Kuvíková (2015) and Hertzberg, Liberman, and Paravisini (2017) use Czech personal loans and Lending Club data, respectively to show that borrowers that opt for long maturity are of lower credit quality. Cox (2017) estimates maturity elasticities with respect to interest rates in a sample of private student-loan borrowers as evidence on intertemporal substitution elasticities.

[8] Stango and Zinman (2014) find that consumers are efficient at allocating debt to the lowest interest rate credit card, while Gathergood et al. (2017) find evidence to the contrary.

expenses over the life of a loan in return for having a larger savings balance to guard against financial shocks in the interim; see related discussion in footnote 6.

Bounded rationality, including the use of budgeting heuristics and mental-accounting biases, could also distort debt decisions away from first-best levels through emphasis on monthly payments. Budgeting heuristics reduce the cognitive complexity of lifetime budget maximization and may also address self-control problems by reducing a dynamic problem to a static per-period affordability problem governed by budget-category limits in monthly budgets. If borrowers neglect the present value of the loan because of low financial literacy or because the cognitive costs incurred to attend to the present value of the loan are sufficiently high, this could manifest as borrowers who are more attuned to monthly payments than total costs. See, for example, work on the failure to appreciate the importance of seemingly small one-time decisions (termed the "peanuts effect" by Read et al., 1999 and Bertrand and Morse, 2011). Stango and Zinman's (2009) work on exponential growth bias documents the role of the failure to appreciate the power of compound interest in borrowing.[9]

Our second empirical finding that is inconsistent with our benchmark model is that borrowers appear to fully adjust their spending on cars and car loans in response to price changes in auto loans as opposed to reoptimizing across all possible expenditure categories. While this could be the case if borrowers face binding monthly debt-service coverage constraints (the relaxation of which leads to a first-order increase in car-related spending and a second-order increase in other spending), given evidence on bunching at round-number payment levels, it is perhaps more straightforwardly consistent with mental accounting. Households who do not view their wealth as fungible and instead organize their cash flows into a set of mental accounts as in Thaler (1985, 1990) would spend any savings on car financing on a more expensive car instead of reallocating across categories, consistent with recent empirical evidence by Hastings and Shapiro (2013, 2107).

[9]Keys and Wang (2016) show that 29% of credit card borrowers make debt service payments at or near the required minimum, incurring substantial interest expenses. Other papers highlighting credit card-related repayment issues include Soll, Keeney, and Larrick (2013) and Navarro-Martinez et al. (2011).

Our third finding that is anomalous relative to the classical model is that many borrowers seem to target specific levels of monthly payments. The institutional or behavioral frictions cited above could drive consumers to take minimizing monthly payments as their objective function instead of minimizing the present (marginal utility) value of loan costs, but why would many borrowers target specific monthly payment levels (such as $300, $400, etc.)? This behavior is difficult to rationalize with credit constraints or myopia. Instead, we view this as suggestive that many consumers attempt to commit to not overspending by imprecisely forming a sense of affordability based on monthly expenses. This behavioral response to pricing also has precedent in the marketing literature. Wonder, Wilhelm and Fewings (2008) present survey evidence that consumers focus heavily on monthly payments, including an undue focus on the first digit of monthly payment amounts. Thomas and Morwitz (2005) also detail domains in which prices ending in 99 (dollars or cents) is an optimal response by firms to consumer heuristics.

Finally, our paper is also related to other studies that have used discrete changes in credit-market rules for inference. For example, Agarwal et al. (2017) estimate borrowing elasticities with respect to credit limits using a regression-discontinuity design based on FICO scores. Our analysis of monthly payment bunching joins other papers that use bunching to shed light on consumer optimization in response to various institutional features of mortgage markets, including Adelino, Schoar, and Severino (2014), Best and Kleven (2017), DeFusco and Paciorek (2017), and Di Maggio, Kermani, and Palmer (2016).

In summary, debt decisions driven by borrowing-cost minimization should be more sensitive to variation in interest rates, whereas debt decisions driven by monthly payment targeting are more effectively accomplished through variation in loan maturities. Our work contributes to the existing literature, including studies that document high maturity elasticities, in three ways. First, we estimate large extensive- and intensive-margin demand elasticities with respect to maturity using loan decisions by individual borrowers. Second, we extend the literature's understanding of consumer debt decisions by identifying the potential frictions that influence borrowers demand for maturity relative to preferences over price (i.e., loan interest rates). Third, we provide novel evidence that consumers target monthly payments, smooth their payments when the cost of financing changes, and use budgeting heuristics resulting in bunching at salient payment amounts.

3 Data

Our unique data on the (anonymized) auto loan decisions and loan contract features of nearly four million borrowers and 319 lenders comes from a technology firm that provides data warehousing and analytics services to retail-oriented lending institutions nationwide. The vast majority of the loans in our sample (98.5%) are originated by credit unions, with the remainder originated by non-bank finance companies. Similar data are used in Argyle, Nadauld, and Palmer (2017, ANP hereafter).

Loan contract features in the data include borrower FICO scores, loan-to-value (LTV) ratios, car purchase prices, loan dates, and in some cases, DTI ratios. We restrict the data set to only those loans originated directly with the lending institutions (in contrast to so-called indirect loans, which involve loan applications processed through auto dealerships). Although we have borrowers from all 50 U.S. states, the five most represented states in the data are Washington (465,553 loans), California (335,584 loans), Texas (280,108 loans), Oregon (208,358 loans), and Virginia (189,857 loans). The sample includes loans originated between 2005 and 2015, but over 70% of the loans were originated between 2012 and 2015.

We supplement the originated loan data with the applications of 1.92 million borrowers from 45 lending institutions (not all lenders in our data share loan application data with our data provider). The application data include decisions on loan approvals, denials, and funding outcomes, in addition to the credit attributes of applicants. Seeing this stage of the loan origination process allows us to evaluate the relative importance of loan terms on loan decisions at the extensive margin, a feature we view as an important contribution of this paper.

Table 1 reports basic summary statistics of the cleaned sample, after removing loan sizes over $100,000 and interest rates over 15%. Panel A summarizes the loan-application data; Panel B summarizes the originated loans. As reported in Panel B, the median loan size is $16,034, the median FICO score is 714, and median DTI is 26%. The median interest rate over the full sample period is 4.0%, and trends down over our sample period. Median loan maturities rise from 60 months in the early years of the sample to 66 months in 2014 and 2015. We discuss potential causes and the implications of rising maturities in Section 6 of the paper.

As discussed in ANP, the auto loans in our data mostly secure the purchase of used cars by prime borrowers and are originated by a slightly older, slightly less-racially diverse, and slightly-higher average credit quality demographic.[10] Our sample draws heavily from the 2012-2015 time period, a reflection of the growth in our data providers client base over this period. However, auto loan originations also increased substantially over this period. Nationwide outstanding auto debt increased 44.5% between 2012 and 2015, outpacing even the growth in student loans over the same period. According to Experian data in 2015, credit unions originated 22% of all used car loans and 10% of new car originations. We are unaware of aggregate statistics on the relative composition of direct versus indirect loans, but roughly half of the auto loans in our data provider's database are direct loans. Indirect borrowers are of slightly higher credit quality (median FICO for indirect of 718 versus FICO 714 for direct) and spend more on purchased cars (median purchase of $20k versus $16k); see ANP for further details on the comparison between indirect and direct. Any non-representativeness should be less of an issue in our setting given our reliance on a regression-discontinuity design that relies only on the local validity of our identifying assumptions. We return to the question of representativeness in the context of Section 6 when we extrapolate from our data

[10]Over 41% of our borrowers are between the ages of 45-65, compared to 34% in the U.S. census. Our sample is estimated to be 73% white, compared to 64.5% in the census. Median FICO scores in our sample are 714, compared to a median FICO of 695 in the NY Fed Consumer Credit Panel (CCP).

to draw conclusions about trends in aggregate indebtedness.

4 Empirical Strategy

The basic challenge in understanding the relationship between contract terms and demand for debt is that loan contract terms are endogenously determined. Our identification strategy relies on quasi-random variation in the supply of interest rates and maturities offered to borrowers by exploiting observed discontinuities in offered loan terms across various rule-of-thumb FICO thresholds. Unlike the mortgage setting in Keys et al. (2010), there is not an industry standard FICO score (e.g. FICO 620) at which institutions vary their lending standards in the auto market or around which treatment by the secondary market for loans changes. Instead, discontinuities in offered interest rates and loan maturities exist at various points across the FICO spectrum.[11]

While the FICO thresholds identify quasi-random variation in the supply of credit terms, the colocation of maturity and rate discontinuities also presents a unique empirical challenge. Interest rates and maximum loan maturities often jump discontinuously at the same FICO thresholds, making it difficult to differentiate the relative contribution of interest-rate supply versus loan-maturity supply in determining equilibrium loan amounts. Below, we develop a two-stage least squares procedure that makes use of heterogeneity across lenders in the magnitude of the otherwise standard first stages for rates and maturities. If all lenders had discontinuities for rates and maturities at the same FICO thresholds, and if those discontinuities were of equal magnitude, we would not be able to separately identify demand elasticities with respect to rate and maturity.

In this section, we first discuss the process we follow to detect rate and maturity discontinuities. We then present our regression-discontinuity strategy to estimate the magnitude of

[11]See ANP (2017) for a discussion of why lenders may choose step-function pricing. Anecdotally, multiple conversations with credit union executives confirm the existence of FICO thresholds and their (admittedly crude) purpose of pricing risk in loan offerings. We note, however, that the precise reason for discrete lender pricing rules is not important to our study here insofar as these reasons are not correlated with borrower quality or demand, which we verify below.

these discontinuities along with first-stage results and a series of tests of the RD identifying assumptions. After detailing our instrumental-variables regression-discontinuity estimator, we report elasticity estimates at both the intensive and extensive margins.

4.1 Detecting Discontinuities

To illustrate the lending rules we are seeking to detect in this section, Panel A of Figure 1 provides an example of interest rate drops around FICO thresholds for a single (anonymous) lender in our sample. The figure plots point estimates and confidence intervals arising from a 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 FICO 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 for each FICO bin represents the average interest rate on loans contained in the bin, relative to the estimated constant. The average interest rate movements are large, ranging from a 360 basis-point (bp) drop around FICO 600 to a 7 bp drop around FICO 720.

Panel B of Figure 1 provides a similar estimation of a single lender's maturity rules, which jump around FICO thresholds. As in Panel A, we estimate average maturities and confidence intervals for loans within 5-point FICO buckets. For the institution plotted in Panel B, loan maturities jump an average of 2.7 months around FICO 600, an average of 2.8 months at FICO 640, and an average of 3.3 months at FICO 680. Importantly for our identification strategy, note that different thresholds are associated with varying magnitudes of discontinuities within an institution; the same is true across institutions. Underlying the maturity plot in Panel B is likely a lender-specific rule about maximum allowable maturity that we do not observe and of which not all borrowers avail themselves. This likely contributes to the pattern we see comparing Panels A and B of Figure 1 where pricing discontinuities are more precisely estimated than maturity rules. Still, the discontinuities in maturity are economically and statistically significant, a point we return to below.

To identify every institution with discontinuous loan pricing rules, we first estimate interest rate-FICO bin regressions separately by lender. We classify interest-rate discontinuities as those FICO thresholds where 1) the interest rate difference across consecutive bins is larger than 50 basis points, 2) the p-value for the difference between those two coefficients is less than 0.1, and 3) the identified discontinuity is not within 20 FICO points of another identified discontinuity within the same institution. This screening criteria selects only those discontinuities that are economically and statistically significant and generated by stable lending rules.[12] Further, the third criterion 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.[13] Finally, in an effort to maximize the statistical power in our RD design, we require each candidate threshold to have 100,000 loans within a span of 38 FICO points around the threshold (19 on each side). Implementing each of these restrictions ultimately results in large and meaningful discontinuities in interest rates at FICO scores of 600, 640, and 700 across 173 institutions and 489,315 loans.[14] For convenience, we normalize FICO scores relative to each threshold to allow a standardized interpretation of the size of the treatment discontinuities at a given distance from the location of the relevant FICO score discontinuity.

