

Monthly Payment Targeting and the Demand for Maturity*

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March 2019

Abstract

In this paper, we provide evidence of the importance of monthly payments in the market for consumer installment debt. Auto debt in particular has grown rapidly since the Great Recession and has eclipsed credit cards in total debt outstanding. Auto-loan maturities have also increased such that most auto-loan originations now have a term of over 72 months. We document three phenomena we jointly refer to as monthly payment targeting. First, using data from 500,000 used auto loans and discontinuities in contract terms offered by hundreds of lenders, we show that demand is more sensitive to maturity than interest rate, consistent with consumers managing payment size when making debt decisions. Second, many consumers appear to employ segregated mental accounts, spending exogenous payment savings on larger loans. Third, consumers bunch at round-number monthly payment amounts, consistent with the use of budgeting heuristics. These patterns hold in subsamples of constrained and unconstrained borrowers, challenging liquidity constraints as a complete explanation. Our estimates suggest that borrower focus on payment size, combined with credit-supply shocks to maturity, could significantly affect aggregate outstanding debt.

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

*We thank conference, seminar, and workshop participants at the 2018 AFA meetings, Berkeley, BYU, Consumer Financial Protection Bureau, Federal Reserve Bank of Philadelphia, MIT, University of Utah, and Wharton, Corina Boar, Chris Carroll, Damion English, Amy Finkelstein, Brigham Frandsen, Peter Ganong, Simon Gervais, Itay Goldstein, Dan Greenwald, Amir Kermani, David Laibson, Brad Larsen, Lars Lefgren, Andres Liberman, Adair Morse, Pascal Noel, Brennan Platt, Ryan Pratt, Andrei Shleifer, Bryce Stephens, and Jialan Wang for helpful comments. Tommy Brown, Sam Hughes, Ammon Lam, Tammy Lee, and Lei Ma provided excellent research assistance. An anonymous information-technology firm provided the data.

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1 Introduction

In this paper, we ask how households make decisions about optimal debt contracts in practice. We show that many consumers appear to target specific monthly payment amounts rather than minimizing total borrowing costs or satisfying debt-service coverage constraints. Existing theories of household debt decisions are relatively silent on the role of monthly payment management. In a standard 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, focusing instead on the level of monthly payments could be rational (or boundedly rational) if borrowers are credit constrained, if cognition costs are large, or in the presence of commitment problems.

Our setting consists of auto loan decisions made by over two million individual borrowers from 319 different lending institutions covering about 5% of the total credit union market and roughly 1.4% of the used car lending market. We employ a 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 or loan maturities that jump discontinuously at various credit-score (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 can be used to identify consumer preferences over loan characteristics.

We present three 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 objective function that minimizes the present value of total borrowing costs, termed “NPV neglect” by Shu (2013). In contrast, a taste for maturity is consistent with consumer focus on the dollar amount of monthly payments, which are much more sensitive to maturity than rate.

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

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, 2013 and 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 as a counterfactual, untreated borrower.² 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 (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 (DTI) 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.

We summarize the phenomena we jointly observe (high maturity elasticities, monthly payment smoothing, bunching at salient monthly payment amounts) as *monthly payment targeting*. Such behavior is consistent with consumers making debt decisions via a form of mental accounting using rules of thumb. 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). We evaluate whether a liquidity explanation alone could be sufficient to explain the characteristics of budgeting decisions we observe by segmenting our estimation sample by credit score under the assumption that low credit-score borrowers are more likely to be constrained in their access to credit markets. We find that each of our three empirical findings holds within each credit-score subgroup. The low likelihood that household budget constraints or underwriting policies would bind uniquely at salient hundred-dollar

²Note, too, that in our data, payment-smoothing borrowers do not appear abnormally constrained by underwriting rules around maximum loan-to-value or debt-to-income ratios.

payment amounts together with the other empirical patterns we document suggests that liquidity constraints alone are not sufficient to explain monthly payment targeting.

Our results are also relevant to efforts to understand shrouded marketing in consumer financial markets (e.g., Gabaix and Laibson, 2006; Bertrand and Morse, 2011; Stango and Zinman, 2011; Gurun, Matvos, and Seru, 2016; Alan, Cemalcilar, Karlan, and Zinman (2018)). Consumers who are fixated on monthly payment levels when making debt decisions may ignore product attributes that are nevertheless consequential for future utility. Such myopia could lead to taking on debt contracts with higher present values and larger loan sizes. Though under certain assumptions such behavior could be utility maximizing, these two margins coupled with longer maturity loans could also lead to more 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.

Finally, 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 represent the second-fastest growing segment of consumer debt over the past decade and are currently the third-largest category of consumer debt (behind mortgages and student loans) with over \$1 trillion outstanding and \$400 billion originated annually. 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 on average larger, made to less creditworthy borrowers, and more likely to end up in default.

Given the importance of auto debt in the household credit complex, we conclude with the policy implications of monthly payment targeting. Maturity represents a largely ignored dimension of the credit surface in the literature evaluating the real effects of credit supply.

For example, our maturity-elasticity estimates indicate that policies focusing on the supply of maturity could have a larger impact on credit demand than policies focusing on interest rates, despite policy analysis focus on the interest-rate channel. Using aggregate data and our elasticity estimates, we provide back-of-the-envelope estimates of the effect that monthly payment targeting could have on aggregate auto debt, demonstrating that credit supply shocks may affect consumer debt more through maturity than through rates and warranting additional policy focus on monthly payment levels.³

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, and originations. We detail our empirical strategy for estimating demand elasticities in section 4 and present our core empirical results. In section 5, we provide auxiliary evidence to help interpret our elasticity estimates. Section 6 concludes and offers a set of calculations to estimate the relative importance of monthly payment targeting on total outstanding household debt.

2 Related Literature and Theoretical Framework

Our diagnosis that consumers target monthly payment levels when making debt decisions is informed by the joint evidence of high maturity elasticities, borrowers' smoothing of monthly payments, and bunching at salient payment amounts. Various aspects of these results have been established in isolation in other contexts, each with its own candidate explanation. For example, monthly payment-centric arguments have been central to previous estimates of ma-

³We 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 Consumer Financial Protection Bureau report (Brevoort et al., 2017) using nationally representative data and documenting similar trends.

turity and interest-rate elasticities (Juster and Shay, 1964; Attanasio et al., 2008; Karlan and Zinman, 2008) while other studies have made behavioral arguments for consumers preferring to match debt maturity with the duration of asset use (Prelec and Loewenstein, 1998). Thaler (1990) offers evidence on budgeting using mental accounts, and literature in marketing, psychology, and economics has documented left-digit effects in consumer behavior.⁴ While our evidence on monthly payment smoothing and bunching in monthly payment levels is reasonably novel to the literature, our primary contribution is to establish a set of empirical phenomena that, when jointly considered, are most naturally explained with a monthly payment targeting model of household budgeting. Below, we discuss our contribution in the context each of these results finds in the existing literature.

Relative to the literature contrasting rate and maturity elasticities, we offer evidence of a new mechanism distinct from the usual liquidity constraints definition. The earliest estimates of borrowing elasticities are Suits (1958) and Juster and Shay (1964), with more recent rate elasticity estimates in Karlan and Zinman (forthcoming). With respect to estimates of maturity elasticities, Karlan and Zinman (2008) report large loan-size maturity elasticities from a randomized field experiment using micro loan advertisements in South Africa, Attanasio et al. (2008) estimate high maturity elasticities from the Consumer Expenditure Survey, and Kuvikova (2015) estimates high maturity elasticities among low income borrowers.⁵ Notably, both Karlan and Zinman (2008) and Attanasio et al. (2008) interpret high intensive-margin maturity elasticities as evidence of binding liquidity constraints. Though liquidity constraints clearly elevate the importance of payment size and may explain why borrowers prefer long-maturity loans, we find high maturity elasticities even for borrowers with substantially slack liquidity constraints. Auxiliary analyses further suggest that binding liquidity constraints are not the only explanation for large maturity elasticities. Instead, our findings suggest that maturity elasticities are high in large part because changing loan ma-

⁴See, for example Shindler and Kirby (1997), Thomas and Morwitz (2005), Basu (2006), Wonder, Wilhelm, and Fewings (2008), Pope and Simonsohn (2011), and Lacetera, Pope, and Syndor (2012).

⁵See also contrasting evidence from Bachas (2018), who finds that private student-loan refinancers are more sensitive to total interest payments than monthly payment levels.

turity most effectively allows a wide variety of borrowers to target specific budgeted monthly payment amounts. This provides a new mechanism supporting a rich recent literature establishing payment size per se to be a primary consideration in residential mortgage decisions. See, for example, Fuster and Willen (2017), Eberly and Krishnamurthy (2014), Di Maggio et al. (2017), Greenwald (2018), and Ganong and Noel (2018).

Maturity demand could be also driven by long-maturity loans protecting borrowers from the rollover risk associated with needing to frequently interact with credit markets, especially valuable when borrowers have private information about their quality (Flannery, 1986). Maturity could also protect borrowers against credit-limit volatility (Fulford, 2015). Consistent with a maturity-as-insurance argument, Herzberg, Leberman, and Paravisini (2017) document that self-selected longer-maturity borrowers are of worse credit quality. However, such adverse selection appears to be less important in our setting. Using various measures of default, as well as ex-post changes in borrower FICO scores to proxy for private information and ex-ante demand for insurance, we find little difference in loan performance outcomes across borrowers receiving exogenously better loan terms.

Our second empirical finding is that borrowers smooth their monthly payments. On either side of a discontinuity in offered loan terms, borrowers originate loans with statistically indistinguishable monthly payment amounts despite facing significantly different costs of credit. This result suggests that borrowers fully adjust the amount they borrow in response to looser loan terms, as opposed to increasing monthly payments in response to lower prices or using any monthly savings to reoptimize across all possible expenditure categories. While potentially driven by binding liquidity constraints, monthly payment smoothing is also consistent with Thaler's (1985, 1990) conjecture that households organize their cash flows into a set of segmented mental accounts, which has been supported with experimental evidence by Prelec and Loewenstein (1998) and Ranyard et al. (2006). Using such a budget in installment-debt decisions could help overcome the commitment problems documented by Kuchler and Pagel (2018). Our evidence also complements the results of Hastings and Shapiro (2013, 2107),

who show that households do not treat gasoline savings and food-stamps benefits as fungible across expenditure categories. Our findings on monthly payment smoothing demonstrate the prevalence of mental accounting even in a high-stakes long-term debt setting.⁶

Could such smoothing behavior be a feature of an optimal liquidity management strategy? Borrowers could optimally target low monthly payments if they expect to 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. Stango and Zinman (2014) find that consumers are efficient at allocating debt to the lowest interest-rate credit card, while Gathergood et al. (2019) find evidence to the contrary. A buffer-stock model could also feature consumers willing to incur higher interest 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 section 2.1). However, because such considerations would motivate consumers to minimize their monthly payments, our smoothing result—that consumers adjust their borrowing upward in response to cheaper loan terms more than would be predicted by estimated demand elasticities—is not consistent with a general liquidity management strategy.

Of course, there are other reasons borrowers would smooth their monthly payments for motives besides monthly budgeting, motivating our final set of results. Our third finding is that many borrowers seem to target specific, salient levels of monthly payments. As discussed above, certain forms of liquidity constraints, such as binding monthly debt-service coverage constraints (e.g., as in Greenwald, 2018), could lead to a first-order increase in car-related spending and a second-order increase in other spending. However, we find that many borrowers target specific round monthly payment levels (e.g, \$300, \$400, etc.). Such behavior is difficult to rationalize with liquidity constraints, liquidity management, or myopia. Instead, we view these results as consistent with behavioral budgeting models wherein

⁶See also Zhang (2017), who documents large durable consumption effects to transitory windfall income shocks, consistent with mental accounting.

consumers attempt to commit to not overspend by imprecisely forming a sense of affordability based on monthly expenses. This behavioral response also has precedent in marketing and psychology. Wonder, Wilhelm and Fewings (2008) present survey evidence in marketing that consumers focus heavily on monthly payments, including a particular focus on the first digit of monthly payment amounts. Retailers behave accordingly, frequently advertising prices ending with nine (Schindler and Kirby, 1997). Thomas and Morwitz (2005) also detail domains in which ending posted prices in 99 (dollars or cents) is the optimal response by firms to hypothesized consumer heuristics. Qualitative work in psychology finds consumers engaging in monthly budgeting via categories (Ranyard et al., 2006). Keys and Wang (2018) show in a large sample of US consumers that a large fraction of credit card borrowers anchor at minimum payment amounts, complementing previous experimental evidence shown in Navarro-Martinez et al. (2011). Again, while prior literature provides evidence with varying degrees of external validity that borrowers fixate on certain payment amounts, a key contribution of our paper is to demonstrate that such behavior persists even when considering substantially sized long-term debt contracts in a way that cannot be entirely explained by binding liquidity constraints.

In summary, we make several contributions to this eclectic literature on household budgeting using evidence from millions of actual borrowers making high-stakes long-run debt and durable consumption decisions. We estimate credit demand elasticities with respect to price and non-price features, the segmentation with which households view budget categories, and the heuristics they use to determine affordable expenditure levels at monthly intervals. While prior estimates of large maturity elasticities in isolation could not distinguish a monthly-payment hypothesis from a liquidity-constraints hypothesis, the combination of our findings uniquely supports a monthly payment targeting hypothesis. Relative to the existing mental accounting literature, our evidence of monthly payment smoothing represents new evidence that borrowers appear to consume out of mental accounts even in large-dollar settings. Furthermore, documenting monthly budgeting behavior in installment debt decisions

ties together work on the importance of payment size with the mental accounting literature. Finally, because the combination of large elasticities and monthly payment smoothing cannot distinguish a liquidity management hypothesis from monthly payment targeting, we present evidence that consumers more frequently choose salient round payment amounts. Taken together, these empirical facts indicate that many households make debt decisions targeting specific monthly payment levels.

2.1 Theoretical Framework

In this section, we demonstrate the extent to which standard consumer optimization models can generate behavior consistent with our empirical findings. While some of the aspects of borrower behavior we observe is consistent with previous models of credit constraints, as we show below, other evidence points to a mental accounting optimization framework.