While we observe lender-specific discontinuities in maturity rules throughout the FICO spectrum, we restrict our attention here to jumps in allowable maturity that occur coincident with our detected rate discontinuities. Although in principle, observing rate and maturity discontinuities at separate FICO locations could facilitate holding one fixed to isolate consumer response to the other, this would require a high degree of confidence in locating an

[12]For example, this procedure would not classify the FICO 520 coefficient in the lender in Panel A of Figure 1 as a discontinuity because of the third criterion even though the first two criteria are satisfied. Given the relative magnitude of the confidence intervals in Panel A of Figure 1 and the underlying distribution of FICO scores in the population, it is likely that the volatile FICO bin estimates for FICO scores well below 600 are driven by very small sample sizes as opposed to a volatile underlying lending rule.

[13]We also examine each potential threshold visually to ensure that the identified discontinuities are well behaved around the candidate thresholds.

[14]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.

exhaustive set of discontinuities. In particular, the strictness of our classification criteria could lead to a Type II error on one dimension, biasing our estimates of demand elasticities with respect to the other. For example, missing an actual discontinuity in allowable maturity that occurs at the same location as a lender's pricing discontinuity would induce upward bias in our estimated rate elasticity. As credit union executives indicate that maturity discontinuities frequently exist at the same FICO thresholds as rate discontinuities, we focus on maturity discontinuities that happen when our running variable (normalized FICO scores) crosses an identified threshold for an interest-rate discontinuity.[15]

4.2 First-Stage Results

We form our discontinuity sample by restricting the sample to applications and loans at lenders with discontinuities at 600, 640, and 700 and within 19 FICO points of a discontinuity. To check for representativeness, we compare summary statistics for this sample (reported in Appendix Table A1) with the full-sample summary statistics in Table 1. Observable characteristics such as interest rates, loan terms (in months), FICO scores, loan sizes, and debt-to-income ratios are similar across the two samples. For the remainder of the paper, we focus our attention on this discontinuity sample.

Our baseline RD specification is

$$\begin{aligned} y_{ict} &= \beta_1 \widetilde{FICO}_{ict} + \beta_2 \mathbb{I}(\widetilde{FICO}_{ict} \geq 0) \\ &\quad + \beta_3 \widetilde{FICO}_{ict} \cdot \mathbb{I}(\widetilde{FICO}_{ict} \geq 0) + \alpha_{cz(i)} + \delta_t + \varepsilon_{ict} \end{aligned} \tag{6}$$

where y_{ict} is an outcome for loan i originated by lending institution c in quarter t. The indicator variable $\mathbb{I}(\widetilde{FICO}_{ict} \geq 0)$ equals one if the normalized FICO ($\widetilde{FICO}$) is above the nearest FICO threshold. Using a uniform kernel, our estimates use bandwidths of 19 FICO points on either side of the threshold. For ease of exposition, equation (6) presents the

[15]Such an approach is conservative—to the extent that a lender does not have a maturity discontinuity at a given rate threshold (Type I error), this will be captured by the first stage and bias the maturity elasticity downward.

specification as linear in the running variable on either side of the discontinuity. In practice, we control for local linear functions of the running variable. The inclusion of commuting zone (CZ) fixed effects $\alpha_{cz(i)}$ capture any unobserved CZ-specific influence and quarter-of-origination fixed effects δ_t adjust our estimates for vintage effects. Using institution instead of CZ-based fixed effects produces qualitatively similar estimates. We cluster standard errors at the normalized FICO level and use the boundary-bias-corrected RD estimator of Calonico et al. (2014).

Figure 2 plots our first-stage regressions of interest rate (Panel A) and loan maturity in months (Panel B). For both contract features, there is a visibly apparent discontinuity as the running variable (normalized FICO score) crosses the threshold. The estimated discontinuities contrast with the otherwise smooth relationship between FICO scores and rates and maturities estimated nonparametrically on either side of the discontinuities. Comparing Panels A and B, and the relative magnitude of the discontinuity with the confidence interval widths, the interest-rate first stage seems more precise and lender maturity rules more volatile. We attribute this difference in precision across the two contract features as a result of not all consumers taking up the maximum allowable loan length.

Table 2 reports the first-stage coefficients $\hat{\beta}_2$ corresponding to Panels A and B of Figure 2. On average, interest rates decline an estimated 1.46 points across FICO thresholds (column 1). Loan maturities increase by an estimated 1.19 months over the threshold (column 2), which likely averages allowable maturities increasing at the discontinuity by more than 1.2 months and a fraction of consumers not responding to the increase in maximum maturity. As apparent in Figure 2, the rate first stage has a much higher t-statistic than the discontinuity coefficient for loan maturity, although both discontinuities are highly statistically significant.

4.3 Validating RD Exogeneity Assumption

For our RD estimates to isolate consumer sensitivity to loan features, we need the identifying assumption that other demand factors do not change discontinuously at our detected FICO thresholds. This smoothness condition allows for a counterfactual interpretation of outcomes around thresholds by mimicking the local random assignment of borrowers to interest rate and maturity offers. Conceptually, there is no clear process by which borrowers may select into one side of the threshold versus another. Though borrowers are unlikely to know their credit score precisely, it is even more unlikely that they know the location of a given institution's rate cutoffs. Given the volatility in FICO scores across credit bureaus and across weeks, it's also unlikely that assignment to the left or right of a threshold is correlated with demand shifters. Manipulation of credit scores is also difficult to achieve in the short-run and of little expected return without exact knowledge about lender pricing rules.

In practice, researchers point to smoothness of other observables and the density of the running variable as suggestive evidence that only treatment is changing discontinuously at the relevant running-variable threshold. We refer the reader to ANP for more detailed discussion and evidence on the exogeneity of the discontinuities. In Appendix Figure A1 and Table 3, we summarize that analysis using loan-application data to test whether other borrower characteristics change discontinuously around FICO discontinuities. Panels A-E of Appendix Figure A1 show that borrowers on either side of FICO thresholds do not appear meaningfully different in terms of their debt capacity, willingness to borrow, or demographics. Panel F plots a McCrary (2008) test showing that the number of applicants is statistically indistinguishable on either side of the threshold, suggesting that borrowers are likely unaware of the existence or location of the FICO thresholds when they apply. Table 3 shows that the discontinuity point estimates corresponding to the RD plots in Appendix Figure A1 are all statistically insignificant.

4.4 Elasticity Estimation

We are interested in estimating the elasticities of demand with respect to interest rate and maturity (sometimes referred to as term)

$$\begin{aligned} \eta^{rate} &\equiv \frac{\partial \ln Q}{\partial \ln r} \\ \eta^{term} &\equiv \frac{\partial \ln Q}{\partial \ln T} \end{aligned}$$

where Q is the quantity of debt originated and r and T are loan interest rate and maturity, respectively.[16] In a traditional simultaneous equations setup for demand and supply, we identify the demand equation by instrumenting for price with factors that affect supply but not demand. In our setting, we have variation in r and T coming from discontinuities in supply-side determined lending rules, which we show are uncorrelated with several characteristics that drive demand. To account for the simultaneous movement of interest rates and loan maturities at the discontinuities in our elasticity estimation, we exploit cross-sectional variation in the *magnitude* of the discontinuities across institutions. The magnitude of differences in the size of discontinuities is driven by institution-specific differences in loan pricing and maturity policies at a given threshold.

In a two-stage least-squares (2SLS) setting, we specify a framework for estimating rate and maturity elasticities and estimate the equation separately at both the extensive and intensive margin, as follows. Our second stage demand equation is given by

$$y_{ict} = \eta^{rate} \ln r_{ict} + \eta^{term} \ln T_{ict} + f(\widetilde{FICO}_i, \beta) + \alpha_{cz(i)} + \gamma_t + \varepsilon_{ict} \tag{7}$$

where y_{ict} is either the log loan size of loan i at lender c in quarter t (intensive-margin elasticity) or a dummy variable equal to one if the approved applicant i accepted the loan (extensive-margin elasticity). The relevant elasticities are given by η^{rate} and η^{term}, corre-

[16]Note that our hypothesis is that consumers have preferences over the total cost of a loan and payment size, not over rate and term per se. Still, we estimate elasticities with respect to rate and maturity since the total cost of the loan and its payment size each depend on the endogenous choice of loan size.

sponding to the log of the interest rate (r_{ict}) and log loan maturity (T_{ict}), respectively. The terms $\alpha_{cz(i)}$ and γ_t are commuting zone (CZ) and quarter fixed effects, and the normalized-FICO running variable $\widetilde{FICO}$ enters quadratically in the usual RD way as

$$f(\widetilde{FICO}, \beta) \equiv \beta_1 \widetilde{FICO} + \beta_1 \widetilde{FICO}^2 + \beta_3 \mathbb{I}(\widetilde{FICO} \geq 0)$$
$$+ \beta_4 \widetilde{FICO} \cdot \mathbb{I}(\widetilde{FICO} \geq 0) + \beta_5 \widetilde{FICO}^2 \cdot \mathbb{I}(\widetilde{FICO} \geq 0)$$

We include this function of $\widetilde{FICO}$ to approximate the nonlinear ways through which auto-loan demand may vary with credit scores.

The first-stage equations are given by

$$\ln r_{ict} = \sum_b \pi_b^{rate} \mathbb{I}(b = c) \cdot \mathbb{I}(\widetilde{FICO}_i \geq 0) + f(\widetilde{FICO}_i, \delta^{rate}) + \theta_{cz(i)} + \zeta_t + v_{ict}^{rate} \tag{8}$$

$$\ln T_{ict} = \sum_b \pi_b^{term} \mathbb{I}(b = c) \cdot \mathbb{I}(\widetilde{FICO}_i \geq 0) + f(\widetilde{FICO}_i, \delta^{term}) + \xi_{cz(i)} + \psi_t + v_{ict}^{term} \tag{9}$$

where the instruments are a set of lender-specific dummy variables $\mathbb{I}(\cdot)$ interacted with the discontinuity indicator $\mathbb{I}(\widetilde{FICO} \geq 0)$ and all of the controls in the second stage equation (7) are also included in the first-stage equations (8) and (9).

The demand specification in (7) has two right-hand-side endogenous variables requiring instrumenting, rate and maturity, and 174 instruments (a separate discontinuity indicator for each lender). The 2SLS relevance condition will be satisfied so long as rate and maturity discontinuities are jointly significant at the lender-level conditional on the other controls in the first stage. In order for this to be true given the main effect for $\mathbb{I}(\widetilde{FICO} \geq 0)$ included in the first stages as part of $f(\widetilde{FICO}, \delta)$, it needs be that not all lenders have the same discontinuity magnitudes for rate and term (otherwise, $\pi_c = 0 \ \forall \ c$). The standard partial F-statistic corresponding to the null hypothesis that the coefficients on the instrument set are not all equal to zero will test this relevance requirement for valid instrumental variables.

The exclusion restriction is met under the assumption that differences in the magnitudes of discontinuities across institutions are driven by institutional features that are exogenous to other factors affecting auto-loan demand (supply factors excluded from the demand equation). Commuting-zone and time fixed effects rule out selection into large or small discontinuity sizes on characteristics that move slowly across space (income, financial sophistication) or vary across time (aggregate economic conditions). Moreover, given the results of Section 4.3 above that there isn't sorting around the discontinuities on any observable dimension, it is plausible that the *size* of rate and maturity discontinuities is also unrelated to unobserved demand factors. If borrowers lack the information and ability to successfully target the right side of a lender's FICO discontinuity, it follows that they would be unable to target lenders that have large or small discontinuities.

To illustrate the intuition behind this identifying assumption, consider a stylized example with two institutions and no other controls. Lender A features a discrete 75 basis-point interest-rate reduction and a six-month increase in maturity offered at a FICO threshold of 600. Lender-A borrowers with a FICO score of 601 on average originate loans of $20,800, whereas 599 FICO borrowers take out $20,000 loans on average. Lender B also features a discontinuity at FICO 600 and offers a 100 basis point interest rate reduction and 12-month longer maturity at the threshold, leading 601 FICO borrowers to borrow $1,000 more than 599 borrowers. In this just-identified case with quasi-random assignment of discontinuity magnitudes, our demand estimation problem reduces to solving a system of two equations with two unknowns. The first equation, using data from Lender A, specifies changes in loan amounts as the dependent variable as a function of the 75 basis point rate discontinuity and the 6 month maturity discontinuity. The second equation is specified similarly using the data from Lender B. Quasi-random assignment of discontinuity magnitudes will hold insofar as any systematic differences between borrowers at Lenders A and B are unrelated to the fact that Lender A had discontinuities of 75 basis points and six months and Lender B had discontinuities of 100 basis points and 12 months. As in this example, our identification strategy relies on variation in the magnitude of rate and maturity discontinuities across lenders combined with this variation being unrelated to borrower demand shocks across lenders.

Extensive-margin results

Column 1 of Table 4 reports extensive margin results from estimating equation (7) by 2SLS with first stages as specified in equations (8) and (9). Our statistical power is limited relative to the intensive-margin estimates below because we necessarily rely on the application data for this margin, which are only available for a fraction of institutions in our data (see Panel A of Table 1 for summary statistics on the application data). Still, the partial F-stat testing the strength of the instrument set is over 100 for both the rate and term first stages. We estimate an extensive-margin demand elasticity with respect to interest rate of -0.55 and a demand elasticity with respect to loan term of 2.15. Facing a ten-percent increase in interest rate reduces the likelihood that a prospective borrower accepts an approved loan offer by 5.5 percentage points. Meanwhile, a ten-percent decrease in offered loan length reduces borrower take-up by 21.5 percentage points. Both estimates are statistically significant, though the maturity elasticity is only marginally so. The elasticity magnitudes are also statistically different from one another.

Intensive-margin results

Column 2 of Table 4 reports elasticities of loan size conditional on origination (the intensive margin) with respect to contract terms, where our sample size is substantially larger (see Panel B of Appendix Table 1 for summary statistics on the origination sample). Again, our instrument set is highly significant, with first stage partial F-stats of 50 and 200 for maturity and interest rate, respectively. Here, we estimate a demand elasticity with respect to rate of -0.17 and a maturity elasticity of 1.16. Both coefficients are estimated precisely with statistically significantly different magnitudes from one another and maturity sensitivities exceeding rate sensitivities by a factor of roughly seven.

To quantify the magnitude of these results, consider a typical observation in our data:

a $20,000 loan with a 5-year maturity and 5% interest rate. The results of Table 4 suggest that a ten percent increase in offered loan maturity (from 60 to 66 months) would result in a 11.6% increase in the equilibrium loan amount, from $20,000 to $22,320. In comparison, a ten percent decrease in offered loan rates, from 5% to 4.5%, would result in an increased loan amount of 1.7%, from $20,000 to $20,340.

Borrowers take out larger loans and are more likely to take out a given loan offer when they are offered a 10% increase in loan maturity than a 10% decrease in interest rates. These results are consistent with previous work (Attanasio et al., 2008 and Karlan and Zinman, 2008) that documents loan origination decisions having high maturity elasticities. What accounts for this differential sensitivity to contract terms? As we show below, the relative importance borrowers place on maturity is consistent with debt decisions that are less concerned with lifetime loan costs than monthly payment amounts.

5 Interpreting High Maturity Elasticities

Rational theoretical predictions regarding the relative magnitude of rate and maturity elasticities depend on the extent of credit constraints in the given model, as discussed in Section 2 above. Summarizing, when household discount rates are lower than interest rates, borrowers who are unconstrained in their ability to borrow across periods would optimally minimize the total present value of debt-service payments by selecting the contract with an optimal combination of low interest rates and short maturities.[17] However, given the relative importance of maturity in determining monthly payments, a preference for long maturities could arise from plausible real-world frictions. Borrowing constraints as in Zeldes (1989) create a wedge in the household's intertemporal Euler equation and, in the extreme scenario of no credit-market access, essentially reduce the intertemporal budget constraint based on

[17] In a frictionless world, taste for maturity depends on the relative magnitude of a given contract's interest rate and the household's discount rate. If borrowers discount the future at a higher rate than the loan's interest rate, they would prefer long-maturity loans. Of course, wealthy car buyers who discount future (utility-weighted) cash flows less than borrowing interest rates would prefer to pay cash rather than finance a purchase with a loan. Cash buyers are relatively rare in the U.S. (Brevoort et al., 2017).

total lifetime wealth to a per-period budget constraint. Similarly, in a buffer-stock model of saving and consumption decisions (e.g., Carroll, 1997), households may choose to attend to monthly payment levels in order to maintain a constant wealth-to-income ratio. Other borrowing frictions such as incomplete credit markets, credit rationing, credit limits, and late fees could lead consumers to rationally focus on monthly payments.

Behaviorally, several forms of bounded rationality could also explain borrower emphasis on monthly payments and thus high maturity elasticities. Failure to appreciate the power of compound interest, termed exponential-growth bias by Stango and Zinman (2009), could lead borrowers to ignore the negative consequences of long-maturity loans on the total cost of the loan. Other behavioral frictions such as cognitive costs or general financial illiteracy could drive households to adopt a monthly budget as a heuristic to ensure per-period consumption is affordable and sustainable, which in turn would lead to excess sensitivity to loan maturity.

While liquidity constraints and behavioral frictions are not mutually exclusive, in this section we discuss additional evidence that provides unique support for the presence of each channel.

Monthly Payment Smoothing

Borrowers with acute liquidity needs are likely to make borrowing decisions with monthly payments as a primary consideration. Using the monthly payment of each loan in our sample, we estimate differences in monthly payments around FICO thresholds and report results in Table 5. Column 1 results show that borrowers offered lower rates and longer maturities *increase* their monthly payment amounts by about \$6.53 relative to untreated borrowers (left-hand side of lending discontinuities). Although treated borrowers are offered lower rates and longer maturity loans, they respond endogenously by increasing loan sizes enough that monthly payments increase slightly. If there were no demand response, better credit terms on the right of a FICO discontinuity of the order reported in Table 2 would lead to a *decrease* in monthly payments of about \$20 for the typical loan. Given the balance in borrower characteristics across the discontinuities (especially the similarity of debt-to-income ratios in Panel A of Appendix Figure A1), these results suggest that at a minimum, not everyone faces binding liquidity constraints. In particular, if all borrowers were constrained away from their optimal level of consumption by strongly binding credit constraints, there would be no scope for borrowers to *increase* monthly payments in response to more favorable credit conditions.

However, not all borrowers are likely to be equally credit constrained. To differentiate borrowers that are likely constrained from borrowers that are likely not, we create subsamples based on attributes that plausibly proxy for credit constraints. We begin with borrowers who self-report DTI ratios of zero. Alternatively, we consider borrowers purchasing expensive cars (those in the top 10% of car values in our sample). The resulting hypothesized-to-be-unconstrained sample (zero DTI or highest 10% of car values) contains about 20% of the full sample. Column 2 of 5 reports RD estimates with monthly payment amounts as the dependent variable for the unconstrained sample, while column 3 reports estimates for the unconstrained sample complement. For the unconstrained borrowers, monthly payments increase $12.81 across the threshold. In comparison, as reported in column 3, for the majority of borrowers in our sample, monthly payments are smooth over the threshold.

When exogenously offered lower rates and longer maturities, constrained borrowers increase their loan amounts and ultimately the amount they spend on a car, but only up to an amount that keeps their monthly payment constant relative to otherwise similar borrowers not randomly treated with easier credit. This result is consistent with a heuristic approach to budgeting where borrowers have a monthly payment in mind when making the loan decision. Alternatively, if constrained borrowers face binding debt-service constraints, they may increase their car expenditure towards its first-best level when credit constraints are relaxed by better credit terms.

Monthly Payment Bunching

Basic budgeting heuristics, motivated by cognitive costs or commitment problems, could also call for loan decisions to be made based on a targeted monthly payment amount. In this section, we explore the possibility that borrowers adhere to rough budget category-specific expenditure limits when making loan decisions.

Figure 3 shows histograms of monthly payment amounts with borrowers sorted into monthly payment bins in \$2 increments. Panel A is centered around monthly payments of \$300. The histogram reveals a large and discontinuous break in the number of borrowers with monthly payments in the \$298-299 range compared to borrowers with monthly payments at \$300 or \$301. Panel B repeats this exercise for monthly payments around \$400, again showing significant bunching just below \$400. We more formally test the significance of the bunching in the histograms using McCrary tests below. This bunching is consistent with two demand-side explanations for how consumers make debt decisions. First, these results are consistent with survey evidence in the marketing literature that borrowers focus on the first digit of monthly payment amounts as a mental shortcut (Wonder, Wilhelm and Fewings, 2008). Second, they are also consistent with a model where households attempt to approximate lifetime budget optimization with rough round-number category-specific budget limits.

This bunching evidence does not rule out the possibility that borrowers are also liquidity constrained, although it is a priori unlikely given heterogeneity in household income and balance sheets that an excess mass of consumers have binding liquidity constraints exactly at monthly payments that are multiples of \$100. To test for bunching heterogeneity by liquidity constraints, we again split our sample into unconstrained borrowers (zero DTI or top 10% of car values) and its complement. We test whether bunching exists at salient anchor points of even hundred dollar monthly payment amounts by normalizing all payment amounts relative to the nearest hundred. Payment amounts of \$200, 300, etc, up through \$700 are included in the normalization. Figure 4 plots McCrary tests (point estimates and confidence intervals) of significant differences in the bunching at the normalized hundred dollar anchors. The McCrary tests indicate that borrowers in both samples exhibit significant bunching at salient payment amounts. These results favor a budgeting heuristic explanation relative to liquidity constraints as an explanation for monthly payment targeting given that it is unlikely for borrowers' liquidity constraints to bind exactly at salient hundred dollar increments.

We consider a number of additional subgroups that might capture cross-sectional differences in liquidity constraints and borrower's propensity to adhere to budgets. Using median tract income data made available by the census, we split our sample by borrowers in the top tercile of median tract income and bottom tercile of median tract income. Then within each of the three tract-income categories, we further split our sample into top-tercile FICO and bottom-tercile FICO borrowers. The conditional sorts create four unique buckets of borrowers. These include high income $\times$ high FICO (HIHF), high income $\times$ low FICO (HILF), low income $\times$ high FICO (LIHF), and low income $\times$ low FICO (LILF).

To learn about what types of borrowers are most likely to stick to a round-number monthly budget in their capital budgeting, we are particularly interested in testing for bunching behavior within two specific borrower categories. HILF borrowers are borrowers that could be classified as borrowers that are less in need of sticking to a budget (high income), but appear to do a poor job of managing their credit (low FICO). We contrast this group with LIHF borrowers, those most in need of budgeting (low income) and appear to have managed their finances effectively (high FICO). Using a series of McCrary tests we again test whether payment bunching exists at salient anchor points for each subgroup, normalizing payment amounts to the nearest even hundred (again using $200-$700 payment amounts). The McCrary plots are shown in Figure 5 with corresponding test statistics in the notes. All types of borrowers exhibit some degree of bunching at salient anchor points, although high income $\times$ high FICO and low income $\times$ low FICO borrowers seem to rely less on round-number budgets. Notably, bunching appears equally pronounced among those with poor credit quality despite high income (HILF in Panel B) and those with high credit quality despite their low income (LIHF in Panel C).