Consider a simple 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 consumer's Lagrangian is then

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

where β is the discount factor, $u(\cdot)$ is the separable flow utility function, λ_t is the marginal utility of wealth, and 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 . For simplicity, debt and savings earn the same rate of return 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). This formulation yields a standard intertemporal Euler equation

$$\frac{u'(c_t)}{u'(c_{t+1})} = \beta(1+r). \quad (2)$$

Borrowing constraints may prevent the consumer from achieving the first-best consumption level characterized by (2). If the borrower faces credit constraints, the marginal utility of wealth will be too high this period as constrained borrowing prevents sufficiently high c_t

today to drive down $u'(c_t)$. Consider the case of an exogenously specified per-period payment-to-income limit $\bar{D} > 0$, where debt commitments as a fraction of income $-A(1+r)/y$ cannot exceed \bar{D} . In this case, the credit-constrained optimization problem could be written with a second constraint with corresponding Lagrange multiplier μ

$$\max_{\{c_t, A_t\}} \sum_t \beta^t [u(c_t) + \lambda_t(A_{t-1}(1+r) + y_t - c_t - A_t) + \mu_t(\bar{D} + A_t(1+r)/y_t)], \quad (3)$$

yielding credit-constrained Euler equation

$$\frac{u'(c_t) - \mu_t(1+r)/y_t}{u'(c_{t+1})} = \beta(1+r). \quad (4)$$

When credit limits are binding (i.e., $\mu_t > 0$), debt payments will be $\bar{D}y_t$ and (4) will be satisfied at a lower level of consumption than would satisfy (2). Such a constraint could explain both sensitivity to payment levels and payment smoothing. Faced with shocks to interest rates or maturity, constrained borrowers might adjust the amount of debt to leave their payment sizes unchanged. When credit limits are never binding, $\mu_t = 0$ for all t , and the borrower will be able to attain her first-best consumption path, with debt endogenously determined as a function of optimal consumption and income. Importantly, whether or not credit constraints bind, monthly payments will be continuously distributed so long as income is continuously distributed in the cross-section of borrowers (and given a continuously differentiable utility function $u(\cdot)$).⁷

Extending this framework to consider optimal one-time contract choice from a menu of long-term, non-callable debt contracts, let ℓ index the set of available consumer loans characterized by their interest rate r_ℓ and maturity T_ℓ .⁸ The household's objective then

⁷Of course, alternative forms of credit constraints are plausible, including credit limits constraining total debt (Zeldes, 1989 and Gross and Souleles, 2002) or loan-to-value limits (common in secured credit markets). Credit limits and asset values tend to be individualized and continuously distributed across borrowers, again yielding the prediction that debt payments would have a smooth cross-sectional distribution.

⁸See Bachas (2018) for a model of maturity demand in continuous time for a fixed loan size without budget or liquidity constraints.

becomes

$$\max_{\{c_t, S_t, D, \ell\}} \sum_t \beta^t [u(c_t) + \lambda_t B_t^\ell + \mu(\bar{D} - m(D, r_\ell, T_\ell)/y_{t_0})] \quad (5)$$

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

$$\begin{aligned} B_t^\ell \equiv & S_{t-1}(1 + r_S) + y_t - c_t - S_t + D \cdot 1(t = t_0) \\ & - m(D, r_\ell, T_\ell) \cdot 1(t_0 \leq t \leq t_0 + T_\ell). \end{aligned} \quad (6)$$

To differentiate between asset savings and debt, here 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 such that at the origination date, the household receives D to spend or save. For all time periods t starting with the origination month and extending until month $t_0 + T_\ell$ when the loan characterized by contract ℓ matures and is paid off, the household must make fixed, amortizing installment payments m that depend only on the amount of debt D , the loan's interest rate r_ℓ , and maturity T_ℓ . In the case of the fixed-rate, self-amortizing consumer loans we study here, $m(D, r, T) = \frac{Dr}{1 - (1+r)^{-T}}$. The borrowing constraint is again a limit on the payment-to-income ratio and is enforced at origination.

The key observation from the budget-constraint specification in (6) is that an unconstrained household's optimal loan-contract choice ℓ^* is related to the present value of per-period (e.g., monthly) payments. Formally, the optimality condition for ℓ yields

$$\ell^* = \arg \min_\ell \sum_{t=t_0}^{t_0+T_\ell} \beta^t \lambda_t m(D, r_\ell, T_\ell), \quad (7)$$

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. Here, preferences over bundles will depend on the specific menu offered. Faced with two equally sized debt contracts, a longer one with lower monthly payments but a higher present value and a shorter contract with higher monthly payments but lower present value, a classical consumer (with constant marginal utility of wealth λ for the sake of argument)

would choose the loan with lower present value. This has implications for unconstrained consumer preferences over interest rates and maturity. Given that the present value of an amortizing contract is relatively more sensitive to interest rates and monthly payments are more sensitive to loan maturity, consumers targeting monthly payments will be particularly elastic to maturity.

At the intensive margin, the choice of loan size will also be a function of offered terms. For each given debt contract ℓ , optimal debt is characterized by the first-order condition of (5) with respect to D

$$\lambda_{t_0}(D_\ell^*) - \mu(D_\ell^*) = \sum_{t=t_0}^{t_0+T_\ell} \beta^{t-t_0} \lambda_t(D_\ell^*) \cdot m'(D_\ell^*, r_\ell, T_\ell), \quad (8)$$

where $m'(\cdot, \cdot, \cdot)$ is the derivative of monthly payments with respect to loan size, and $\lambda(\cdot)$ and $\mu(\cdot)$ are the corresponding Lagrange multipliers, evaluated at optimal choices implied by D_ℓ^* . Borrowers select D_ℓ^* to trade off the benefit of relaxing the budget constraint at the time of origination (including the dynamic effects this has on subsequent periods' budget constraints) with the impact of higher loan sizes on the marginal-utility-weighted present-value of future debt service payments. Again, when borrowers face binding credit limits \bar{D} , the marginal utility of wealth λ_{t_0} will be too high relative to the unconstrained case. Given optimal loan size D_ℓ^* for each contract ℓ and the corresponding optimal path of consumption and savings $\{c_{\ell t}^*, S_{\ell t}^*\}$, the household's optimal loan-contract ℓ^* is

$$\ell^* = \arg \max_{\ell} \sum_t \beta^t [u(c_{\ell t}^*) + \lambda_t B_t^\ell(c_{\ell t}^*, S_{\ell t}^*, D_\ell^*) + \mu(\bar{D} - m(D_\ell^*, r_\ell, T_\ell)/y_{t_0})] \quad (9)$$

As before, given that an increase in maturity affects monthly payments more than a commensurate decrease in interest rates, demand from constrained (unconstrained) borrowers will naturally be more (less) sensitive to maturity than rates. Despite their demand being sensitive to both interest rates and maturity, constrained borrowers faced with shocks to offered loan characteristics will smooth their monthly payments to satisfy their payment-to-

income ratio constraints. Unconstrained borrowers, however, would respond to better credit terms by increasing loan sizes and monthly payments.

In practice, several of the aspects of consumer behavior we document are inconsistent with the predictions of the classical model with credit constraints. Consistent with monthly payment constraints binding, we find excess demand sensitivity to maturity and evidence of monthly payment smoothing (monthly payments are relatively constant across otherwise similar consumers facing different (r, T) menus). However, in contrast to the above model, we find monthly payment smoothing and maturity preferences even for consumers unlikely to be credit constrained. Moreover, we observe bunching in monthly payment levels at round numbers, especially multiples of \$100. Such a distribution of monthly payments is difficult to rationalize with a simple model of liquidity constraints, and we observe a statistically significant fraction of each borrower type bunching. Even for constrained borrowers, it is unlikely that credit constraints would happen to bind more frequently just below a \$100 threshold than just above given the continuous distribution of income, car values, loan sizes, interest rates, and maturities.⁹ Instead, targeting salient, round-number amounts is consistent with households developing a monthly categorical budget prescribing the level of spending.¹⁰ While both monthly borrowing constraints and a categorical budget would both predict monthly payment smoothing, a human tendency to form monthly budgets with round numbers, perhaps arising from cognitive costs of a more exact optimization process, could rationalize the round-number monthly payment bunching we see even for unconstrained borrowers.¹¹ In our framework, many households forming a round-number budget could take the form of an additional constraint

$$m(D_\ell, r_\ell, T_\ell) \leq M \tag{10}$$

⁹Nevertheless, we verify below that the excess mass below each \$100 multiple is not driven by bunching in popular underwriting ratios.

¹⁰The use of such a budget is widely prescribed by personal finance courses and is consistent with stated behavior in the lab (e.g., Ranyard et al., 2006).

¹¹See, for example, Wonder et al. (2008) for survey evidence that borrowers place emphasis on the left digit when considering monthly payments.

with M the amount budgeted monthly for car-loan payments. Such a constraint with predetermined round number M would be consistent with excess sensitivity to maturity, monthly payment smoothing, and payment-level bunching. In particular, we show below that payment-level bunching is especially pronounced for borrowers taking out loans with non-standard maturities (maturities not multiples of twelve months). This suggests a new explanation for the importance borrowers place on maturity. While longer loans allow borrowers to get beneath underwriting constraints, even unconstrained borrowers using a monthly budget will value maturity for its ability to control payment size.

3 Data

Our unique data on the (anonymized) auto-loan decisions and loan contract features of 2.4 million borrowers and 319 lenders come 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.

Loan contract features in the data include borrower FICO scores, loan-to-value (LTV) ratios, car purchase prices, loan dates, and in some cases, back-end DTI ratios (the ratio of current debt payments to income excluding the auto loan in question). We restrict the data set to only those loans originated directly with a lending institution (in contrast to so-called indirect loans, which involve loan applications processed through auto dealerships) to avoid the possibility that dealers steer buyers to a particular lender.¹² 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 2016,

¹²We 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).

but over 70% of the loans were originated between 2012 and 2015.

We supplement the originated loan data with the applications of 1.3 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 estimate demand elasticities at the extensive margin, though a limited sample size reduces our power to detect discontinuities.

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.

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.¹³ Our sample draws heavily from the 2012-2015 time period, a reflection of the growth in our data provider’s 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 (2016), credit unions originated 23% of all 2015 used car loans and 10% of new car originations. 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.¹⁴

¹³Over 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 2010 Census. Median FICO scores in our sample are 714, compared to a median FICO of 695 in the NY Fed Consumer Credit Panel (CCP).

¹⁴A related discussion regarding representativeness exists in Argyle et al. (2017), which uses the same data.

4 Estimation

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 FICO thresholds.¹⁵ Unlike the mortgage setting in Keys et al. (2010), there is not an industry standard FICO score (e.g. FICO 620) in the auto market at which institutions vary their lending standards or around which treatment of loans changes in the secondary market. Instead, discontinuities in offered interest rates and loan maturities exist at various points across the FICO spectrum. Anecdotally, conversations with credit-union executives confirm the existence of FICO thresholds and their (admittedly coarse) purpose of pricing risk in loan offerings. Possible explanations for the persistent use of pricing thresholds include the continued use of rate sheets, fear of overfitting, and the slow adoption of recently developed analytical tools that would render rate sheets obsolete. 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.

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 these discontinuities along with first-stage results and a series of tests of the RD identifying assumptions. While the FICO thresholds identify quasi-random variation in the supply of credit terms, the colocation of maturity and rate discontinuities within a lending institution also presents a unique empirical challenge. Interest rates and maximum loan maturities often jump discontinuously at the same FICO thresholds (though at different thresholds across lenders), complicating differentiating the relative contribution of interest-rate supply

¹⁵Methodologically, other studies have used discontinuous credit policies for inference. For example, Agarwal et al. (2017) estimate borrowing elasticities with respect to credit limits and also use a regression-discontinuity design based on FICO scores. In mortgage markets, Adelino et al. (2014), Best and Kleven (2017), DeFusco and Paciorek (2017), Di Maggio et al. (2017), and Ganong and Noel (2018) each use the nonlinear treatment of credit attributes to identify aspects of consumer debt optimization.

from 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. After detailing our instrumental-variables regression-discontinuity estimator, we report elasticity estimates at both the intensive and extensive margins. In section 5 we employ a similar estimation framework to evaluate differences in equilibrium monthly payment amounts in response to exogenous variation in rates and maturity.

4.1 Detecting Discontinuities

To illustrate the lending rules we seek 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 from a regression of realized interest rates on a set of indicator variables for 5-point FICO bins. The 5-point FICO bins begin at FICO 500, where the first bin includes FICO scores in the 500-504 range, the second bin includes 505-509 FICO scores, 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 omitted category (FICO > 800). 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 policy that also jumps at several 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 rate discontinuities are more precisely estimated than maturity rules. Still, the discontinuities in maturity are economically and statistically significant as discussed below.

To identify every institution in our sample with discontinuous loan pricing rules, we first estimate interest rate-FICO bin regressions separately by lender. We define 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 0.001, and 3) the differences between coefficient estimates on either side of a potential discontinuity have a p -value that is greater than 0.1.¹⁶ This last criterion ensures smoothness to the left and right of a candidate discontinuity. We also examine each potential threshold visually to ensure that the identified discontinuities are well behaved around the candidate thresholds. This screening criteria selects only those discontinuities that are economically and statistically significant and generated by stable lending rules.¹⁷

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 con-

¹⁶For example, to classify a discontinuity at FICO 600, we require that $\hat{\beta}_{600-604}$ (the estimated average interest rate of borrowers with FICO scores between 600 and 604) be 50 bp less than $\hat{\beta}_{595-599}$ and that the p -value testing that difference has to be less than 0.001. In addition, the p -values testing $\beta_{600-604} = \beta_{605-609}$ and $\beta_{590-594} = \beta_{595-599}$ must be greater than 0.1.