The bunching evidence sheds light on potential frictions that drive high maturity elasticities. Though liquidity constraints appear to be at play in driving monthly payment smoothing behavior, liquidity constraints are not able to explain bunching patterns that we detect in a variety of borrower types. Bunching at salient monthly payment amounts is also consistent with the large observed maturity elasticities given that flexibility in loan maturities more efficiently (in a mathematical sense) allows borrowers to move to salient monthly payment amounts. Evidence that maturity is the lever used by many borrowers to target a specific payment level is plotted in Figure 6. The first plot in Panel A is a test of monthly payment bunching using a sample of borrowers with standard maturity in their loan contracts, i.e. maturities of four, five, six, or seven years. The second plot in Panel B tests for bunching in a set of contracts with non-standard maturity lengths, i.e. 49-59 months, 61-71 months, 73-83 months, 85-95 months. The non-standard maturity loans feature substantially more pronounced bunching at even hundred-dollar payment amounts, providing additional evidence that maturity is a contractual feature used by consumers to obtain a desired payment size.

6 Aggregate Implications

Borrowers appear to make debt decisions in consideration of monthly payment levels, leading to large elasticities with respect to loan maturity. What aggregate implications for household debt might this taste for maturity have?

Data from the NY Fed Consumer Credit Panel show an aggressive increase in aggregate auto loan balances since the Great Recession. From 2010 Q1 to 2015 Q4, aggregate auto debt outstanding increased 50% from $705 billion to $1.06 trillion. Student debt is the only consumer loan segment that grew faster over the same period, although auto debt has outpaced even student debt from 2013–2015. Over the same period, median auto loan maturities increased 10% in our data from 60 months to 66 months after remaining flat from 2010–2012.[18] While car prices have roughly kept pace with inflation, increases in maturity over the past decade have led average monthly payments to grow much more slowly than loan sizes (Brevoort et al., 2017).

Can increases in equilibrium loan maturities be explained by increases in the aggregate supply of maturity? Or are increasing maturities a natural response to increasing prices? Demand for cars over time may increase with income growth or from consumers valuing technological improvements. Improved durability may lead to both an outward shift in vehicle demand and maturity supply by creditors, the latter through a collateral channel. A reduction in supply of car inventories could have the effect of increasing car prices as well. Whatever the potential source of an increase in car prices, more expensive purchase prices would result in larger loan amounts and endogenously increasing maturities in an attempt to keep monthly payments low. In this section, we examine the importance of the maturity channel in transmitting credit supply shocks, attempting to disentangle it from reverse-causality factors that first cause prices and originations to rise, with equilibrium maturity increase in response.

Figure 7 plots average interest rate spreads in the auto loan market against median maturities in the auto loan market. The interest rate spreads are calculated as the spread between the average five-year new auto-loan interest rate and the constant-maturity interest rate on five-year Treasury notes. Both interest rates are reported by the Federal Reserve and median auto maturities are taken from our sample. The plot shows an inverse relationship between aggregate auto loan spreads and median maturities. Increases in loan maturities could be driven by increases in aggregate supply or demand. However, the downward trending auto loan spreads are suggestive of an aggregate increase in the supply of credit in the auto loan market; in a standard supply-and-demand framework, if quantity is increasing but prices are

[18] Consistent with our data, CFPB data shows that the fraction of auto loans with maturities more than five years has increased from 25% to 45% (Brevoort et al., 2017). Federal Reserve G.20 data on finance companies also shows a 10% increase in average used-car loan terms from 55 to 61 months between 2010–2017.

falling, then at a minimum positive supply shocks exceed demand shocks.

In general, an aggregate shock to the supply of auto credit has important implications for the amount of total outstanding auto debt and outstanding household debt, especially to the extent that a supply shock is responsible for the observed increase in loan maturities given the high maturity elasticities we estimate here. A back of the envelope calculation of the aggregate role of the maturity channel suggests the following. We begin with the observation that loan maturities increased 10% between 2013–2015. Given that auto loan spreads were declining over this period, a conservative lower bound is that credit supply increases are responsible for at least 50% of the increase in maturities. Thus, if 50% of the 10% increase in loan maturities is due to increases in credit supply then based on our estimated maturity elasticities at the extensive and intensive margin, we would estimate total auto-loan borrowing to have increased by 12.5 percentage points ($.50 \times .10 \times$(2.15 extensive margin)$\times$(1.16 intensive margin) = 12.5%). A 12.5 percentage point increase in auto debt outstanding represents approximately 29% of the growth in auto loan originations from 2013–2015. Given that auto debt was responsible for half of the growth in aggregate household debt over this period (according to NY Fed CCP data), our calculations suggest that an aggregate increase in the supply of loan maturities can explain at least 15% of the growth in total household debt.

7 Conclusion

In this paper, we document and interpret several empirical facts about consumer installment debt. First, using a novel auto loan data set combined with a robust RD research design, we estimate that demand for installment debt is more sensitive to loan maturity than to interest rates. This result is not consistent with a frictionless model of household finance, under which loan amounts would be more responsive to equally sized (proportional) changes in rates than maturities.

Nevertheless, a reasonable set of frictions could explain high maturity elasticities. These include liquidity constraints and behavioral optimization frictions. Consistent with these possible explanations, we show in a quasi-experimental setting that constrained borrowers smooth monthly payments across contract offers, even when exogenously offered more favorable loan terms. For the bulk of our sample, borrowers borrow larger amounts when offered better terms, but only up to amounts that allow them to keep monthly payments the same.

While this monthly payment smoothing could be explained by credit constraints alone, we also provide evidence that borrowers make debt decisions in a mental-accounting framework using rough affordability rules of thumb. Borrowers disproportionately choose loan amounts and terms that result in salient monthly payment amounts of $300, $400, etc. Because it is unlikely that liquidity constraints bind exactly at these salient round-number amounts, this is consistent with the notion that many households follow a loose capital budget that specifies category-level expenditure limits. Notably, monthly payment bunching occurs in each subset of borrowers we consider. Low-income, high-FICO borrowers (a proxy for income-constrained but financially responsible) bunch at salient payment amounts, as do high-income, low-FICO borrowers (a proxy for wealthy but financially irresponsible borrowers).

In the final section of the paper, we demonstrate important aggregate implications of high maturity elasticities. Our results suggest that borrowers have an appetite for loans with maximal maturity levels in large part because because they target specific monthly payment levels. Coupling this constant preference for long-maturity loans with credit supply increases can lead to a rapid increase in total indebtedness. We estimate that the combination of large demand elasticities with respect to maturity and aggregate increases in the supply of maturity appears to be driving a significant portion of the increase in outstanding auto debt and total household debt.

Given behavioral frictions and the cognitive costs required of lifetime budget optimization, monthly payment targeting could be rational. However, paying attention only to monthly payment levels could make consumers susceptible to shrouded marketing that pushes costlier loans and larger loan sizes than intended. Long-maturity loans may also raise the potential that borrowers are stuck in negative equity loans if purchased vehicles depreciate more quickly than the associated loans amortize, raising the risk of default. Negative equity in auto loans would be particularly distressing for low-income borrowers, for whom cars represent a substantial share of net worth. More generally, monthly payment targeting has the potential to amplify credit supply shocks, increasing household leverage and increasing the exposure of the household sector to the business cycle.

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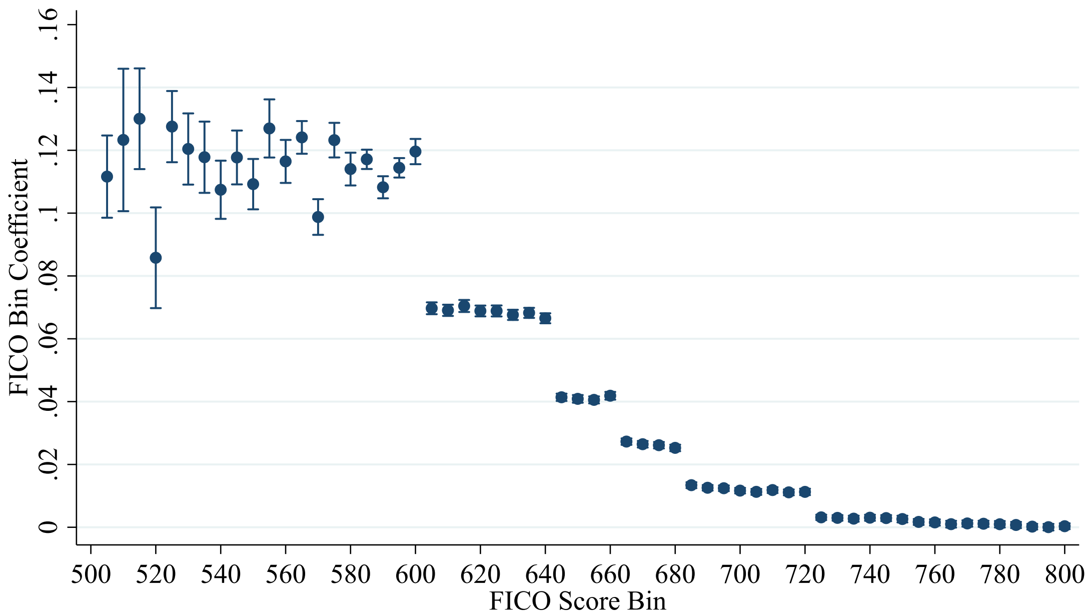
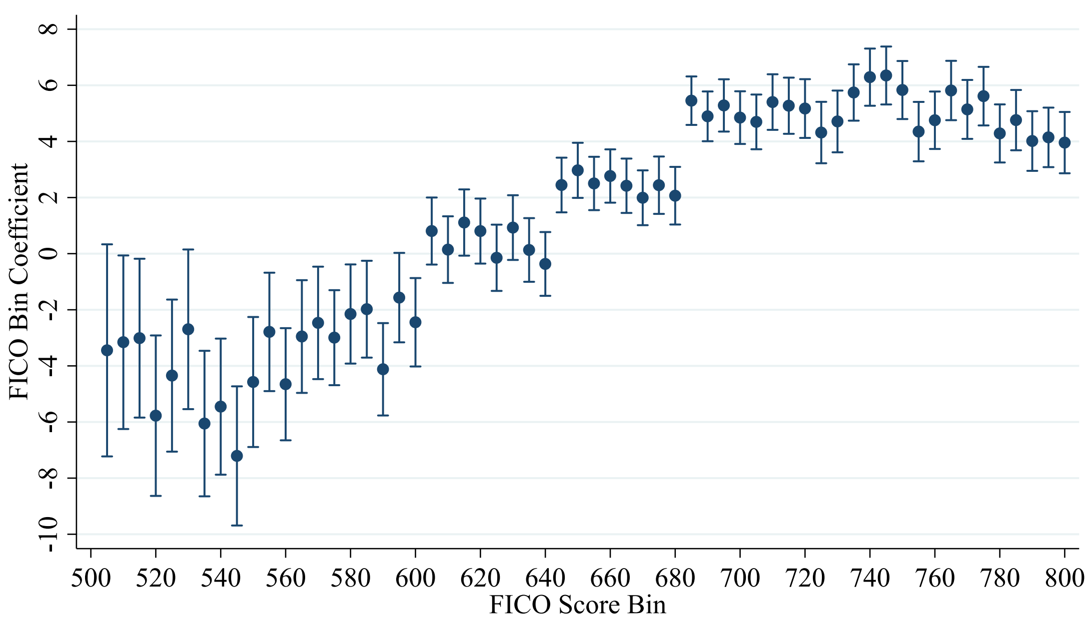
Figures and Tables

Figure 1: Example Estimated Lender Decision Rules

A. Example Estimated Pricing Rule for Individual Lender



B. Example Estimated Maturity Rule for Individual Lender

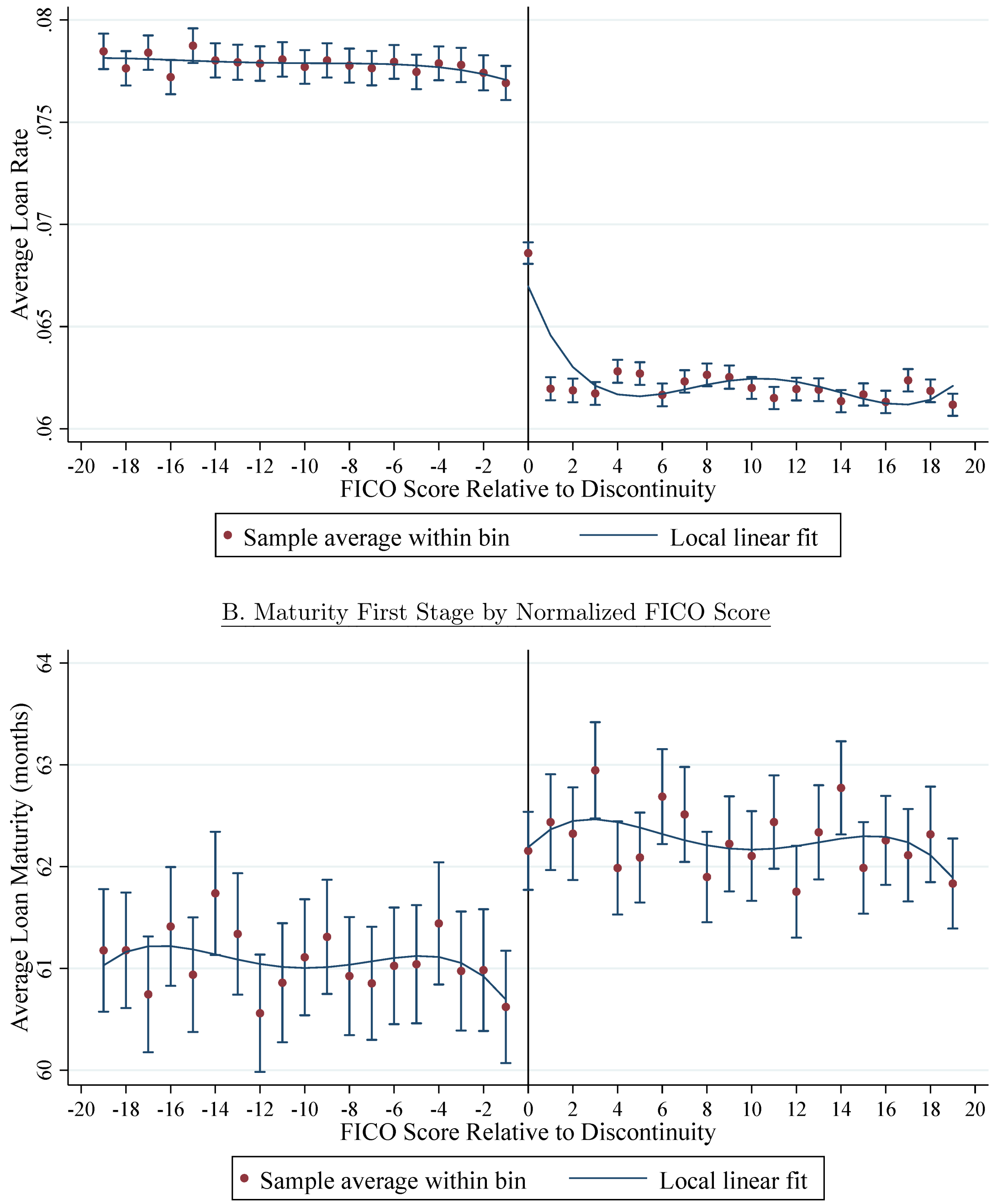


Notes: Figure plots an estimated pricing rule for an anonymous credit union in our data (Panel A) and an estimated maturity rule for a different anonymous lender in our data (Panel B). Interest rates and loan maturities, respectively, are regressed against dummies representing 5-point FICO bins. Coefficients and 95% confidence intervals are plotted against FICO scores.

Figure 2: First-Stage Regressions of Interest Rates and Maturities on FICO Scores

A. Interest-Rate First Stage by Normalized FICO Score

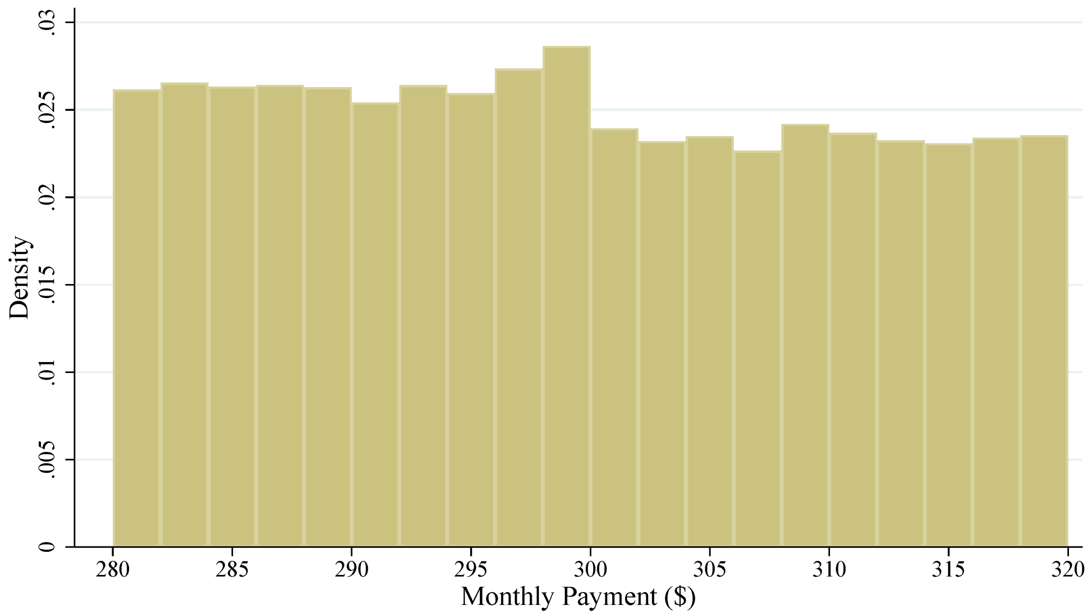
B. Maturity First Stage by Normalized FICO Score



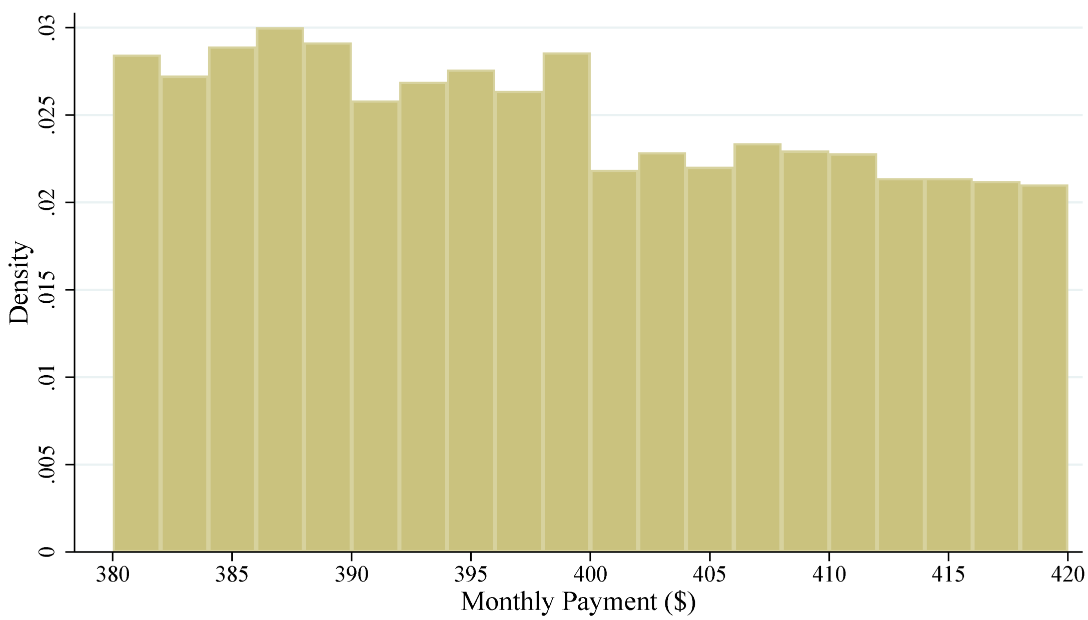
Notes: Average interest rates on the vertical axis against borrower FICO scores normalized to each threshold along the horizontal axis for institutions with pricing discontinuities.

Figure 3: Monthly Payment Histograms around Salient Cutoffs

A. Distribution of Monthly Payments around \$300



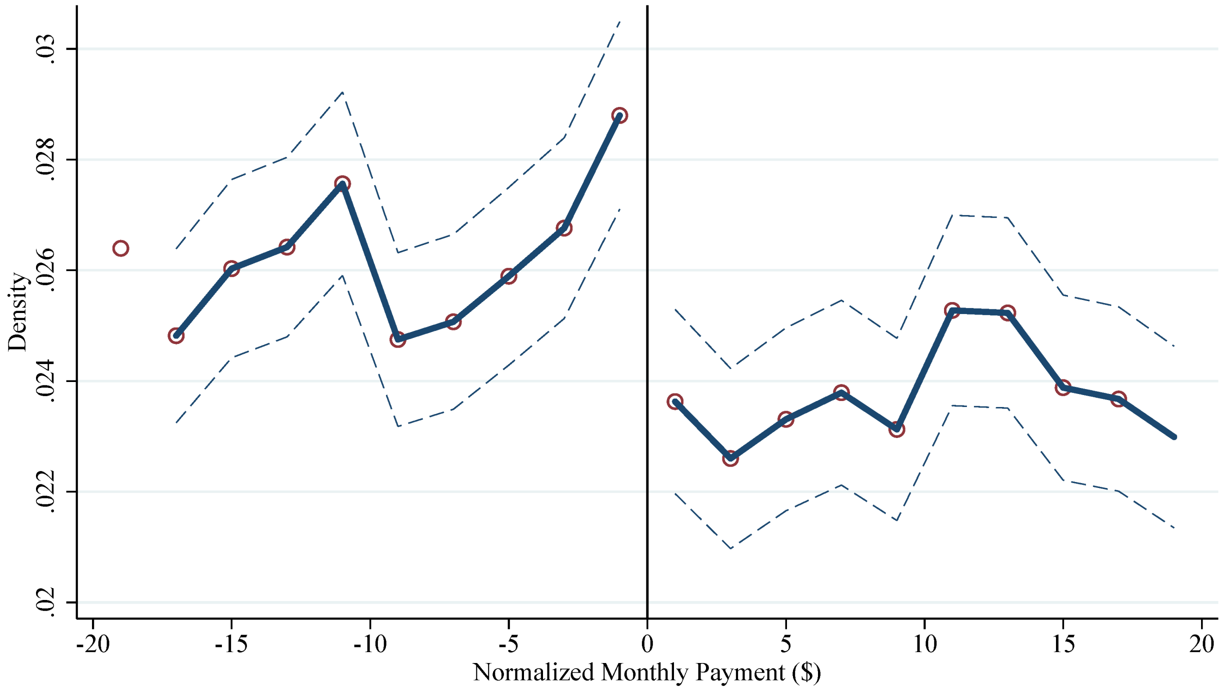
B. Distribution of Monthly Payments around \$400