¹⁷For example, this procedure would not classify the FICO 520 coefficient for 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.

sumer response to the other, this would require a high degree of confidence in locating an exhaustive set of discontinuities. As maturity and rates are almost always offered as a bundle, it is difficult to isolate exogenous movements in one loan parameter that does not impact the other, consistent with anecdotal evidence from credit-union executives that have indicated that maturity discontinuities frequently exist at the same FICO thresholds as rate discontinuities. FICO-based maturity discontinuity detection is further complicated by consumers not always originating loans of the max offered maturity, in contrast to interest rates where consumers almost always originate loans with the lowest offered rate. We therefore assume that maturity discontinuously changes whenever rates discontinuously change. We believe this approach is conservative with respect to understanding differences between rate and maturity elasticities. Falsely identifying maturity discontinuities will create downward bias in our average maturity elasticity estimates because the estimates will include maturity estimates of zero at the false positive discontinuities. In contrast, our rate elasticities should be estimated with precision given the strictness of the criteria employed to identify the rate discontinuities. Falsely assuming the existence of maturity discontinuities could lead to a weak instrument problem, but the partial F -statistics reported in section 4.2 suggest this is not a problem.¹⁸

Our discontinuity detection strategy results in just over two discontinuities for the average institution in our sample. Of the 319 institutions we evaluate, 233 display discontinuities. Appendix Figure A1 presents a histogram of the frequency of discontinuities by FICO score. The most common discontinuities occur at FICO 600, 640, 680, and 700 and 80% of the discontinuities are concentrated between FICO 600 and 700. To check for representativeness, we compare statistics for the discontinuity sample (Table 2) with the full-sample summary statistics (Table 1) and report tests of differences between the two samples in Appendix Table A1. Differences in observable characteristics between the full sample and the discontinuity sample (e.g. average FICO of 710 in the full sample compared to average FICO of 663

¹⁸Requiring jumps to also exceed a maturity hurdle reduces the sample size but leads to qualitatively similar results.

in the discontinuity sample) reflect the fact that the majority of loans near discontinuities have FICO scores between 600 and 700, whereas in the full sample a larger fraction of borrowers have FICO scores above 700. The concentration of discontinuities between FICO 600 and 700 also explains why average loan amounts and collateral values are lower in the discontinuity sample. Higher FICO score borrowers purchase more expensive cars, on average, and originate larger loans to finance those purchases.

4.2 Isolating Exogenous Variation in Contract Terms

In order to estimate the elasticity of loan amounts with respect to interest rates and maturities, we use our detected FICO discontinuities to isolate quasi-random variation in contract terms. Our RD specification combines all classified discontinuities \mathcal{D} to explain originated interest rates r and maturities T for consumer i in commuting-zone g borrowing from lender l in quarter t

$$r_{iglt} = \sum_{d \in \mathcal{D}} 1(il \in \mathcal{D}_d) \left(\delta^r 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi^r) + \psi_{dl}^r \right) + \xi_{gt}^r + v_{iglt}^r \quad (11)$$

$$T_{iglt} = \sum_{d \in \mathcal{D}} 1(il \in \mathcal{D}_d) \left(\delta^T 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi^T) + \psi_{dl}^T \right) + \xi_{gt}^T + v_{iglt}^T \quad (12)$$

where for the RD running variable, we normalize FICO scores relative to each detected discontinuity d with $\widetilde{FICO}_{id} = FICO_i - \text{cutoff}_{dl}$.¹⁹ The exogenous term in equations (11) and (12) is the discontinuity indicator $1(\widetilde{FICO}_{id} \geq 0)$. Conditional on the smooth relationship $f(\cdot; \cdot)$ between the running variable and first-stage outcomes, the coefficients δ^y report how each contract characteristic y changes discontinuously for otherwise identical borrowers when $\widetilde{FICO} = 0$. The indicator $1(il \in \mathcal{D}_d)$ equals one when the FICO score associated with loan i is within 19 FICO points of a discontinuity detected in the policy of lender l such that only loans within 19 points of a given discontinuity are used to estimate the magnitude of

¹⁹For example, a loan with FICO score of 613 would have \widetilde{FICO} value of -7 relative to a 620 FICO discontinuity and a \widetilde{FICO} value of -37 relative to a 650 FICO discontinuity.

that discontinuity.²⁰ To capture the independent effects of credit scores on loan-product attributes, we model the effect of the running variable as a quadratic function $f(\widetilde{FICO}; \pi)$ that changes at the discontinuity

$$f(\widetilde{FICO}; \pi) = \pi_1 \widetilde{FICO} + \pi_2 \widetilde{FICO}^2 + 1(\widetilde{FICO} \geq 0) \left(\pi_3 \widetilde{FICO} + \pi_4 \widetilde{FICO}^2 \right), \quad (13)$$

although our results are also robust to a cubic specification. The terms ψ_{dl}^y and ξ_{gt}^y are lender-specific discontinuity-neighborhood fixed effects and commuting zone-by-quarter fixed effects, respectively. These fixed effects capture any unobserved heterogeneity in the levels of rates and maturities driven by such things as borrower selection into lenders or time varying-local economic conditions that could impact the supply and demand for loans. The RD function coefficients δ and π capture the average relationship between normalized FICO scores and contract terms relative to each lender’s baseline level of rates around each discontinuity. We cluster standard errors by FICO score.

Panels A and B of Figure 2 plot predicted values of interest rates and loan maturity, respectively. 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, especially the relative magnitude of the discontinuity and 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 and our detection procedure conservatively including false-positive maturity discontinuities.

Table 3 reports results using the larger origination sample (panel A), and, given that our balance tests below use data from the application sample, a sample restricted to only

²⁰This specification amounts to a uniform kernel and a bandwidth of 19. Our results are robust to other choices of RD kernel and bandwidth.

those approved loans in the application data (panel B). The discontinuity estimates $\hat{\delta}^r$ for the change in interest rates at a detected FICO discontinuity range from -130 to -40 basis points in panels A and B, respectively. Despite a smaller application sample, both are estimated with reasonable precision. Loan maturities increase by an average of 0.74 to 0.33 months in panels A and B, respectively. As discussed in the context of Figure 2 above, because observations come from loans that were originated, these effects likely stem from larger changes in maximum allowable maturity than estimated by these coefficients, some consumers not taking up the maximum offered maturity, and some lenders having no change in maturity policy at a detected FICO threshold. As apparent in Figure 2, the first-stage estimate on interest rates has a much higher t -statistic than the discontinuity coefficient for loan maturity, although the discontinuities are statistically significant for both outcomes even in the smaller application sample. The partial F-statistics testing the strength of the instrument set are over 10 for the specifications reported in Table 3, with the exception of a partial F-statistic of 7.9 for maturity in the much-reduced application sample reported in Panel B.

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 locally mimicking random assignment of borrowers to interest rate and maturity offers. Conceptually, there is no clear process by which borrowers could select into one side of the threshold. Borrowers are unlikely to know their credit score precisely and are even less likely to know the location of an institution’s rate cutoffs. Given the volatility in FICO scores across credit bureaus and across weeks, it is also unlikely that assignment to one side 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 of

lender pricing rules.

We also test for the smoothness of other observables (and the density of the running variable) as further evidence that only treatment is changing discontinuously at each detected discontinuity. Appendix Figure A2 and Table 4 use loan-application data to test whether average ex-ante borrower characteristics change discontinuously around FICO discontinuities. Panels A-E of Appendix Figure A2 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 similar 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 4 shows that the discontinuity point estimates and McCrary test statistic corresponding to the RD plots in Appendix Figure A2 are all statistically insignificant.

Smoothness in observables at the time of application does not rule out the possibility of selection at the time of loan origination. If borrowers pursued an aggressive line of questions to elicit a loan supply schedule from a lender, they might search or wait until their observables put themselves on the cheap side of a discontinuity, leading to concerns of differences in borrower composition on either side of a threshold. To address this possibility, Appendix Table A2 estimates RD regressions with borrower observables as the dependent variable. Again, borrowers on opposite sides of a discontinuity are statistically indistinguishable. Consistent with our conjecture that borrowers smooth monthly payments by increasing loan amounts, the estimates indicate a jump in borrowed amounts (column 1 of Appendix Table A2). We discuss this specific result in much more detail in section 5.

4.4 Demand Elasticity Estimation

We are interested in estimating the elasticities of demand with respect to interest rate and maturity (i.e. term), defined as

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

where Q is the quantity of debt originated and r and T are loan interest rate and maturity, respectively.²¹ 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 correlates of 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 differences in the location of discontinuities on the FICO spectrum and by institution-specific differences in loan pricing and maturity policies at a given threshold.

We specify a two-stage least-squares (2SLS) framework for measuring rate and maturity elasticities and estimate the equation separately at both the extensive and intensive margin. Our second stage demand equation is given by

$$y_{iglt} = \eta^r \log r_i + \eta^m \log T_i + \sum_{d \in \mathcal{D}} 1(il \in \mathcal{D}_d) \left(f(\widetilde{FICO}_{id}; \theta_l) + \varphi_{dl} \right) + \alpha_{gt} + \varepsilon_{iglt} \quad (14)$$

where y_{iglt} is either the log loan size of loan i originated by lender l in commuting zone g at quarter t (intensive-margin elasticity) or a dummy variable equal to one if the approved appli-

²¹Note 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.

cant i accepted an approved loan offer (extensive-margin elasticity). The relevant elasticities are given by η^r and η^m , corresponding to the log of the interest rate r and log loan maturity T , respectively. As in the first stage, the terms φ_{dl} and α_{gt} are discontinuity-by-lender fixed effects and commuting zone-by-quarter fixed effects, respectively. The normalized and discontinuity-specific running variable \widetilde{FICO}_{id} enters quadratically through $f(\cdot; \cdot)$ as defined in (13) above to approximate the nonlinear ways through which auto-loan demand may vary with credit scores around each discontinuity. Note, however, that in this specification, we allow for the RD function to vary by lender, parameterizing $f(\cdot; \cdot)$ with lender-specific θ_l .

The demand specification in (14) has two right-hand-side endogenous variables that need instrumenting for identification. The first-stage equations are log-linear versions of equations (11) and (12) with one important distinction.

$$\log r_{iglt} = \sum_{d \in \mathcal{D}} 1(il \in \mathcal{D}_d) \left(\delta_l^r 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi_l^r) + \psi_{dl}^r \right) + \xi_{gt}^r + v_{iglt}^r \quad (15)$$

$$\log T_{iglt} = \sum_{d \in \mathcal{D}} 1(il \in \mathcal{D}_d) \left(\delta_l^T 1(\widetilde{FICO}_{id} \geq 0) + f(\widetilde{FICO}_{id}; \pi_l^T) + \psi_{dl}^T \right) + \xi_{gt}^T + v_{iglt}^T \quad (16)$$

For our 2SLS estimation, the excluded instruments are a set of lender-specific indicators interacted with the discontinuity indicator $1(\widetilde{FICO}_{id} \geq 0)$, denoted as RD first-stage coefficients δ_l varying by lender l . 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, equivalent to not all lenders having the same discontinuity magnitudes for rate and term. The standard partial F -statistic corresponding to the null hypothesis that the coefficients on the instrument set are jointly zero tests this identification requirement.

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). Given the results of section 4.3 that demonstrate a lack of sorting around the dis-

continuities 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 is unlikely that they would be able to target lenders that have large or small discontinuities. Furthermore, commuting-zone-by-quarter fixed effects ξ_{gt} 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). Discontinuity-by-lender fixed effects ψ_{dl} account for borrower-segment-specific selection into lenders—for example, if borrowers with credit scores around 600 differ on unobservables across lenders.

To illustrate the intuition behind this identifying assumption, consider a stylized example with two institutions and no other controls. Lender A features a discrete 100 basis-point interest-rate reduction and a 12-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 \$21,000, whereas 599 FICO borrowers take out \$20,000 loans on average. Lender B features a discontinuity also at FICO 600 but offers a 75 basis point interest rate reduction and six-month longer maturity at the threshold, leading 601 FICO borrowers at Lender B to borrow \$800 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 100 basis point rate discontinuity and the 12-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 100 basis points and 12-months and Lender B has discontinuities of 75 basis points and six 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 5 reports extensive-margin results from estimating equation (14) by 2SLS with first stages as specified in equations (15) and (16). Here, the dependent variable is an indicator for whether an approved loan application was taken up by the borrower. 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 2 for summary statistics on the application data in the estimation sample).

Our key finding is that we estimate borrowers to be much more sensitive to proportionally equally sized changes in maturity than to changes in interest rates. We estimate an extensive-margin demand elasticity with respect to interest rates of -0.10, slightly lower than the extensive-margin elasticity of -0.3 to advertised interest rates estimated by Karlan and Zinman (2008). We estimate a demand elasticity with respect to loan maturity of 0.83, substantially larger than our estimated interest rate elasticity. Facing a ten-percent decrease in interest rate increases the likelihood that a prospective borrower accepts a loan offer by one percentage point. By contrast, a ten-percent increase in offered loan length increases borrower take-up by 8.30 percentage points. A formal test rejects that the two elasticities are equal to each other in magnitude. Column 2 substitutes zip-code \times quarter fixed effects. While the interest-rate elasticity remains basically unchanged, accounting for shocks to demand at the zip-code by quarter level increases the estimated maturity elasticity such that the maturity elasticity in column 2 is 22 times larger than the rate elasticity.

Intensive-margin results

In column 3 of Table 5, we report elasticities of loan size conditional on origination (the intensive margin) with respect to contract terms using our substantially larger origination sample (see panel B of Table 2 for summary statistics on the origination sample used in estimation). Here, we estimate a demand elasticity with respect to rate of -0.18 and a

maturity elasticity of 0.66. Adding zip code \times quarter fixed effects in column 4 again increases the estimated elasticity with respect to maturity. Both the rate and maturity elasticities are estimated precisely with statistically significantly different magnitudes from one another and maturity sensitivities exceeding rate sensitivities by a factor of five in column 4.²²

To illustrate the magnitude of these results, consider a \$20,000 loan with a five-year maturity and 5% interest rate. The results of Table 5, column 4 imply that a ten-percent increase in offered loan maturity (from 60 to 66 months) would result in a 8.5% increase in the equilibrium loan amount, from \$20,000 to \$21,708. In comparison, a ten-percent decrease in offered loan rates, from 5% to 4.5%, would result in an increased loan amount of only 1.7%, from \$20,000 to roughly \$20,338.

Borrowers are more likely to originate a loan (and take out larger loans conditional on doing so) when they are offered a 10% increase in loan maturity than a 10% decrease in interest rates. These results are consistent with both the liquidity constraints and monthly budgeting model in section 2. What accounts for this differential sensitivity to contract terms? As we show below, such behavior is consistent with consumers focusing on monthly payment amounts rather than lifetime loan costs when making debt decisions.