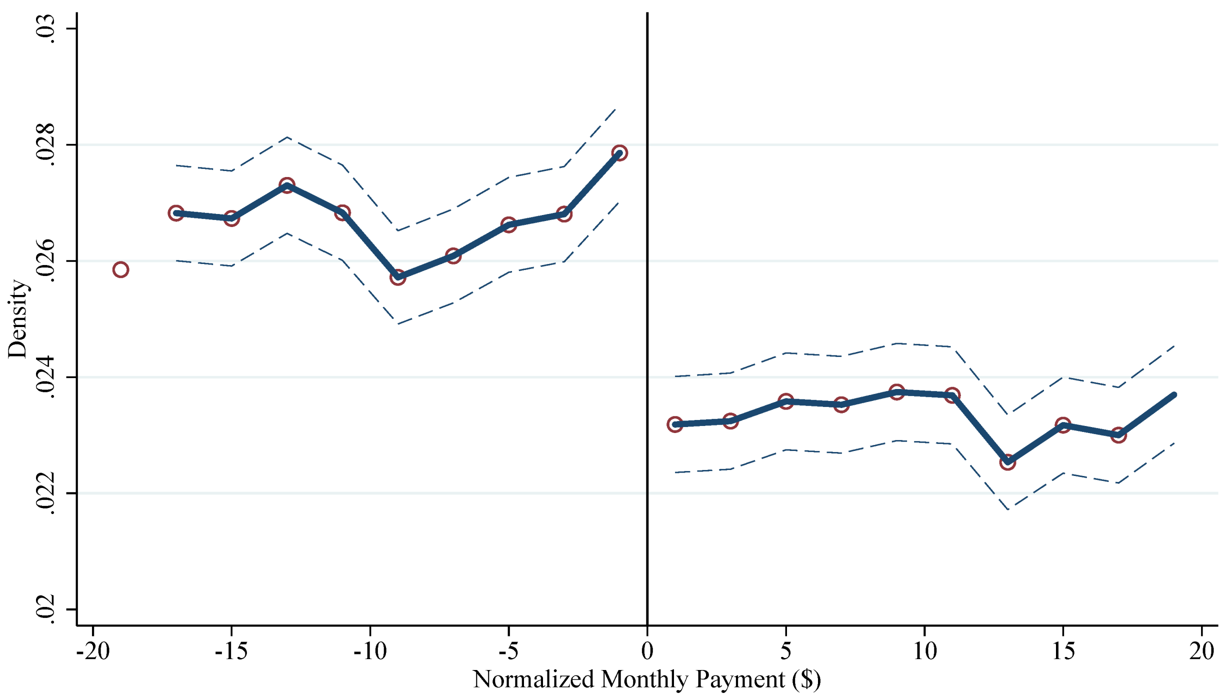
Notes: Figure plots unconditional histograms of monthly payments in a \$20 neighborhood of \$300 and \$400 in Panels A and B, respectively.

Figure 4: Monthly Payment Bunching for Unconstrained and Constrained Borrowers

A. Normalized Payment Frequencies for Unconstrained Borrowers

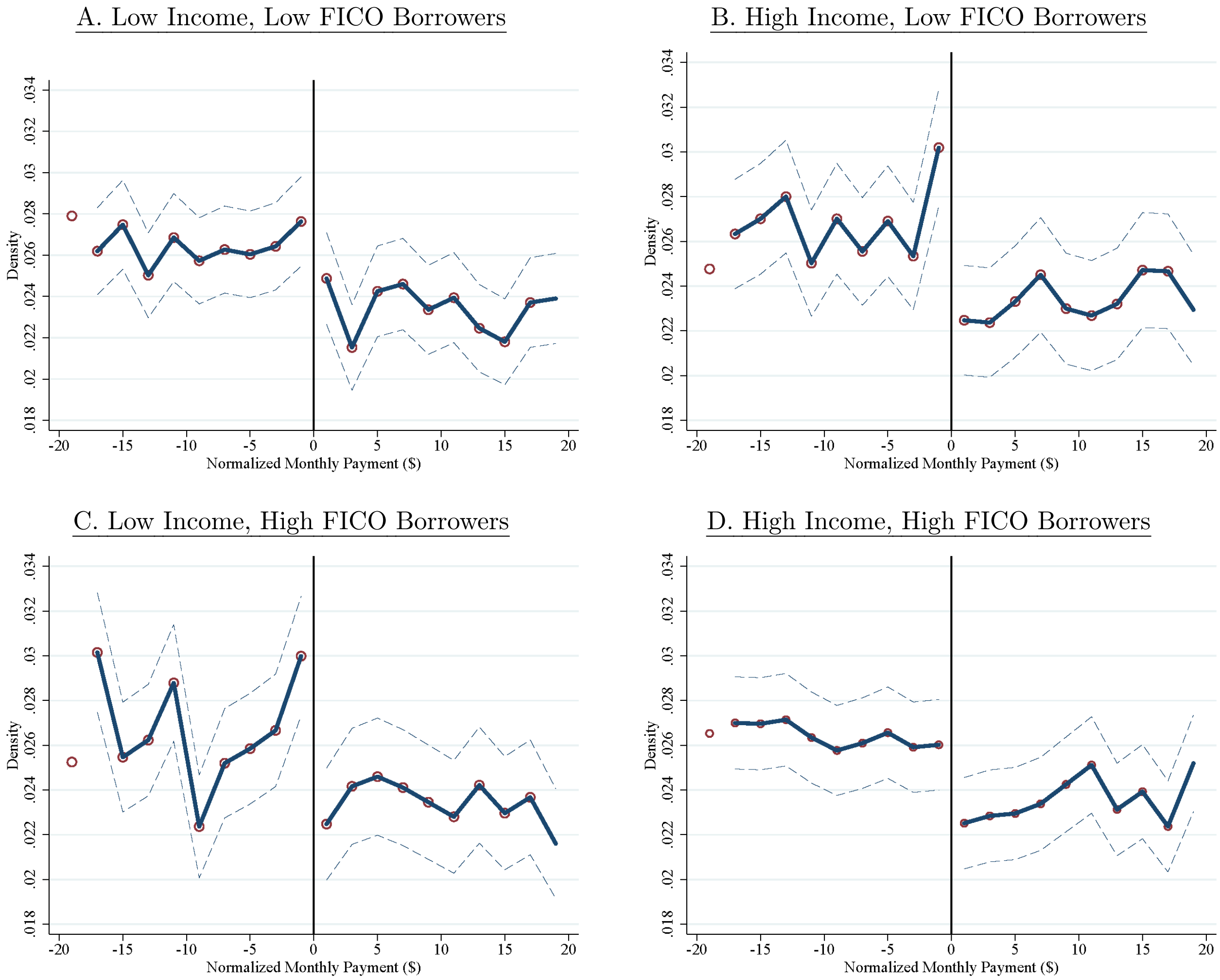


B. Normalized Payment Frequencies for Constrained Borrowers



Notes: Figures plot McCrary bunching tests of normalized monthly payments around hundred dollar increments from $200 to $700 for both the unconstrained sample (DTI equal to zero or loan amounts in the top decile) and constrained borrowers (the complement set) in Panels A and B, respectively. The McCrary log differences in density estimates (and standard errors) are -.201 (.049) and -.204 (.026).

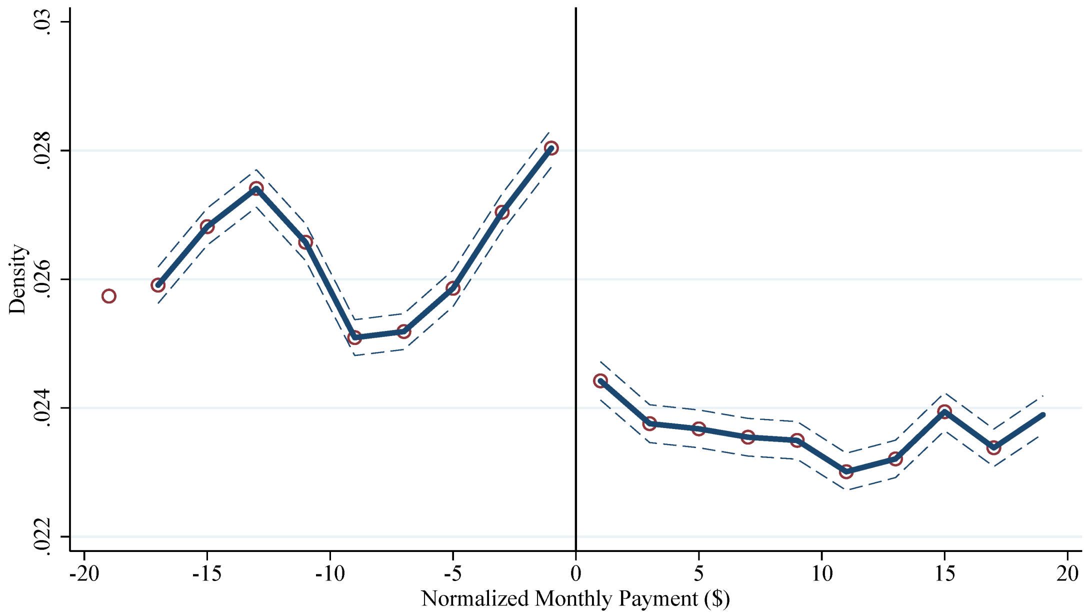
Figure 5: Monthly Payment Bunching by Borrower Subgroup



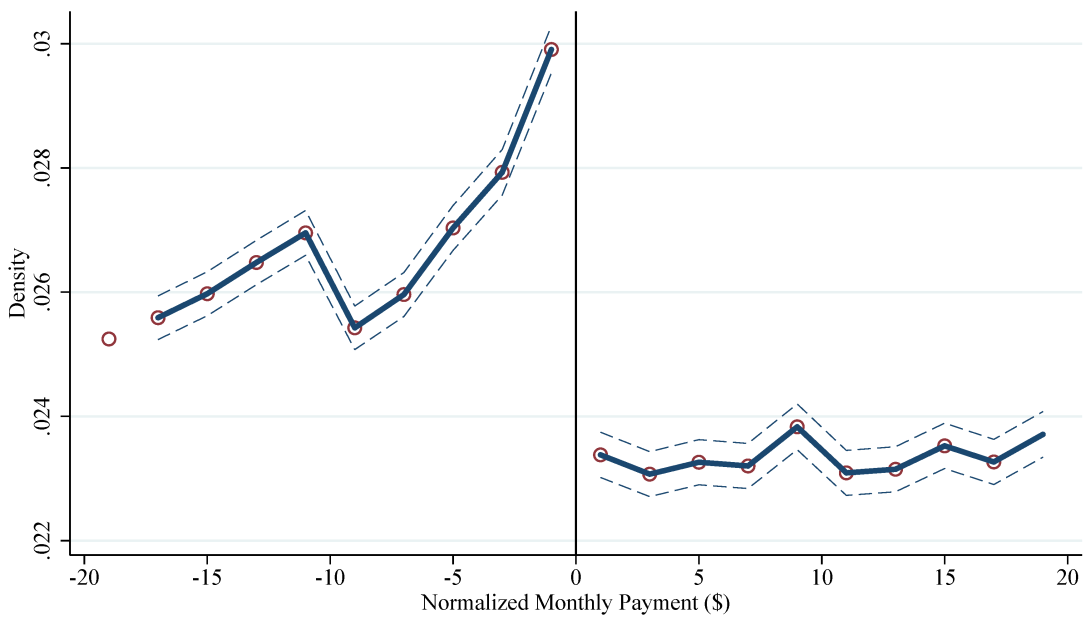
Notes: Figures plot McCrary bunching tests of normalized monthly payments around hundred dollar increments from \$200 to \$700 for four combinations of income and FICO outer tercile bins. McCrary statistics (and standard errors) are Panel A: low income and low FICO -.140 (.055), Panel B: high income and low FICO -.330 (.080), Panel C: low income and high FICO -.344 (.086), and Panel D: high income and high FICO -.150 (.060).

Figure 6: Monthly Payment Bunching for Typical and Atypical Maturities

A. Loans with Typical Maturities

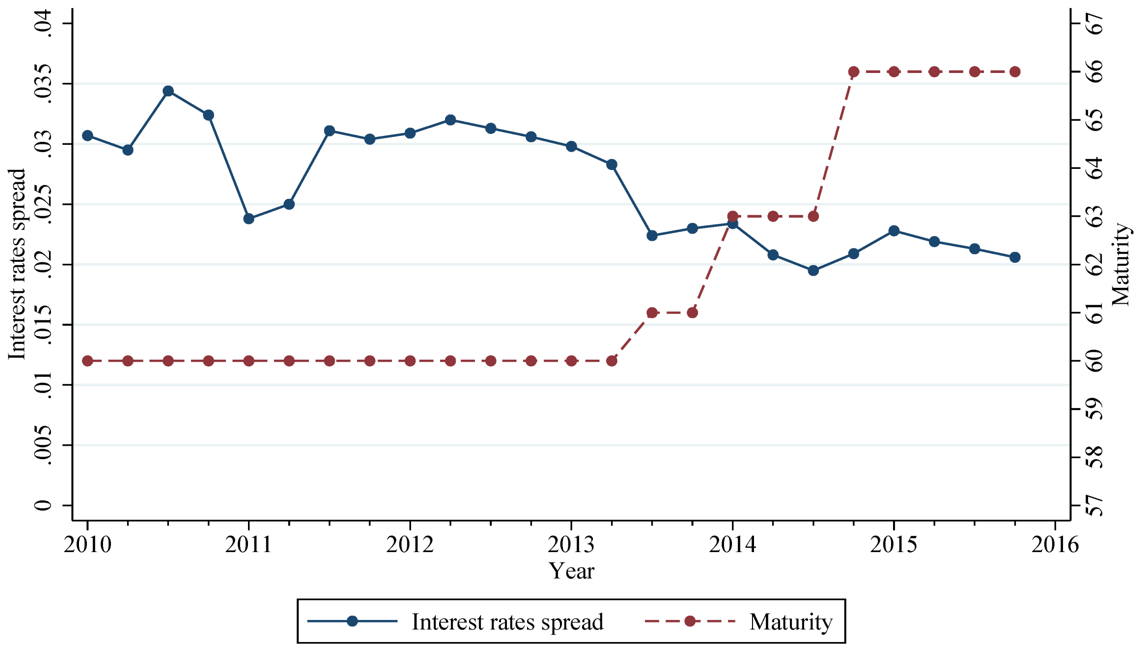


B. Loans with Atypical Maturities



Notes: Figure plots McCrary bunching tests of normalized monthly payments around hundred dollar increments from \$200 to \$700 for typical maturities (36, 48, 60, or 72 month terms) and for those borrowers with atypical maturities in Panels A and B, respectively. McCrary log differences in density estimates (and standard errors) are -0.35 (0.043) and -0.11 (0.03), respectively.

Figure 7: Auto-Loan Interest Rate Spreads and Maturities



Notes: Figure plots interest rate spreads and maturities for auto loans in the United States. Rates spreads are calculated as the difference between the quarterly average interest rate for a five-year loan on a used auto and the constant-maturity yield on the five-year Treasury Note. Median maturities are calculated quarterly using originated loans in our data.

Table 1: Summary Statistics

	Count	Mean	Std. Dev.	Percentile 25th	Percentile 50th	Percentile 75th
			A. Loan Applications			
Loan Rate (%)	1,131,240	0.05	0.05	0.02	0.04	0.06
Loan Term (months)	1,119,153	67.25	24.43	60	72	72
Loan Amount ($)	1,320,109	21,927.26	11,660.68	13,296.02	20,000	28,932.14
FICO Score	898,339	647.94	118.23	605	661	720
Debt-to-Income (%)	833,854	0.26	0.30	0.13	0.27	0.39
Take-up (%)	588,231	.65	.48	0	1	1
			B. Originated Loans			
Loan Rate (%)	2,434,049	0.05	0.03	0.03	0.04	0.06
Loan Term (months)	2,434,049	62.73	22.08	48	60	72
Loan Amount ($)	2,434,049	18,136.52	10,808.97	10,094	16,034	23,892
FICO Score	2,165,173	710.55	74.89	661	714	770
Debt-to-Income (%)	1,276,585	0.25	0.32	0.05	0.26	0.37
Collateral Value ($)	2,434,049	19,895.13	10,929.1	12,046.81	17,850	25,562.28
Monthly Payment ($)	2,434,049	324.4	159.21	210.93	297.02	405.56

Note: Table reports summary statistics for loan applications and originated loans, in Panels A and B, respectively. Loan Rate is the annual interest rate of the loan. Loan Term is the term (in months) of the loan. FICO Score is the credit score used in underwriting and pricing the loan. Debt-to-Income is the ratio of debt service payments to income. Collateral Value is the value of the car at origination.

Table 2: First-Stage Results for Loan Interest Rates and Maturities

	(1)	(2)
	Loan Interest Rate	Loan Maturity (months)
Discontinuity Coefficient	-0.0146***	1.19***
	[-17.25]	[4.60]
Commuting Zone Fixed Effects	✓	✓
Quarter Fixed Effects	✓	✓
Number of Observations	274,029	274,029

Notes: Table reports regression-discontinuity estimates of equation (6) corresponding to Figure 2 by normalizing FICO scores around each threshold and using the estimator of Calonico et al. (2014). All specifications include commuting zone fixed effects and quarter-of-origination fixed effects. Robust t-statistics reported in brackets are clustered by normalized FICO score. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Loan Application Covariate Balance Regressions

	(1) Loan Amount	(2) Debt-to-Income	(3) Age	(5) Male	(6) Minority Race	(7) Applications Count
Discontinuity	-68.75	-2.33	0.274	.014	.00057	0.058
Coefficient	[-0.26]	[-0.45]	[0.31]	[1.00]	[0.15]	[1.07]
CZ FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
N	52,816	35,427	25,702	49,438	49,161	39

Table reports reduced-form RD results for the subset of institutions for which we have detailed loan application data. See notes to Table 2 for more details. Each observation in the data used for column 7 represents a normalized FICO score. Robust t-statistics reported in brackets are clustered by normalized FICO score. *p<0.1, **p<0.05, ***p<0.01.

Table 4: Demand Elasticity Estimates

	(1)	(2)
Margin	Extensive	Intensive
Dependent Variable	$\mathbb{I}$(loan offer accepted)	ln(loan size)
log(interest rate)	-0.55***	-0.17***
	[-3.86]	[-5.47]
log(maturity)	2.15*	1.16***
	[1.72]	[8.61]
First-stage partial F-statistic (rate)	305.14	200.89
First-stage partial F-statistic (term)	132.23	53.58
Regression Discontinuity Controls	✓	✓
Commuting Zone Fixed Effects	✓	✓
Quarter Fixed Effects	✓	✓
N	17,715	274,029

Notes: Table reports 2SLS regressions of an indicator for whether an approved loan offer was accepted by the borrower (column 1) and log loan size (column 2) on log interest rate and log maturity. All regressions include commuting zone fixed effects, quarter fixed effects, and quadratic RD controls for normalized FICO score. The instrument set is a series of lender indicator variables interacted with the discontinuity indicator. The sample in column 1 is approved loans in the application sample within 20 FICO points of a discontinuity, and the sample in column 2 consists of originated loans within 20 points of a discontinuity. Robust t-stats in brackets clustered by normalized FICO score. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Reduced-form Effects of Lending Discontinuities on Monthly Payments

	(1)	(2)	(3)
Sample	Full	Unconstrained	Constrained
Discontinuity Coefficient	6.53***	12.81***	1.57
	[4.97]	[2.99]	[1.26]
Commuting Zone FEs	✓	✓	✓
Quarter FEs	✓	✓	✓
N	274,029	55,460	218,569

Notes: Table reports RD results of monthly payment amounts around financing thresholds. Unconstrained borrowers are defined as borrowers with debt-to-income ratios equal to zero or who originated a loan in the top decile of loan amounts. Constrained borrowers are the complement of this set. Robust t-stats in brackets are clustered by normalized FICO. *p<0.1, **p<0.05, ***p<0.01.

Appendix

In this appendix, we derive the present value of loan payments and the monthly payment of a loan and show the relative importance of interest rates and maturities in proportional changes to these two objects. While some Truth-in-Lending Law regulations emphasize only interest expenses, here we consider the present value of loan payments including principal and interest. While principal repayments are simply a movement on the asset side of a household balance sheet from cash to equity in a vehicle, we view this as a meaningful change in asset liquidity requiring an outlay of funds that is rightfully taken under consideration while choosing contracts. Note that our broad finding that the present value of monthly payments is more sensitive to interest rates while monthly payments are more sensitive to maturities is equally true when we consider only interest payments.

Let D be the principal amount borrowed, r be the monthly interest rate, δ be the discount rate (i.e. $\beta = 1/(1+\delta)$), and T be the time to maturity in months. For a fixed-rate, self-amortizing loan, the monthly payment m is determined by the equation

$$0 = \Big(\big(D(1+r) - m\big)(1+r) - m\Big)(1+r) - m...$$

where each period the outstanding debt is $(1+r)$ times the prior balance and the monthly payment pays down this balance, which includes accrued interest and outstanding principal, to zero by the period the loan matures. Expanding and simplifying,

$$\begin{aligned}
0 &= D(1+r)^T - m(1+r)^{T-1} - ... - m(1+r) - m \\
D(1+r)^T &= m(1+r)^{T-1} + ... + m(1+r) + m \\
D(1+r)^T &= m\frac{1-(1+r)^T}{1-(1+r)} \\
m &= \frac{Dr(1+r)^T}{(1+r)^T - 1}
\end{aligned}$$

The present value PV of the stream of T payments of size m is given by

$$\begin{aligned} PV &= m + \frac{m}{1+\delta} + ... + \frac{m}{(1+\delta)^{T-1}} \\ &= m\left(\frac{1-(1+\delta)^{-T}}{1-\frac{1}{1+\delta}}\right) \\ &= \frac{Dr(1+r)^T}{(1+r)^T-1}\left(\frac{(1+\delta)^T-1}{\delta(1+\delta)^T}\right) \end{aligned}$$

Note that when the debt's payment stream is discounted at the interest rate of the loan ($\delta = r$) the PV becomes D.

Elasticities of Present Value with Respect to Rate and Maturity

Differentiating PV with respect to rates,

$$\frac{\partial PV}{\partial r} = D\left(\frac{(1+\delta)^T-1}{\delta(1+\delta)^T}\right)\frac{(1+r)^{T-1}\left((1+r)^T + r\left((1+r)^T - T - 1\right) - 1\right)}{\left((1+r)^T-1\right)^2},$$

which is always positive; rate increases everywhere increase the present value of loan payments.

Differentiating PV with respect to maturity,

$$\frac{\partial PV}{\partial T} = \frac{Dr(1+\delta)^{1-T}(1+r)^T}{\delta\left((1+r)^T-1\right)^2}\left(\log(1+\delta)\left((1+r)^T-1\right) - \left((1+\delta)^T-1\right)\log(1+r)\right),$$

which is also positive (provided $\delta < r$) meaning that longer maturities increase the present value of loan payments.[19]

To compare the relative magnitudes of the sensitivity of the present value of loan payments with respect to rate and maturity, we consider the difference in elasticities to compare, e.g., a 10% change in interest rates to a 10% change in loan maturities. In Appendix Figure

[19]Note that if $\delta > r$ then households would want to borrow an infinite amount of money and a transversality condition preventing households from dying in infinite debt would be binding.

A2, we plot the difference in elasticities

$$\frac{\partial PV}{\partial r}\frac{r}{PV} - \frac{\partial PV}{\partial T}\frac{T}{PV}$$

for a grid of r and T values, fixing the annual discount rate to be $\delta = .04$. The surface is positive over the range of interest rates and maturities we consider, demonstrating that the present value of the stream of debt-service payments is more sensitive to a given percentage change in rates than maturities.