5 Interpretation

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. To summarize, when household discount rates are lower than interest rates, borrowers who are unconstrained in their ability to borrow across periods would optimally choose among interest rate and maturity pairs to minimize the total present value of debt-service

²²Appendix Table A3 reports extensive and intensive margin elasticity estimates controlling for third-order polynomials in the running variable as well robustness to a 5-point FICO bandwidth. Results are quantitatively similar to those reported in Table 5.

payments.²³ However, given the relative importance of maturity in determining monthly payments, a preference for long maturities could arise from plausible real-world frictions that constrain monthly debt service. 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 total lifetime wealth to a per-period budget constraint where monthly payment levels are paramount. 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 hyperbolic discounting (Laibson, 1997), cognitive costs of optimization (Soll et. al., 2013), or general financial illiteracy (Gathergood, 2012) could drive households to adopt a monthly budget as a heuristic to ensure per-period consumption is affordable, committable, and sustainable, which in turn would lead to excess sensitivity to loan maturity.

While credit 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.

²³In 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 uncommon in the U.S. (Brevoort et al., 2017).

Monthly Payment Smoothing

As discussed in section 2, borrowers adhering to a monthly budget or facing binding credit constraints are likely to make borrowing decisions with monthly payments as a primary consideration. Whether borrowers are constrained by a debt limit constraint as in equation (3) or a mental budget as in (10), consumers facing an exogenous improvement in credit terms will increase their debt to the point where debt payment is unchanged. Note, however, that only a mental-accounting constraint can rationalize monthly payment smoothing by borrowers unlikely to be facing credit constraints. In a model with only credit constraints as in Attanasio et al. (2008), unconstrained borrowers would increase their monthly payments when offered cheaper credit, consistent with their intensive-margin demand elasticities.

Using the monthly payment of each loan in our sample, we estimate differences in monthly payments around FICO discontinuities by estimating the specification in equations (11) and (12) with monthly payments as the single dependent variable. Column 1 of Table 6 shows that borrowers on the right side of a credit-supply discontinuity originate loan amounts with monthly payment sizes that are statistically indistinguishable from the monthly payment amounts of borrowers just to the left of discontinuities (coefficient of \$2.48 with a standard error of \$1.89). With zip-by-quarter fixed effects in panel B instead of the commuting-zone-by-quarter fixed effects in panel A, the point estimate is \$2.20 with a standard error of \$2.17.²⁴ We contrast these results with the prediction of our intensive-margin demand elasticity estimates in Table 5, which indicate average loan sizes and monthly payments should increase by \$1,010 and \$5.38 across the average discontinuity, respectively. Borrowers offered lower rates and longer maturities do increase their loan size in response to more favorable loan offers, but only to the point where their monthly payments are the same as they would have been but for the cost-of-credit shock. These estimates also imply that if borrowers faced constrained consumption in multiple categories, they could choose to respond

²⁴Appendix Table A4 reports monthly payment estimates controlling for third-order polynomials in the running variable as well robustness to a 5-point FICO bandwidth, respectively. Results are quantitatively similar to those reported in Table 6.

to better credit terms by leaving loan sizes unchanged and using any newfound monthly debt-service capacity (\$13/month for the average loan) to increase spending in other consumption categories. That borrowers do not decrease their monthly payments suggests further that any operant credit constraints are likely underwriting driven and not self-imposed monthly cash-flow constraints.

Heterogeneity by Liquidity Constraints

To distinguish likely constrained borrowers from those less likely to be constrained, we stratify our sample based on FICO scores at the time of loan application. Though an imperfect proxy, FICO scores are explicitly designed to correlate with ability to service debt. Borrowers with low FICO scores ($\text{FICO} < 650$) are more likely to have a tougher time obtaining new credit and may have low FICO scores precisely because of tighter liquidity constraints relative to high FICO borrowers. We group the remaining borrowers into $650 < \text{FICO} < 700$ and $\text{FICO} > 700$ categories.²⁵ Columns 2–4 of Table 6 report RD coefficients for borrowers within each of the three FICO buckets. Treated borrowers in the lowest FICO bucket demonstrate statistically identical monthly payment amounts relative to untreated counterfactual low-FICO borrowers. When exogenously offered lower rates and longer maturities, borrowers with the lowest expected access to credit markets 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 similar borrowers not treated with easier credit. While column 2 is consistent with a pure liquidity constraints story, the results in columns 3 and 4 are not, indicating that even borrowers unlikely to be credit constrained smooth monthly payments. These results are consistent with a heuristic approach to budgeting where borrowers have a monthly payment in mind when making a loan decision.

To further test whether liquidity constraints can explain unconstrained borrowers target-

²⁵Our results are reasonably robust to the exact FICO grouping, although we do face a tradeoff between having a low enough FICO score to capture constraints and having sufficient sample size to reject meaningfully sized monthly payment changes. Appendix Tables A5 and A6 report summary statistics for the application and origination samples, respectively, for each of the FICO subgroups.

ing monthly payments, we reestimate rate and maturity elasticities by FICO group in Table 7. The first observation is that all borrowers—not just the constrained—exhibit significantly greater sensitivity to maturity than interest rate. In fact, panel B shows that unconstrained borrowers (columns 5 and 6) increase their loan size the most in response to being offered longer maturity while having the weakest response to interest-rate changes. Such a pattern across FICO groups is inconsistent with an optimization framework that attributes monthly payment targeting to liquidity constraints but consistent with the idea that high FICO borrowers may be the most likely to adhere to a monthly budget. At the extensive margin (panel A), the least-constrained borrowers show the greatest sensitivity to both interest rates and maturity. This could be explained, for example, with high-FICO borrowers being more aware of prevailing market rates and disciplined about not accepting a dominated offer. We lose power when employing more aggressive fixed effects ($\text{zip-code} \times \text{quarter}$) in the application data in such tightly defined FICO subgroups, and the extensive-margin elasticity estimates in columns 2, 4, and 6 of panel A become more noisy.

In sum, in contrast to interpretations of high maturity elasticities and monthly payment emphasis that attribute such preferences entirely to liquidity constraints, we find that large maturity elasticities and monthly payment smoothing behavior are prevalent across the spectrum of borrowers.

Monthly Payment Bunching

Why might borrowers target specific monthly payment amounts if not for liquidity constraints? Basic budgeting heuristics, motivated by cognitive costs or commitment problems, could prompt 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 plots the distribution of monthly payment amounts in our sample of originated loans. Panel A is centered around monthly payments of \$200. The estimated probability

density features a large and discontinuous break in the number of borrowers with monthly payments in the \$198-199 range compared to borrowers with monthly payments at \$200 or \$201. Panels B and C repeat this exercise for monthly payments around \$300 and \$400, respectively, again showing significant bunching just below the round-number threshold. We more formally test the significance of the bunching in the figures using McCrary tests. Such bunching is consistent with a model where households attempt to approximate lifetime budget optimization with rough round-number category-specific monthly budget limits as in Ranyard et al. (2006). The high cognitive accessibility of round numbers likely influences how car dealers and lenders interact with consumers during the purchasing and borrowing decision, similar to Schindler and Kirby (1997) who show that a fixation on 9 as the rightmost digit in sales prices influence how retailers advertise.²⁶

Bunching at round-number payment levels does not rule out the possibility that liquidity constraints are also an important feature of borrower decisions. However, it is hard to rationalize bunching at multiples of \$100 with liquidity constraints as the only explanation. As discussed in section 2, whether liquidity constraints are slack or bind, heterogeneity in household income, balance sheets, loan characteristics, and collateral values would lead to continuously distributed monthly payments without a round-number categorical budgeting constraint as in (10). Consistent with this reasoning, we do not see evidence of consumer bunching at DTI or LTV thresholds (Appendix Figure A3), suggesting that underwriting constraints cannot explain mass points in the payment distribution. To test further whether liquidity constraints can empirically explain our observed bunching behavior, we again split our sample into three borrower groups based on credit scores. We test whether bunching exists at salient anchor points of even hundred dollar monthly payment amounts by normalizing payment amounts relative to the nearest hundred. Payment amounts of \$200, \$300, through \$700 are included in the normalization. Figure 4 plots McCrary tests (point estimates and

²⁶See also survey evidence in marketing that borrowers focus on the first digit of monthly payment amounts (Wonder et al., 2008) and observational evidence in economics (Lacetera et al., 2012) that car buyers focus on the leftmost odometer digits as a cognitive shortcut.

confidence intervals) of significant differences in bunching at \$100 thresholds. The McCrary tests indicate that borrowers in all three FICO sub-samples exhibit significant bunching at salient payment amounts, with the density of monthly payments dropping approximately 16% for payments just above a \$100 multiple.

The prevalence of bunching across the spectrum of borrower constraints supports an independent role for budgeting heuristics in monthly payment targeting. Such heuristics are also likely to explain estimated high maturity elasticities even for unconstrained borrowers given that flexibility in loan maturities allows borrowers to adjust monthly payments to target a specific amount. We plot evidence that maturity is the lever used by many borrowers to target a specific payment level in Figure 5. The first plot in panel A tests for monthly payment bunching in the sample of borrowers originating loans with standard maturity lengths, i.e., maturities of three, four, five, six, or seven years. The McCrary test indicates that the density of monthly payments falls by 11% across the \$100 threshold. 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, with a McCrary statistic detecting roughly double the amount of excess mass relative to panel A, providing additional evidence that maturity is a contractual feature used by consumers to obtain a desired payment size.

6 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 an 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 standard 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, including liquidity constraints and behavioral optimization frictions. Consistent with these possible explanations, we show in a quasi-experimental setting that borrowers smooth monthly payments across contract offers, even when exogenously offered more favorable loan terms. These patterns persist across borrower types. Likely-to-be-constrained and unconstrained borrowers alike borrow larger amounts when offered better terms but only up to amounts that result in monthly payments that are the same as untreated, counterfactual borrowers.

While monthly payment smoothing could be explained by credit constraints alone, we provide evidence that borrowers make debt decisions using affordability rules of thumb. Borrowers disproportionately choose loan amounts and terms that result in monthly payment amounts just below \$100 multiples. Because it is unlikely that liquidity constraints bind exactly at these salient round numbers, this behavior is consistent with many households adhering to a monthly budget that specifies category-level expenditure limits. Notably, monthly payment bunching is present across sub-samples of borrowers with varying degrees of likely credit constraints such that targeting a specific monthly payment is not driven entirely by binding liquidity constraints. Finally, we show that maturity is the mechanism used to obtain a given salient payment amount. Borrowers with loan contracts of non-standard length (e.g., 62 or 73 months) are more likely to originate loans just below salient payment sizes than borrowers with standard maturities (e.g., 60 or 72 months).

To illustrate the relative importance of the maturity and interest-rate channels in the transmission of credit supply shocks to aggregate lending, we apply our elasticity estimates to aggregate data on auto loan activity. According to Equifax, between Q1:2009 and Q3:2018, aggregate outstanding auto debt increased 66% from \$766 billion to \$1.27 trillion. Figure 6 plots Federal Reserve data showing that over the same period, the spread between 60-month auto-loan rates and five-year Treasuries declined 57% from 5.09% to 2.19% while the average

maturity on used-car loans increased 13% from 54.8 to 61.9 months.²⁷ While separating the equilibrium increase in maturity into supply and demand shocks is beyond the scope of this paper, our elasticity estimates are useful in understanding how supply-side increases in maturity and interest rates could impact aggregate auto debt.

For calibration purposes, assume that half of the observed increase in equilibrium maturity (6.5% of the observed 13%) was the result of increases in the supply of maturity.²⁸ Our maturity elasticity estimates suggest that such a supply shift would be responsible for \$76B of the \$504B increase in outstanding auto debt between Q1:2009 and Q3:2018.²⁹ Again, if half of the decline in interest rates resulted from an outward shift in the supply of credit, our elasticity estimates predict a \$62B increase in auto debt.³⁰ Using elasticities conditional on zip \times quarter fixed effects (columns 2 and 4 of Table 5), we estimate aggregate lending effects of \$125B and \$53B due to demand for maturity and interest rates, respectively. While we caveat that we are unable to identify the changes in equilibrium maturity and rates attributable to changes in credit supply, the broader point is that even though rates declined 4.4 times more than maturities increased, credit supply likely impacted total auto debt more through maturity than rates.

What are the implications of these findings for theory and practice? Positively, models of household behavior could consider how policy changes move monthly payment amounts, rather than exclusively evaluating how consumer demand is affected through a pure interest-rate channel. Normatively, both lending regulations and monetary policy could incorporate

²⁷We consider spreads because changes in risk-free rates likely affect household discount rates, something we account for with time fixed effects in our log-linear demand estimation in (14).

²⁸While this assumption is without loss of generality for our purposes here, given that auto-loan rate spreads declined while maturity and volumes increased over this time period (Figure 6), it is plausible that at least half of the observed increase in maturity was the result of shifts in the aggregate supply of maturity. In a supply-and-demand framework, if quantity is increasing but prices are falling, then at a minimum supply accounts for the majority of the net effects of supply and demand shocks.

²⁹From an α percentage change in maturity, outstanding debt would increase by a factor of $(1 + \alpha\eta_{extensive}^T)(1 + \alpha\eta_{intensive}^T) = 1.099$ for $\alpha = 6.5\%$, where η_e^T and η_i^T are the extensive- and intensive-margin elasticity estimates from Table 5 (columns 1 and 3, respectively). The change in outstanding debt associated with the demand-for-maturity channel is $(1.099 - 1) \times \$766B = \$76B$.

³⁰Following the same calculation as above, if half of the 57% decline in rate spreads was from credit supply, then $\alpha = 28.5\%$ and our estimates would predict that debt would rise by a factor of $(1 + \alpha\eta_e^r)(1 + \alpha\eta_i^r) = 1.082$ using the extensive- and intensive-margin rate elasticities in Table 5, columns 1 and 3.

consumer focus on the level of payments per se, similar to the conclusions of the mortgage modification literature cited above. The effectiveness of policies aimed at affecting aggregate demand through credit accessibility and affordability will be modulated by consumers' obedience to self-imposed monthly payment concerns as opposed to binding external credit constraints. Ignoring loan features besides payment levels could also make consumers susceptible to shrouded marketing that pushes costlier and larger loans than intended. The resulting longer maturities may increase the negative-equity share of outstanding loans as longer loans may amortize more slowly than purchased vehicles depreciate (particularly distressing for borrowers whose cars represent a substantial share of their net worth). While monthly payment targeting may valuably address commitment problems, it has the potential to attenuate macroeconomic policy, affect household balance sheets, and drive aggregate indebtedness.