Elasticity of Monthly Payment with Respect to Rate and Maturity

Partial derivatives of monthly payment with respect to r and T are given by

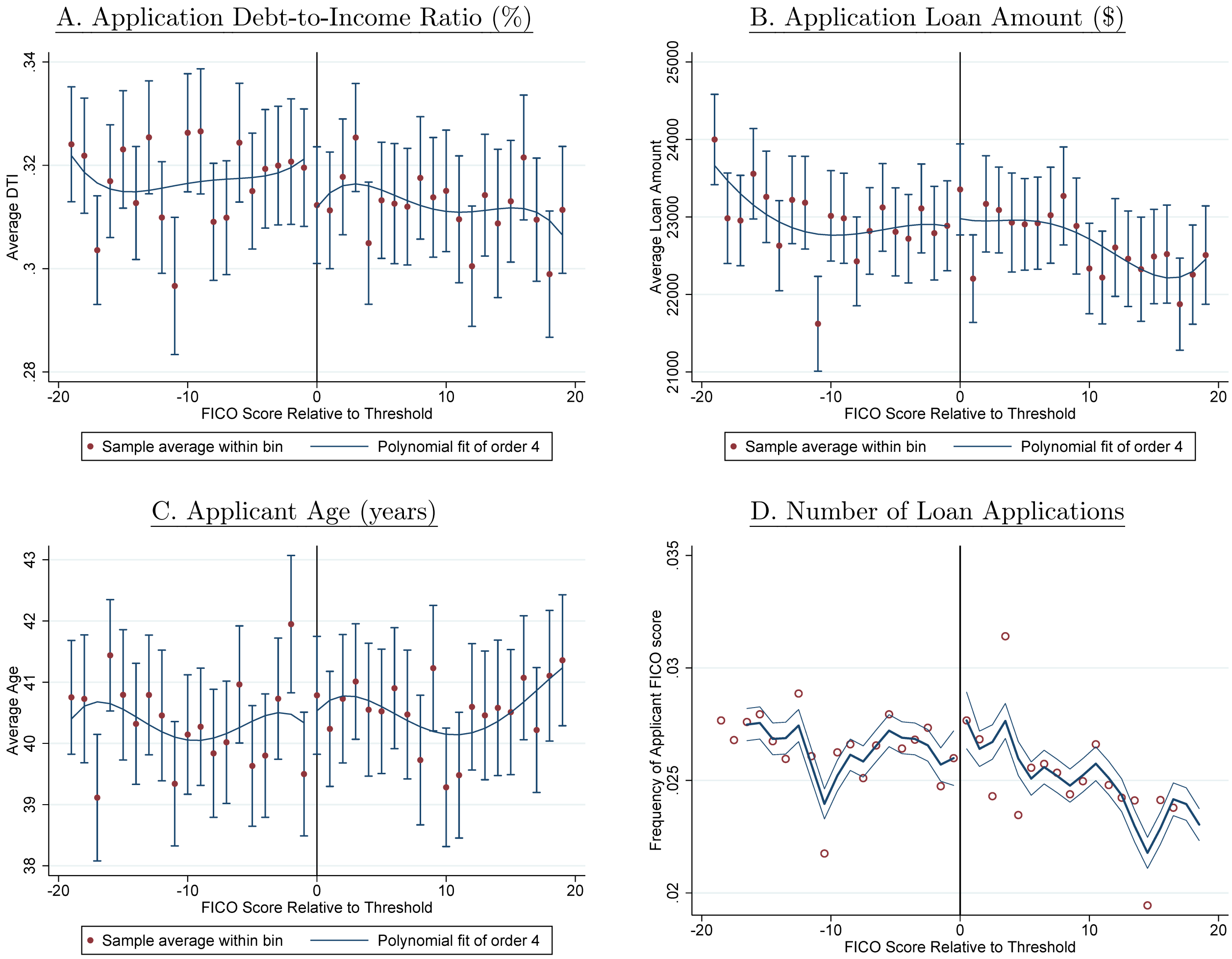
$$\begin{aligned}\frac{\partial m}{\partial r} &= \frac{D(1+r)^{T-1}}{((1+r)^T-1)^2}\left((1+r)^T + r\left((1+r)^T - T - 1\right) - 1\right)\\ \frac{\partial m}{\partial T} &= -\frac{Dr(1+r)^T\ln(1+r)}{((1+r)^T-1)^2}\end{aligned}$$

As expected, monthly payments increase with interest rates r but decrease with loan term T. To compare the relative importance of equal sized proportional changes in rates and terms, we consider the percentage change in monthly payments from a given percentage increase in rates and decrease in maturities by adding the two elasticities, examining the expression

$$\frac{\partial m}{\partial r}\frac{r}{m} + \frac{\partial m}{\partial T}\frac{T}{m}$$

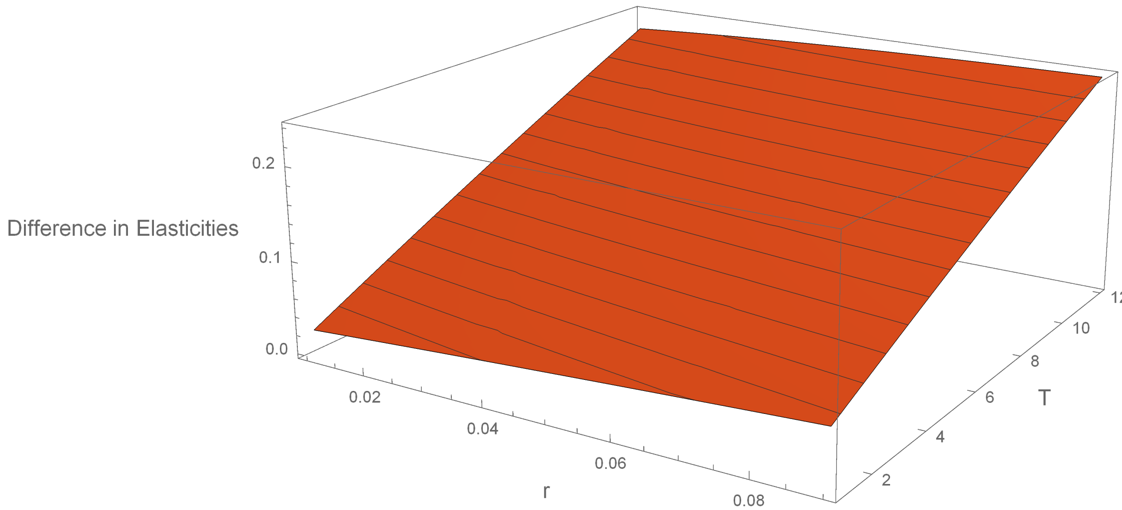
Appendix Figure A3 plots this difference in elasticities. The rate elasticity is smaller in magnitude than the maturity elasticity for all reasonable combinations of interest rates and loan maturities. In other words, monthly payments are more reactive to percentage changes in maturities than equal-sized percentage changes in rates.

Figure A1: Balance of Borrower Characteristics Across FICO Thresholds



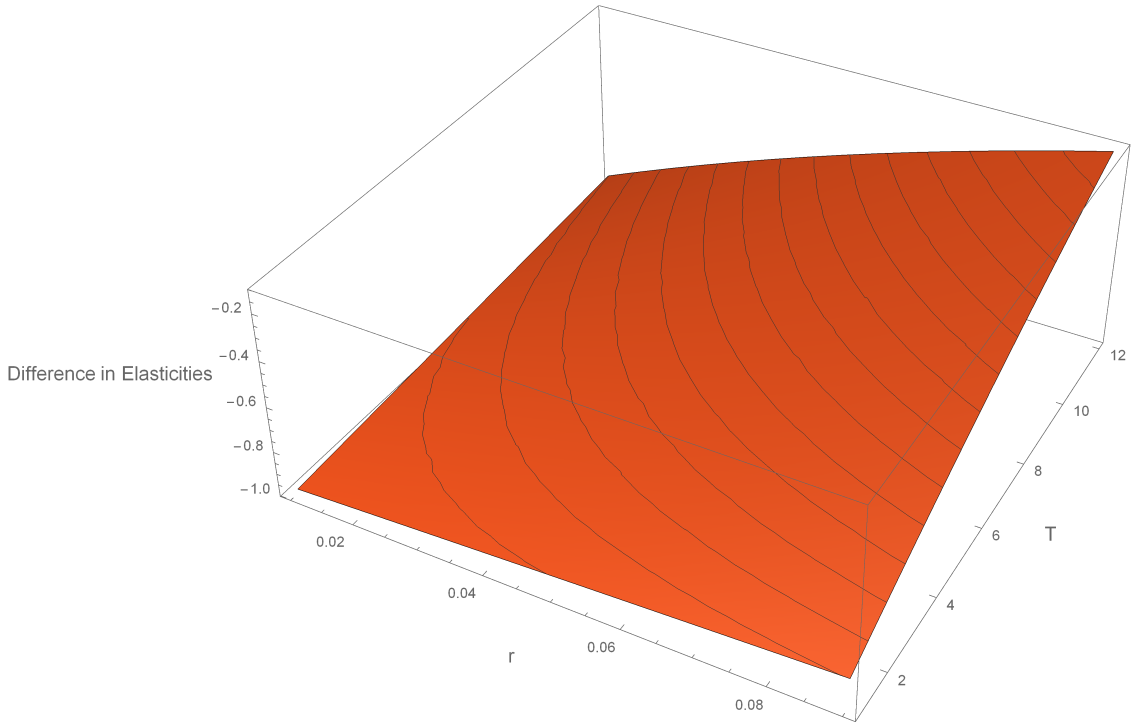
Notes: Figures plot average values of ex-ante borrower characteristics around FICO thresholds for institutions with detected discontinuities using Calonico et al. (2014) local linear estimates and 95% confidence intervals. Panel D plots the application count within each normalized FICO bin along with the estimated McCrary (2008) test.

Figure A2: Difference in Present Value Elasticities



Notes: Figure plots the difference between the elasticity of a loan's present value with respect to rate and with respect to maturity as a function of its annual interest rate (left horizontal axis) and maturity in years (right horizontal axis). For combinations of rate and maturity where the vertical axis is positive, the present value of the loan is more sensitive to equally sized (proportional) changes to rate than maturity. See Appendix for further discussion.

Figure A3: Difference in Monthly Payment Elasticities



Notes: Figure plots the difference between the elasticity of a loan's monthly payment with respect to rate and with respect to maturity as a function of its annual interest rate (left horizontal axis) and maturity in years (right horizontal axis). For combinations of rate and maturity where the vertical axis is negative, the loan's monthly payment is more sensitive to equally sized (proportional) changes to maturity than rate. See Appendix for further discussion.

Table A1: Summary Statistics for Estimation Sample with Identified FICO Discontinuities

	A. Loan Applications	B. Originated Loans
Loan Rate (%)	0.04	0.07
	(0.04)	(0.03)
	N = 51,391	N = 307,061
Loan Term (months)	65.69	61.8
	(34.4)	(22.75)
	N = 53,841	N = 307,061
Loan Amount ($)	22,828.07	16,767.3
	(11,773.89)	(10,230.39)
	N = 58,516	N = 307,061
FICO Score	679.84	649.54
	(36.44)	(36.1)
	N = 58,516	N = 307,061
Debt-to-Income (%)	0.31	0.26
	(0.20)	(0.28)
	N = 40,066	N = 181,667
Take-up	0.52	
	(0.49)	
	N = 22,704	
Collateral Value ($)		17,728.78
		(9,729.16)
		N = 307,061
Monthly Payment ($)		314.89
		(149.12)
		N = 307,061

Note: Table reports summary statistics for the discontinuity sample (restricted to a 19-point bandwidth around detected FICO discontinuities in lender pricing rules). Panels A and B describe loan applications and loan originations, respectively. See notes to Table 1 for further details.