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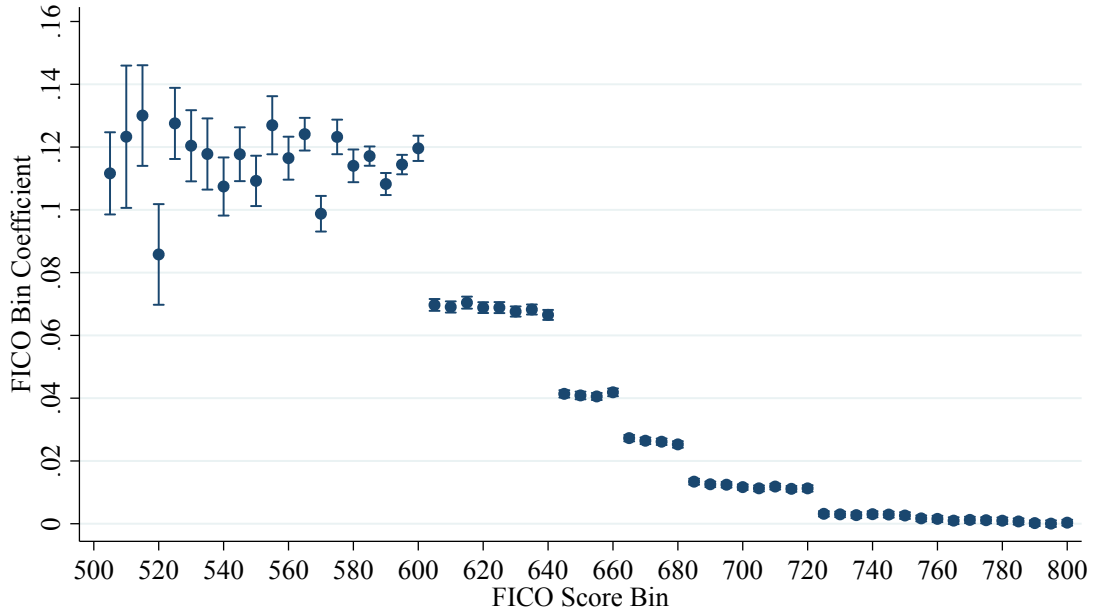
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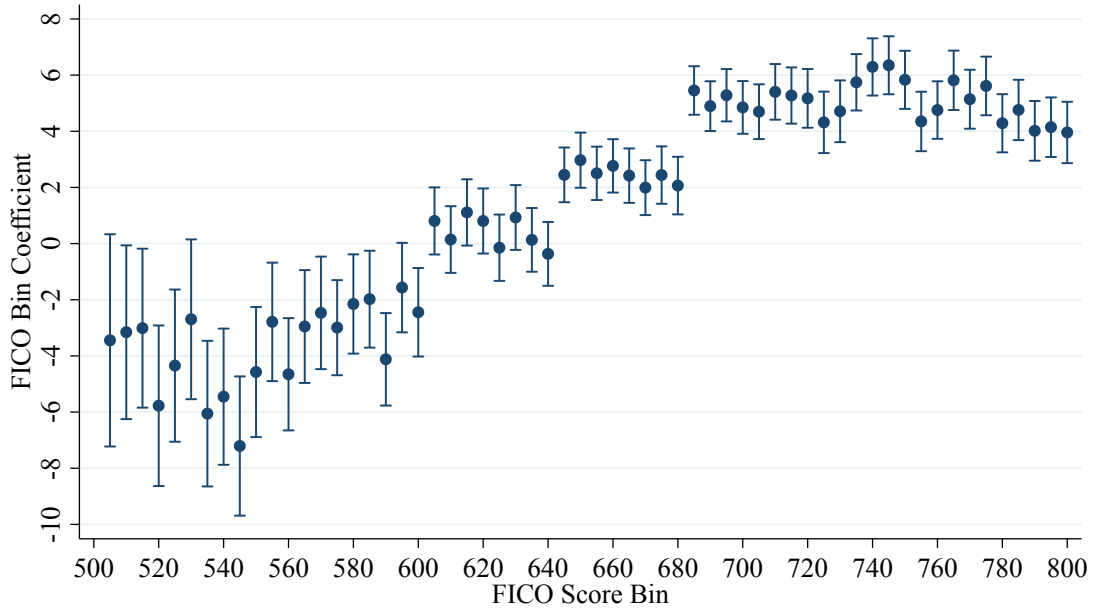
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Figure 1: Example Estimated Lender Decision Rules
A. Example Estimated Pricing Rule for Individual Lender



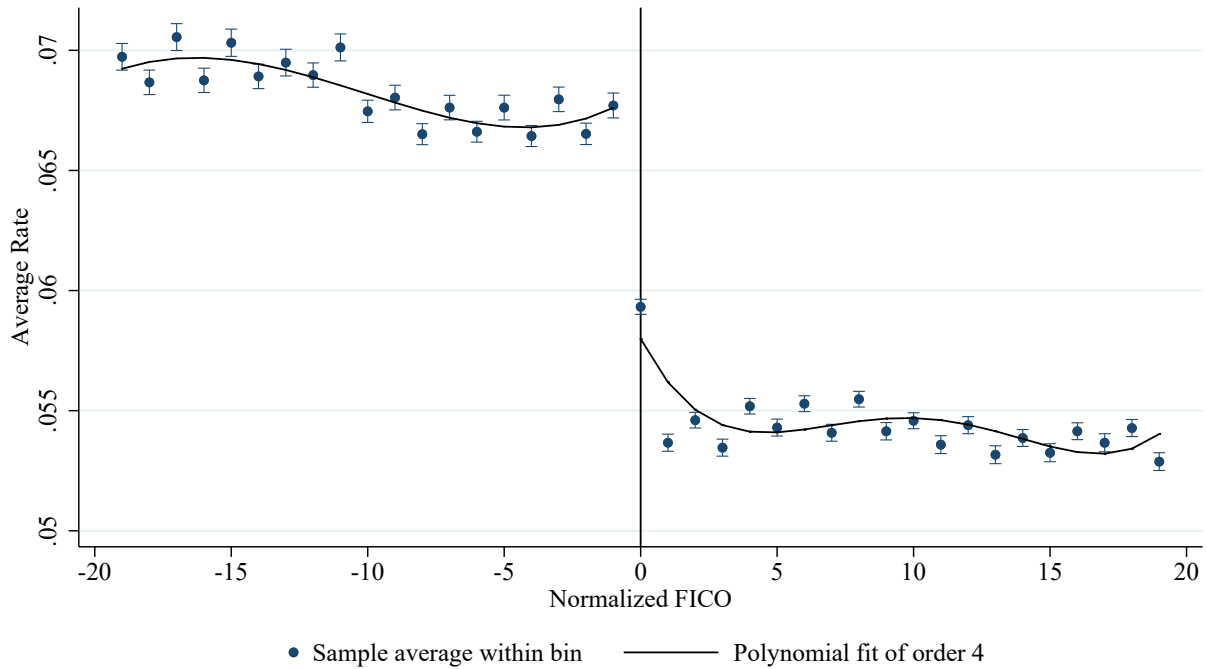
B. Example Estimated Maturity Rule for Individual Lender



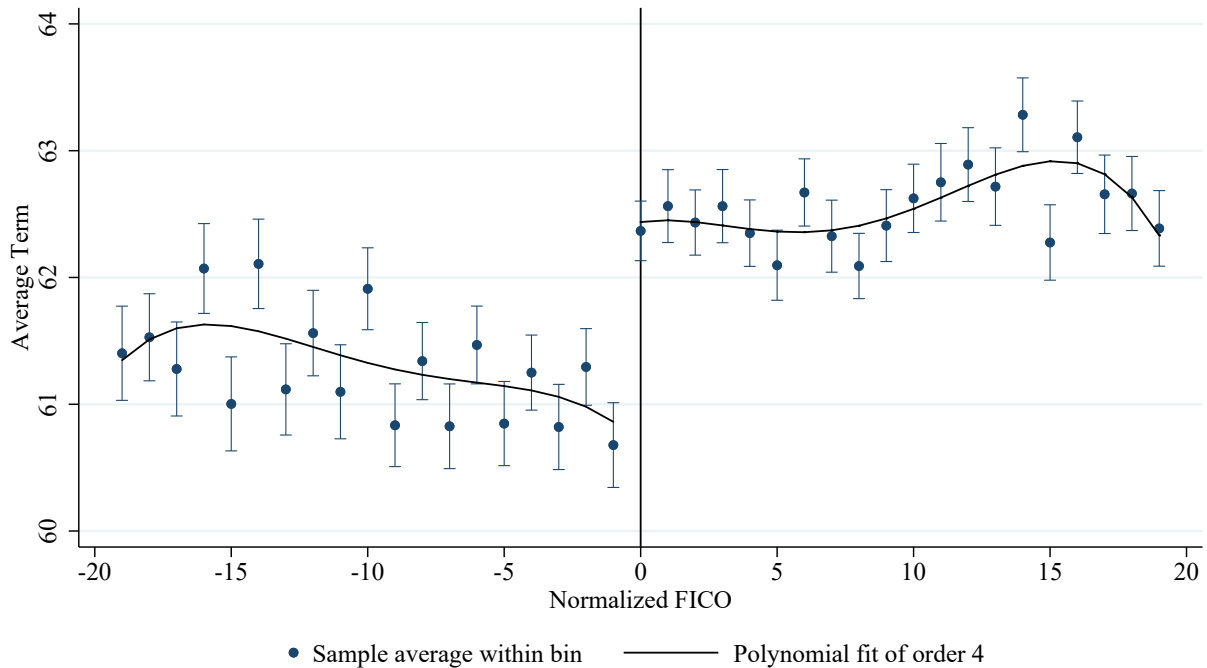
Notes: Figures plot an estimated pricing rule for an anonymous credit union (panel A) and an estimated maturity rule for a different anonymous lender (panel B). Interest rates and loan maturities, respectively, are regressed on 5-point FICO bin indicators. Coefficients and 95% confidence intervals are 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



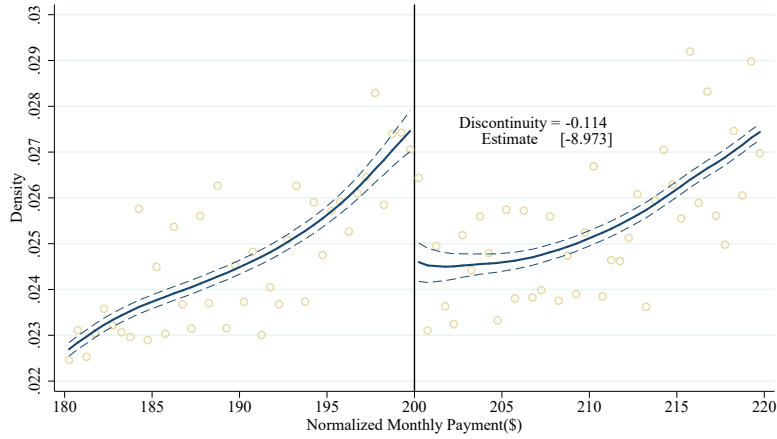
B. Maturity First Stage by Normalized FICO Score



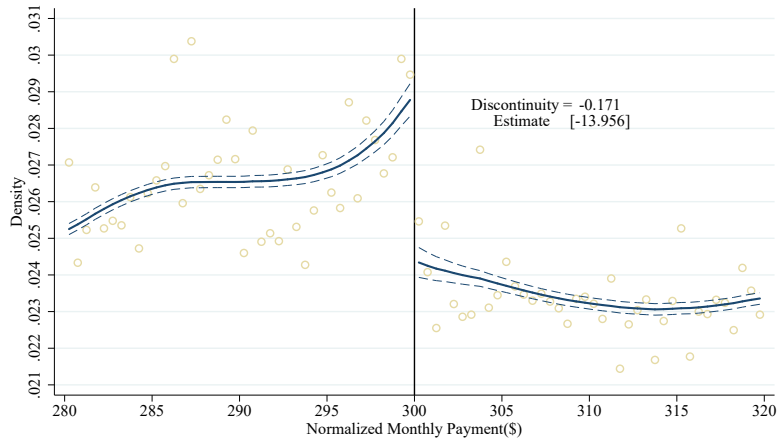
Notes: Figures plot average interest rates (panel A) and maturities (panel B) on the vertical axis against borrower FICO scores normalized to each detected discontinuity for institutions with pricing discontinuities.

Figure 3: Monthly Payment Distributions around Salient Cutoffs

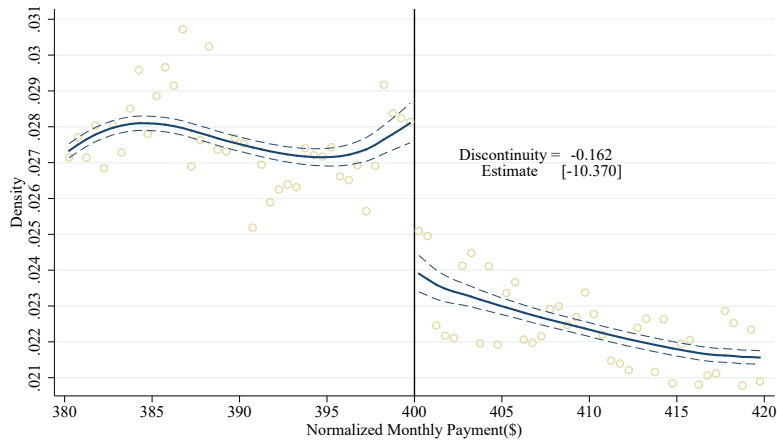
A. Distribution of Monthly Payments around \$200



B. Distribution of Monthly Payments around \$300



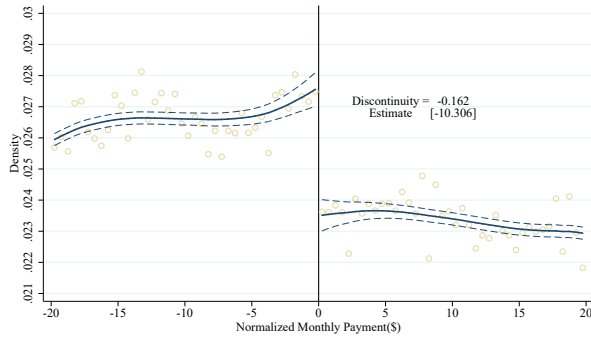
C. Distribution of Monthly Payments around \$400



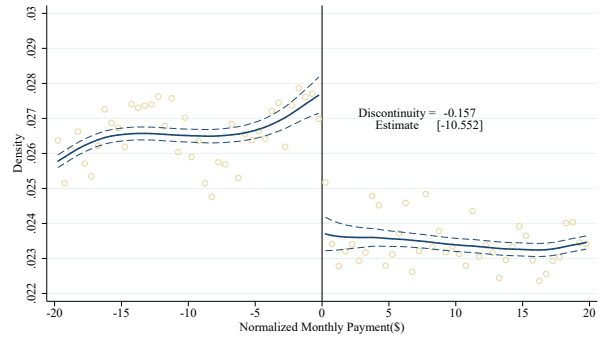
Notes: Figures plot unconditional histograms of monthly payments in a \$20 bandwidth around \$200, \$300, and \$400 in panels A, B, and C, respectively, along with estimated kernel densities and 95% confidence intervals. McCrary statistics (and corresponding t-statistics in brackets) are shown on individual panels.

Figure 4: Monthly Payment Bunching

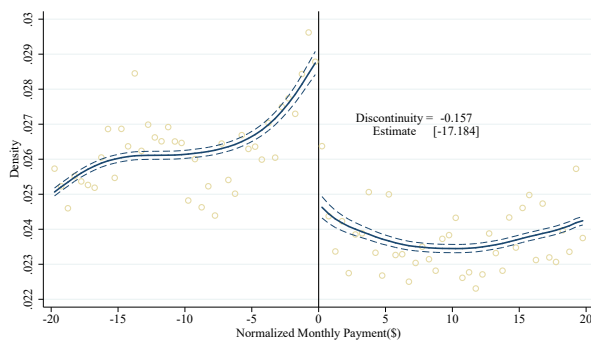
A. FICO ≤ 650



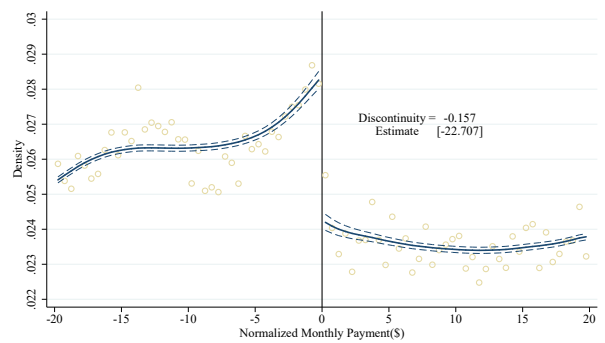
B. $651 \leq FICO \leq 699$



C. $700 \leq FICO$



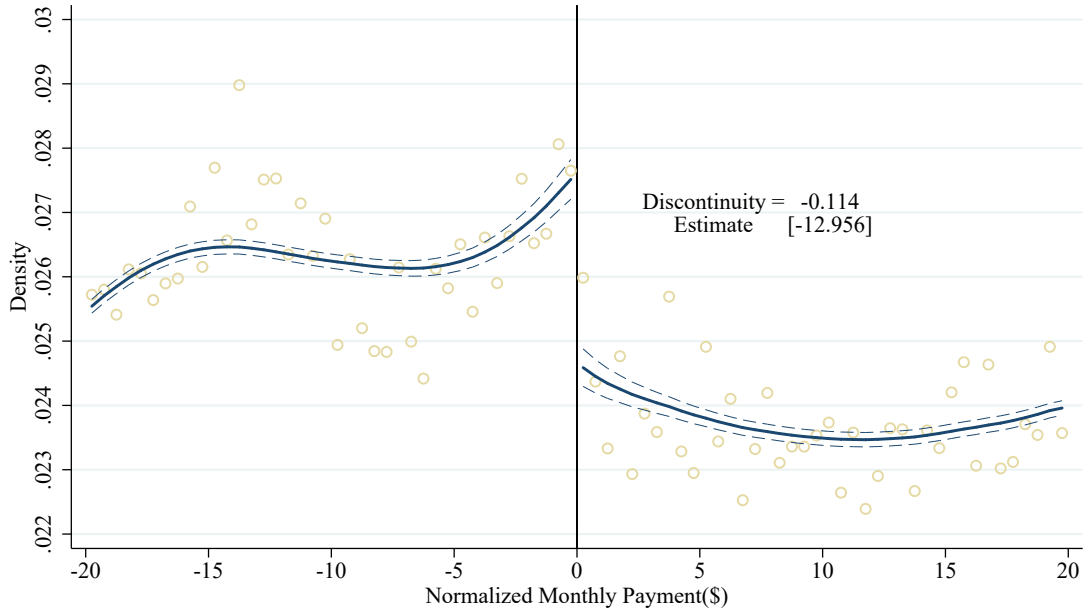
D. All



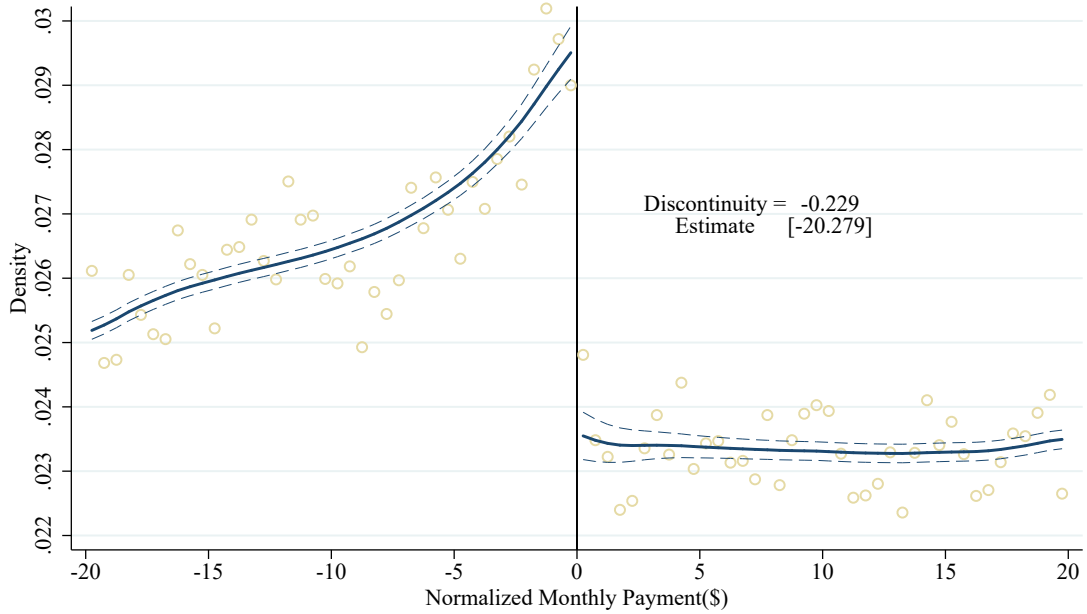
Notes: Figures plot McCrary bunching tests of normalized monthly payments around hundred dollar increments from \$200 to \$700 by FICO score subgroup. McCrary statistics (and corresponding t-statistics in brackets) are shown on each panel.

Figure 5: Monthly Payment Bunching for Typical and Atypical Maturities

A. Loans with Typical Maturities

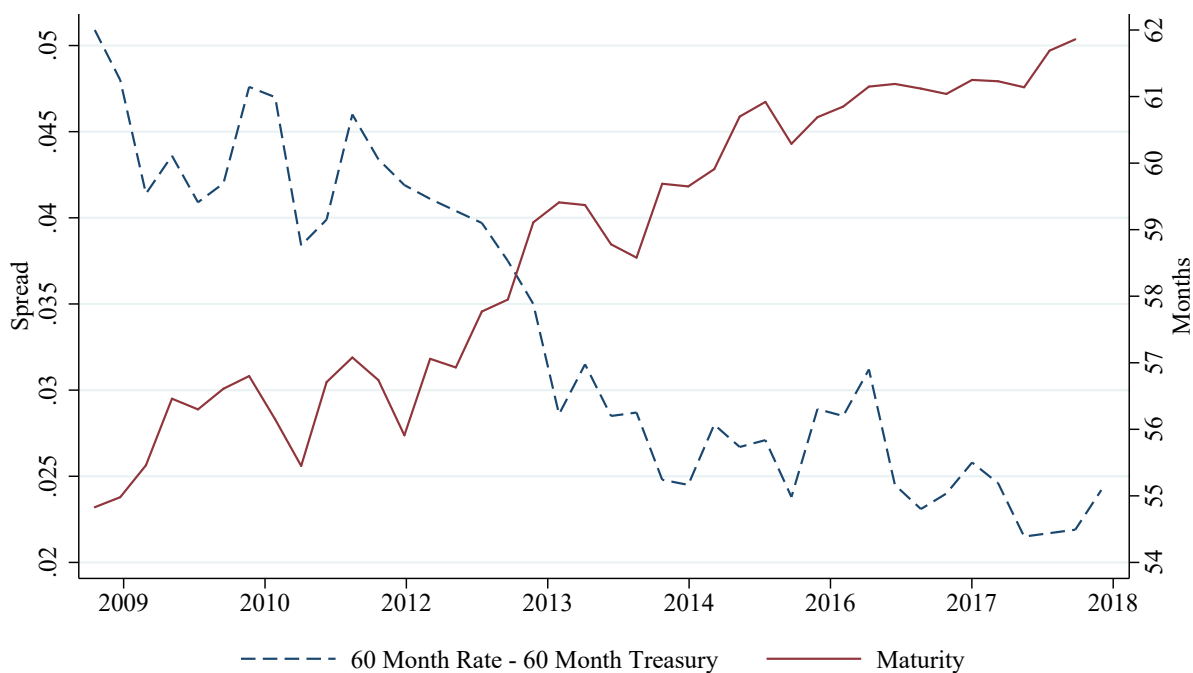


B. Loans with Atypical Maturities



Notes: Figures plot McCrary bunching tests of normalized monthly payments around hundred dollar increments from \$200 to \$700 for typical maturities (36, 48, 60, 72, or 84 month terms) and for those borrowers with atypical maturities in panels A and B, respectively. McCrary statistics (and corresponding t-statistics in brackets) are shown on individual panels.

Figure 6: Auto-Loan Interest Rate Spreads and Maturities



Notes: Figure plots average interest rate spreads and maturities for used auto loans in the United States using Federal Reserve G.20 data. 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.

Table 1: Summary Statistics

	Count	Mean	Std. Dev.	Percentile		
				25th	50th	75th
<i>A. Loan Applications</i>						
Loan Rate (%)	1,131,240	0.05	0.05	0.02	0.04	0.06
Loan Term (months)	1,119,153	67.3	24.4	60	72	72
Loan Amount (\$)	1,320,109	21,927.3	11,660.7	13,296	20,000	28,932.1
FICO Score	898,339	647.9	118.2	605	661	720
Debt-to-Income (%)	833,854	0.26	0.30	0.13	0.27	0.39
Age (years)	763,331	39.3	136.0	30	40	52
Minority Indicator	1,344,407	0.50	0.50	0	1	1
Male Indicator	1,333,514	0.60	0.49	0	1	1
Approved	1,320,109	0.45	0.50	0	0	1
Take-up	588,231	0.65	0.48	0	1	1
<i>B. Originated Loans</i>						
Loan Rate (%)	2,434,049	0.05	0.03	0.03	0.04	0.06
Loan Term (months)	2,434,049	62.7	22.1	48	60	72
Loan Amount (\$)	2,434,049	18,136.5	10,809	10,094	16,034	23,892
FICO Score	2,165,173	710.6	74.9	661	714	770
Debt-to-Income (%)	1,276,585	0.25	0.32	0.05	0.26	0.37
Collateral Value (\$)	2,434,049	19,895.1	10,929.1	12,046.9	17,850	25,562.3
Monthly Payment (\$)	2,434,049	324.4	159.2	210.9	297.0	405.6

Notes: 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 maturity (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 all debt service payments (excluding the auto loan in question) to income. Collateral Value is the value of the car at origination. Minority Indicator is a dummy for whether the lender reported for fair lending purposes that the borrower was predicted to be in a minority group. Approved is an indicator for whether the loan application was approved. Take-up is conditional on approval and indicates whether an approved application was originated.

Table 2: Discontinuity Sample Summary Statistics

	Count	Mean	Std. Dev.	Percentile		
				25th	50th	75th
<i>A. Approved Loan Applications</i>						
Loan Rate (%)	31,618	0.051	0.017	0.037	0.048	0.061
Loan Term (months)	31,618	63.3	11.9	60	60	72
Loan Amount (\$)	31,618	20,226.7	8,458.1	13,736.7	19,467.5	26,025.6
FICO Score	31,618	674.1	27.1	654	676	695
Debt-to-Income (%)	28,513	0.28	0.2	0.2	0.3	0.4
Age (years)	24,909	40.6	13.6	29	39	50
Minority Indicator	31,618	0.43	0.50	0	0	1
Male Indicator	31,618	0.34	0.48	0	0	1
Take-up	31,618	0.55	0.50	0	1	1
<i>B. Originated Loans</i>						
Loan Rate (%)	533,798	0.06	0.03	0.037	0.053	0.075
Loan Term (months)	533,798	61.4	20.1	48	60	72
Loan Amount (\$)	533,798	16,242.2	8,823.7	10,000	14,739	20,679
FICO Score	533,798	663.5	40	638	666	691
Debt-to-Income (%)	248,895	0.24	0.16	0.10	0.27	0.38
Collateral Value (\$)	533,798	17,435.8	8,521.3	11,500	15,800	21,566.1
Monthly Payment (\$)	533,798	305.9	135.5	210.7	284.4	374.8

Notes: Table reports summary statistics for approved loan applications and originated loans for the discontinuity sample, in panels A and B, respectively. See notes to Table 1.

Table 3: First-Stage Regression Discontinuity Results for Interest Rates and Maturities

	(1)	(2)
	Loan Interest Rate	Loan Maturity (months)
<i>A. All Originated Loans</i>		
Discontinuity Coefficient	-0.013*** (0.004)	0.738*** (0.171)
RD Controls	✓	✓
Commuting Zone × Quarter FEs	✓	✓
Partial F -statistic	424.19	49.19
R-squared	0.22	0.13
Number of Observations	533,798	533,798
<i>B. Loans in Application Sample</i>		
Discontinuity Coefficient	-0.004*** (0.000)	0.332*** (0.120)
RD Controls	✓	✓
Commuting Zone × Quarter FEs	✓	✓
Partial F -statistic	1,742.55	7.93
R-squared	0.28	0.11
Observations	31,618	31,618

Notes: Table reports average regression-discontinuity estimates of equations (11) and (12) corresponding to Figure 2 by normalizing FICO scores around each threshold. Panel A sample includes all loans in the origination sample. Panel B loans are restricted to only approved loans in the application sample. RD controls include second-order polynomials of the running variable on either side of each discontinuity. All specifications include commuting zone by quarter-of-origination fixed effects. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Loan Application Covariate Balance Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Debt-to- Income	Age	Minority Race	Male	Application Count	Loan Amount
Discontinuity Coefficient	-0.001 (0.008)	0.24 (0.47)	-0.02 (0.02)	0.005 (0.014)	1.30 (1.74)	339.8 (353.3)
RD Controls	✓	✓	✓	✓	✓	✓
CZ × Quarter FEs	✓	✓	✓	✓	✓	✓
Dep. Var. Mean	0.276	40.59	0.43	0.34	11.98	20,226.7
R-squared	0.312	0.02	0.138	0.323	0.778	0.094
Observations	28,513	24,909	31,618	31,618	2,567	31,619

Notes: Table reports reduced-form RD results for the subset of institutions for which we have detailed loan application data. See notes to Table 3 for more details. Each observation in the data used for column 6 represents a normalized FICO score for a each discontinuity × commuting zone × quarter cell. RD controls include second-order polynomials of the running variable on either side of each discontinuity. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Demand Elasticity Estimates

	(1)	(2)	(3)	(4)
	<i>A. Extensive-margin Elasticities</i>		<i>B. Intensive-margin Elasticities</i>	
log(interest rate)	-0.10*** -(0.02)	-0.07*** (0.03)	-0.18*** (0.01)	-0.17*** (0.02)
log(maturity)	0.83*** (0.25)	1.56*** (0.41)	0.66*** (0.13)	0.85*** (0.14)
RD Controls	✓	✓	✓	✓
CZ × Quarter FEs	✓		✓	
Zip × Quarter FEs		✓		✓
Equality F -statistic	8.26	12.62	12.07	20.83
R-squared	0.08	0.19	0.41	0.62
Observations	31,618	31,618	533,798	533,798

Notes: Table reports 2SLS regressions of an indicator for whether an approved loan offer was accepted by the borrower (extensive-margin) and loan amounts (intensive-margin) on log interest rate and log maturity. All regressions include commuting zone × quarter fixed effects. The instrument set is a series of lender indicator variables interacted with the discontinuity indicator. RD controls include second order polynomials of the running variable on either side of each discontinuity. F -statistics test the hypothesis that the magnitudes of the rate and maturity elasticities are equal. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Lending Discontinuities on Monthly Payments

Sample	(1) All	(2) FICO \leq 650	(3) 651 \leq FICO \leq 699	(4) FICO \geq 700
<i>A. Commuting-zone \times Quarter Fixed Effects</i>				
Discontinuity	2.48	0.57	2.01	2.48
Coefficient	(1.89)	(3.67)	(1.82)	(3.46)
CZ \times Quarter FEs	✓	✓	✓	✓
R-squared	0.10	0.15	0.12	0.13
Observations	533,798	191,140	248,404	94,254
<i>B. Zip-code \times Quarter Fixed Effects</i>				
Discontinuity	2.21	0.73	3.63	0.54
Coefficient	(2.17)	(3.96)	(2.80)	(5.30)
Zip \times Quarter FEs	✓	✓	✓	✓
R-squared	0.38	0.54	0.50	0.57
Observations	533,798	191,140	248,404	94,254

Notes: Table reports RD estimates of changes in monthly payment sizes at FICO thresholds. All specifications include RD controls consisting of second order polynomials of the running variable on either side of each discontinuity. The samples across columns 2-4 are loans for applicants with FICO scores below 650, between 650-700, and above 700, respectively. The first column is the entire sample. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

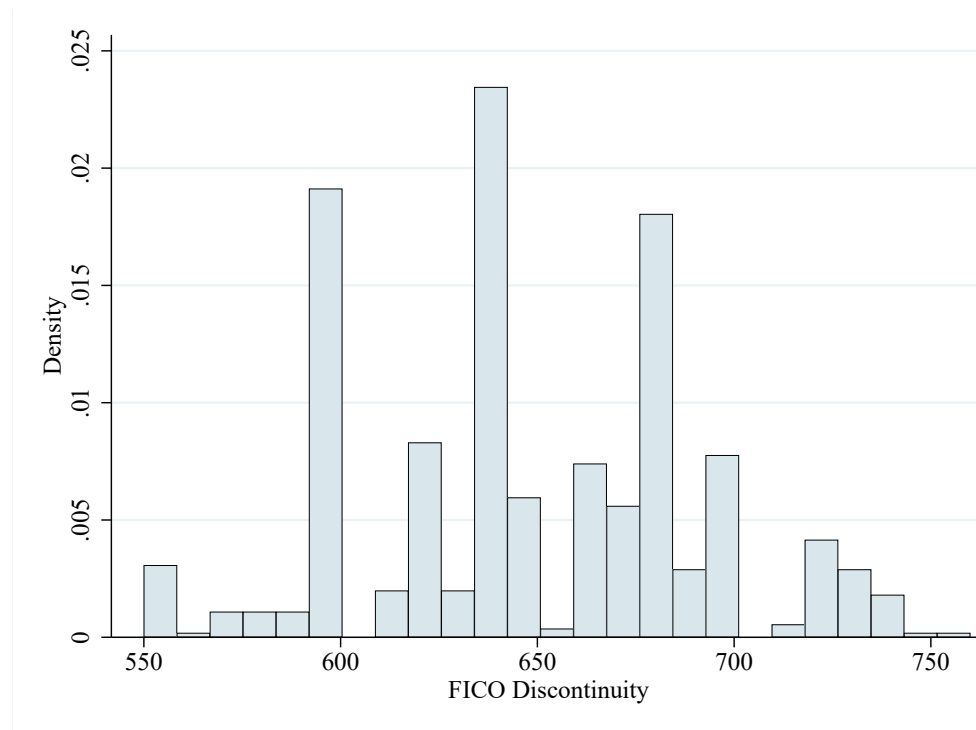
Table 7: Demand Elasticity Estimates by FICO Subgroup

Sample	(1) FICO \leq 650	(2)	(3) 651 \leq FICO \leq 699	(4)	(5) FICO \geq 700	(6)
<i>A. Extensive-margin Elasticities</i>						
log(interest rate)	-0.36*** (0.07)	-0.490*** (0.12)	-0.18*** (0.03)	-0.22*** (0.04)	-0.80** (0.35)	-1.14* (0.65)
log(maturity)	0.75*** (0.25)	-0.493 (0.49)	1.69*** (0.61)	0.67 (0.62)	2.12*** (0.60)	2.26*** (0.67)
CZ \times Quarter FEs	✓		✓		✓	
Zip \times Quarter FEs		✓		✓		✓
Equality F -statistic	2.15	0.01	6.14	0.51	5.05	1.44
R-squared	0.14	0.65	0.28	0.54	0.40	0.51
Observations	6,763	6,763	18,784	18,784	6,071	6,071
<i>B. Intensive-margin Elasticities</i>						
log(interest rate)	-0.22*** (0.02)	-0.21*** (0.03)	-0.10*** (0.03)	-0.12*** (0.03)	-0.09 -0.06	-0.07 (0.07)
log(maturity)	0.61*** (0.11)	0.86*** (0.14)	0.59*** (0.14)	0.85*** (0.15)	1.27*** (0.19)	1.30*** (0.20)
CZ \times Quarter FEs	✓		✓		✓	
Zip \times Month FEs		✓		✓		✓
Equality F -statistic	9.92	16.99	13.12	23.69	30.55	30.06
R-squared	0.44	0.71	0.39	0.68	0.48	0.74
Observations	191,140	191,140	248,404	248,404	94,254	94,254

Notes: Table reports 2SLS regressions of acceptance of an offered loan (extensive-margin) and log loan size (intensive-margin) on log interest rate and log maturity. All regressions include commuting zone \times quarter fixed effects. The instrument set is a series of lender indicator variables interacted with the discontinuity indicator. Columns 1-2, 3-4, and 5-6 are originated loans for borrowers with FICO scores below 650, between 650-700, and above 700, respectively. RD controls include second order polynomials of the running variable on either side of each discontinuity. F -statistics test the hypothesis that the magnitudes of the rate and maturity elasticities are equal. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

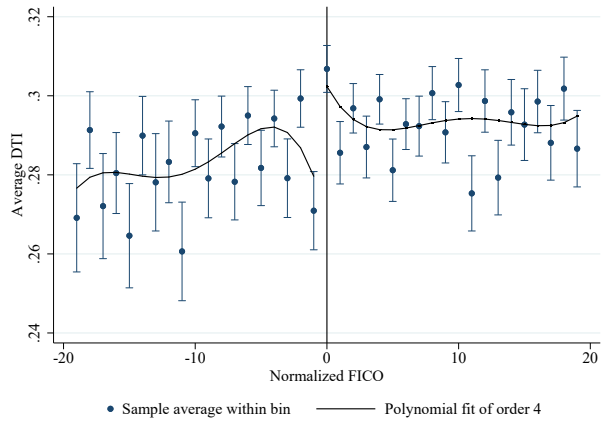
Figure A1: Distribution of FICO Discontinuities



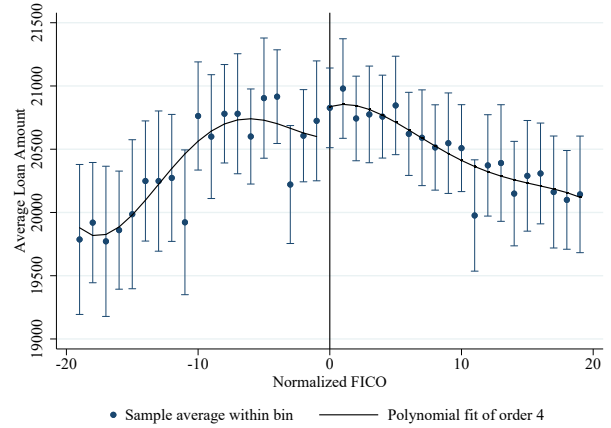
Notes: Figure plots the histogram of identified discontinuities for the discontinuity sample of the data.

Figure A2: Balance of Borrower Characteristics Across FICO Thresholds

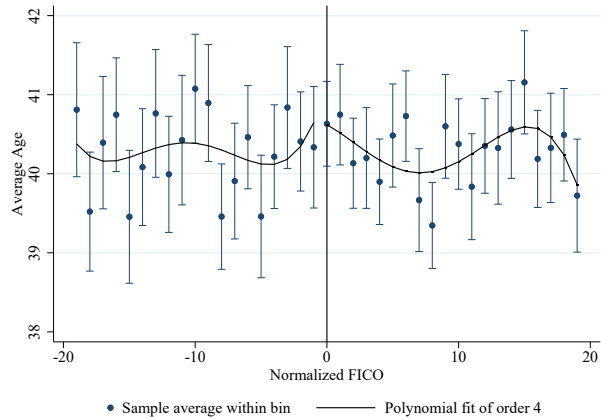
A. *Application Debt-to-Income Ratio (%)*



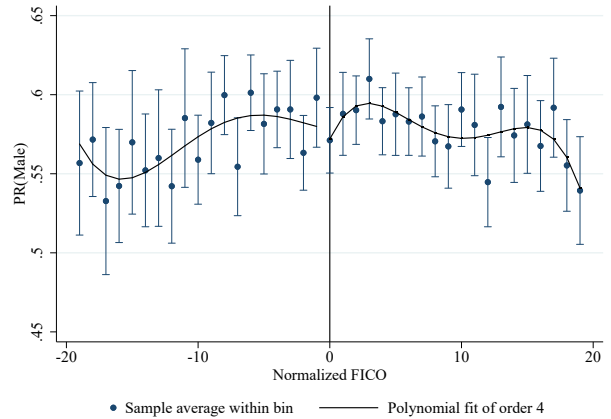
B. *Application Loan Amount (\$)*



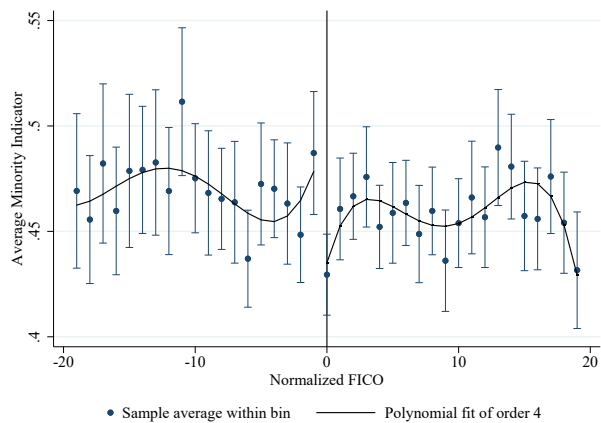
C. *Applicant Age (years)*



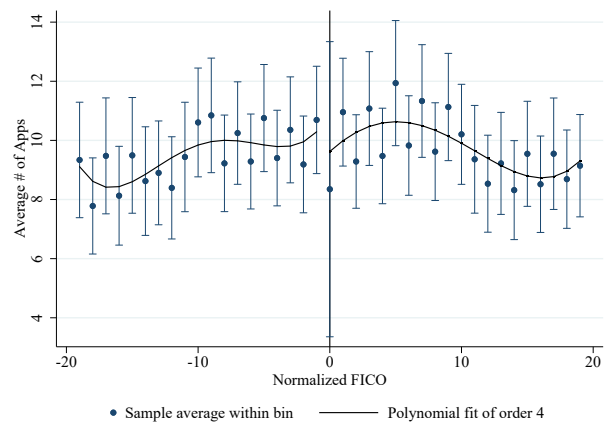
D. *Male Indicator*



E. *Minority Indicator*

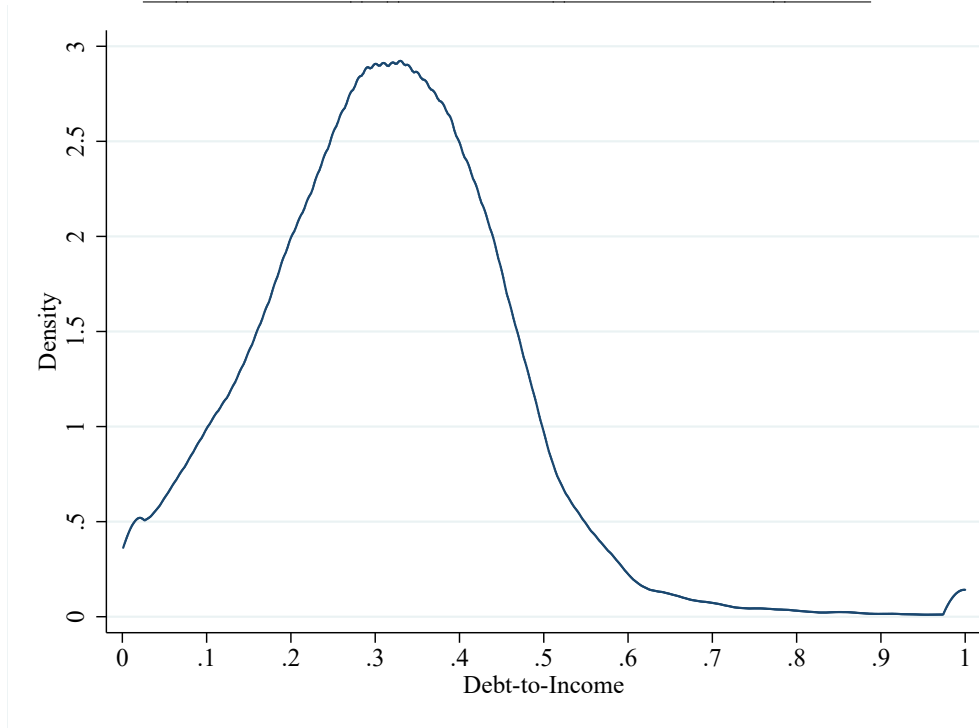


F. *Number of Loan Applications*

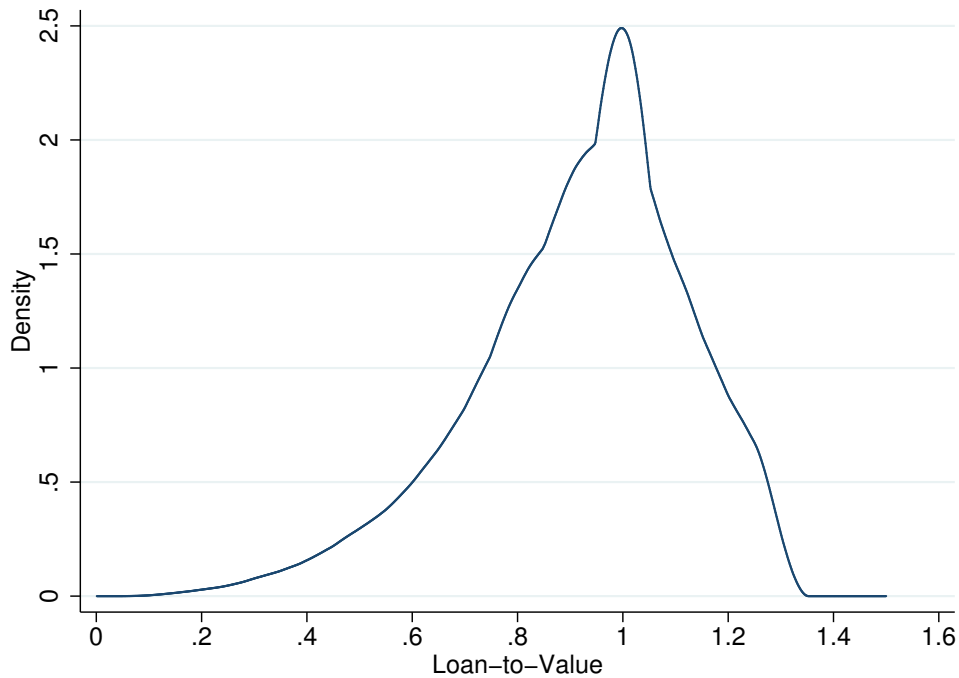


Notes: Figures plot average values of ex-ante borrower characteristics around FICO thresholds for institutions with detected discontinuities and 95% confidence intervals.

Figure A3: Distribution of Application Underwriting Ratios
A. Distribution of Application Debt-to-Income Ratios



B. Distribution of Application Loan-to-Value Ratios



Notes: Figures plot kernel densities for application back-end debt-to-income ratios (panel A) and application loan-to-value ratios (panel B) using Epanechnikov kernels with minimum-MSE bandwidths of 0.0117 and 0.0234 in panels A and B, respectively.

Table A1: Mean Differences between Estimation Sample and Full Sample

	(1)	(2)
	Mean Difference	Standard Error
<i>A. Approved Discontinuity Applications vs. Full Application</i>		
Loan Rate (%)	0.001	(0.001)
Loan Term (months)	-3.91***	(0.02)
Loan Amount (\$)	-1,700.6***	(0.53)
FICO Score	26.1***	(0.03)
Debt-to-Income (%)	0.016***	(0.002)
Age (years)	1.3***	(0.03)
Minority Indicator	-0.069***	(0.004)
Male Indicator	-0.25***	(0.004)
Take-up	0.10***	(0.004)
Approved (%)	0.35***	(0.001)
<i>B. Discontinuity Origination vs. Full Origination</i>		
Loan Rate (%)	0.01***	(0.0003)
Loan Term (months)	-1.38***	(0.007)
Loan Amount (\$)	-1,894.3***	(0.14)
FICO Score	-47.1***	(0.01)
Debt-to-Income (%)	-0.006***	(0.0009)
Collateral Value (\$)	-2,459.3***	(0.14)
Monthly Payment (\$)	-18.53***	(0.02)

Notes: Table reports difference of means (column 1) and their standard errors (column 2) between the discontinuity samples used in estimation and the full sample. Negative numbers indicate that the mean of a given variable was smaller in the discontinuity sample than the full sample. Panel A includes all approved applications. Panel B includes all originated loans. See notes to Tables 1 and 2 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Loan Origination Covariate Balance Regressions

	(1)	(2)	(3)	(4)	(5)
	Loan Amount	Debt-to- Income	Age	Minority Race	Male
Discontinuity Coefficient	755.50*** (259.8)	-0.0009 (0.001)	-0.40 (0.45)	0.003 (0.006)	-0.002 (0.005)
RD Controls	✓	✓	✓	✓	✓
CZ × Quarter FEs	✓	✓	✓	✓	✓
R-squared	0.11	0.13	0.02	0.19	0.04
Observations	533,798	248,895	323,998	501,118	492,219

Notes: Table reports reduced-form RD results for the sample of originated loans. RD controls include second order polynomials of the running variable on either side of each discontinuity. All regressions include commuting zone × quarter fixed effects. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Robustness of Demand Elasticity Estimates to Alternative RD Specifications

	(1)	(2)	(3)	(4)
	<i>A. Extensive-margin Elasticities</i>		<i>B. Intensive-margin Elasticities</i>	
log(interest rate)	-0.10*** (0.02)	-0.12*** (0.03)	-0.18*** (0.00)	-0.18*** (0.01)
log(maturity)	0.81*** (0.25)	1.25*** (0.38)	0.66*** (0.03)	0.74*** (0.14)
RD Controls	Cubic	Quadratic	Cubic	Quadratic
RD Bandwidth	19	5	19	5
CZ \times Quarter FEs	✓	✓	✓	✓
Observations	31,618	10,308	533,798	166,865

Notes: Table reports 2SLS regressions of acceptance of an offered loan (extensive-margin) and log loan size (intensive-margin) on log interest rate and log maturity. All regressions include Commuting Zone \times quarter fixed effects. The instrument set is a series of lender indicator variables interacted with the discontinuity indicator. RD controls include third-order polynomials of the running variable on either side of each discontinuity for columns 1 and 3 and second-order polynomials for columns 2 and 4. Bandwidths are 19 for columns 1 and 3; bandwidths are 5 for columns 2 and 4. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness of Monthly Payments Effects to Alternative RD Specifications

Sample	(1) All	(2) FICO \leq 650	(3) 651 \leq FICO \leq 699	(4) FICO \geq 700
<i>A. 3rd Order Polynomial Control</i>				
Discontinuity Coefficient	1.95 (3.01)	-3.15 (4.63)	2.63 (3.43)	2.15 (4.02)
RD Controls	Yes	Yes	Yes	Yes
CZ \times Quarter FEs	Yes	Yes	Yes	Yes
R-squared	0.10	0.15	0.12	0.13
Observations	533,798	191,140	248,404	94,254
<i>B. 5-point Bandwidth</i>				
Discontinuity Coefficient	0.78 (4.22)	-6.39 (7.87)	5.13 (4.59)	3.32 (5.69)
RD Controls	✓	✓	✓	✓
CZ \times Quarter FEs	✓	✓	✓	✓
R-squared	0.13	0.20	0.17	0.22
Observations	166,865	66,468	73,775	26,622

Notes: Table reports RD estimates of changes in monthly payment sizes at FICO thresholds. In panel A, RD controls include third-order polynomials of the running variable on either side of each discontinuity with a 19-point bandwidth. In panel B, the RD controls are second-order polynomials with a bandwidth of 5 FICO points. All regressions include Commuting Zone \times quarter fixed effects. Robust standard errors in parentheses are clustered by FICO score. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Summary Statistics of Approved Loans by FICO Subgroup

	Count	Mean	Std. Dev.	Percentile		
				25th	50th	75th
<u>A. $FICO \leq 650$</u>						
Loan Rate (%)	6,763	0.067	0.014	0.057	0.070	0.078
Loan Term (months)	6,763	61.9	12	60	60	72
Loan Amount (\$)	6,763	19,001.9	8,050	12,930.4	18,000	24,729
FICO Score	6,763	635.4	11.3	628	638	644
Debt-to-Income (%)	6,432	0.27	0.15	0.14	0.28	0.4
Age (years)	6,065	39.5	13.0	29	37	49
Minority Indicator	6,763	0.43	0.50	0	0	1
Male Indicator	6,763	0.24	0.43	0	0	0
Take-up	6,763	0.60	0.49	0	1	1
Approved	6,763	1	0	1	1	1
<u>B. $651 \leq FICO \leq 699$</u>						
Loan Rate (%)	18,784	0.049	0.014	0.040	0.047	0.057
Loan Term (months)	18,784	63.3	12	60	60	72
Loan Amount (\$)	18,784	20,380.3	8,520	13,861	19,740	26,324
FICO Score	18,784	676.2	13.9	665	677	688
Debt-to-Income (%)	16,737	0.3	0.2	0.2	0.3	0.4
Age (years)	15,097	40.8	13.6	30	39	50
Minority Indicator	18,784	0.4	0.5	0	0	1
Male Indicator	18,784	0.3	0.5	0	0	1
Take-up Indicator	18,784	0.5	0.5	0	1	1
Approved (%)	18,784	1	0	1	1	1
<u>C. $FICO \geq 700$</u>						
Loan Rate (%)	6,071	0.036	0.009	0.030	0.035	0.040
Loan Term (months)	6,071	65.2	11.2	60	66	72
Loan Amount (\$)	6,071	21,116.6	8,560.2	14,509	20,082.6	27,328
FICO Score	6,071	710.5	8.2	704	709	715
Debt-to-Income (%)	5,343	0.3	0.2	0.2	0.3	0.4
Age (years)	3,744	41.7	14.2	29	41	52
Minority Indicator	6,071	0.4	0.5	0	0	1
Male Indicator	6,071	0.6	0.5	0	1	1
Take-up Indicator	6,071	0.5	0.5	0	1	1
Approved (%)	6,071	1	0	1	1	1

Notes: Table reports summary statistics of the approved application discontinuity sample by FICO subsample. See notes to Table 2 for further details.

Table A6: Summary Statistics of Originated Loans by FICO Subgroup

	Count	Mean	Std. Dev.	25th	Percentile	
					50th	75th
<i>A. FICO ≤ 650</i>						
Loan Rate (%)	191,140	0.083	0.031	0.060	0.008	0.103
Loan Term (months)	191,140	61.8	23.1	48	60	72
Loan Amount (\$)	191,140	15,044.5	8,063.1	9,270	13,780.5	19,120
FICO Score	191,140	620.7	24.1	607	626	640
Debt-to-Income (%)	92,278	0.3	0.2	0.1	0.3	0.4
Collateral Value (\$)	191,140	16,192.8	7,792.4	10,750	14,775	19,925
Monthly Payment (\$)	191,140	301.4	131.7	208.8	282.6	368.8
<i>B. 651 ≤ FICO ≤ 699</i>						
Loan Rate (%)	248,404	0.051	0.021	0.035	0.047	0.060
Loan Term (months)	248,404	61.3	18.8	48	60	72
Loan Amount (\$)	248,404	16,655.2	9,047.5	10,069	15,000	21,282
FICO Score	248,404	675.2	14.1	663	676	687
Debt-to-Income (%)	110,942	0.2	0.2	0.1	0.3	0.4
Collateral Value (\$)	248,404	17,744.6	8,659.1	11,731	16,090	21,979
Monthly Payment (\$)	248,404	306	136	209.9	283.7	375.6
<i>C. FICO ≥ 700</i>						
Loan Rate (%)	94,254	0.037	0.015	0.027	0.033	0.043
Loan Term (months)	94,254	60.6	16.4	49	60	72
Loan Amount (\$)	94,254	17,582.7	9,391.9	10,785	15,884	22,458
FICO Score	94,254	719.3	13.4	708	717	730
Debt-to-Income (%)	45,675	0.3	0.2	0.1	0.3	0.4
Collateral Value (\$)	94,254	19,143	9,175.2	12,725	17,355	23,800
Monthly Payment (\$)	94,254	314.5	140.3	216	290	385.5

Notes: Table reports summary statistics for the discontinuity sample of originated loans used in estimation by FICO subsample. See notes to Table 2 for further details.