Heterogeneous Sensitivities to Interest Rate Changes: Evidence from Consumer Loans

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Abstract

This paper empirically analyzes the credit contract decisions made by borrowers. In particular, I exploit a new source of quasi-experimental variation in interest rates to study borrowers' choices of loan amounts within a credit contract and whether borrowers' sub-optimal decisions can be used for screening. In the setting, the interest rate schedule features discrete jumps at specific loan amount thresholds, which create strong incentives for bunching below the cutoffs. First, using bunching methods, I find substantial heterogeneity in sensitivities to interest rate changes across broad credit-rating groups. Subsequently, I examine different hypotheses for the lack of responsiveness. I find that sophistication accounts for most of the heterogeneity, while liquidity constraints, adjustment costs, and information availability play marginal roles. Finally, exploiting the introduction of the interest rate notches, I find that unresponsive borrowers are 18% more likely to default, are 24% less likely to receive funding from institutional lenders, and their loans take 20% more time to get funded. The findings suggest that borrowers' sub-optimal credit decisions can be used to reduce information asymmetries in credit markets.

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The rapid growth of household leverage and its link to the recent financial crisis have sparked interest in how borrowers make their credit choices (Mian and Sufi, 2011; Lusardi and Mitchell, 2014). It has been documented that borrowers often fail to choose the best credit contract, and this can be correlated with consumer attributes, such as borrower sophistication (e.g., Agarwal et al. 2017). However, it remains unclear if these optimization failures are purely due to lack of sophistication or if they are the product of an interaction with other optimization frictions, such as liquidity constraints, search and adjustment costs. Therefore, a better understanding of borrowers' credit choices is needed to design the optimal policy response. This paper contributes to this debate by examining borrowers' decisions in a low friction setting and by providing first evidence that sub-optimal choices can be used to reduce information asymmetries in credit markets.

In this paper, I exploit a new source of quasi-experimental variation in interest rates to study borrowers' choices of loan amounts within a credit contract and whether sub-optimal decisions are informative about their unobserved creditworthiness. In the setting, Lending Club (LC), the world's largest Peer-to Peer (P2P) lending platform, offers to prime borrowers (i.e, those with FICO scores higher than 660 and Debt-to-Income ratios lower than 30%) unsecured loans for amounts between $1,000 and $35,000 (in $25 increments) at fixed interest rates for 36 and 60 month maturities. Important for the research design, between December 2012 and October 2013, LC introduced publicly available interest rate schedules. These menus feature discrete jumps at thresholds for specific loan amounts, which differ based upon borrowers' creditworthiness. For example, at the $25,000 threshold, the interest rate for borrowers with the highest creditworthiness (Grade-A) was 1.59 percentage points higher than at $24,975. Thus, borrowing only $25 more for 36 months would cost the borrower $18.15 every month, corresponding to a present value of $582.31. The standard model predicts that if information is readily accessible and adjustment costs are low, borrowers should minimize financing costs by bunching below those thresholds.

This setting offers multiple advantages. First, sub-optimal behaviors are well defined. Second, the setting allows the ruling out of frictions, such as liquidity constraints and adjustment costs, that are present in other settings (e.g., credit cards and mortgages). Third, the richness of it also enables the examination of the lenders' behavior.

To examine the heterogeneity in borrowers' responses to changes in interest rates, I use the bunching approach (Saez, 2010; Chetty et al., 2011; Kleven and Waseem, 2013).[1] This

[1]This method was originally developed in Saez (2010) in the context of taxation. However, it has been recently applied to study agents' responses to kinks and notches in many other areas, such as social security,

econometric technique exploits the incentives for bunching, created by notches, to study the behavior of agents and estimate elasticities.[2] The intuition for the approach is to combine estimates of the interest rate change with a measure of the excess mass of individuals who bunch at notches to quantify the interest rate elasticity of credit demand. In addition, the methodology also accounts for the presence of optimization frictions or errors. Furthermore, the advantages of this approach are twofold. First, the elasticity quantifies how sensitive borrowers are when they face different interest rate schedules. Second, the approach allows the quantification of the fraction of borrowers who fail to minimize financing costs.

Subsequently, I analyze whether borrowers' bunching decisions uncover unobservable information about their future ability to repay. A starting point is to compare default rates between borrowers around the thresholds (i.e., bunchers and non-bunchers). However, any difference in repayment could be due to both the selection effect (i.e., bunching decision) and the differences in interest rates. To overcome this challenge, I follow Karlan and Zinman (2009) who show that any selection effect can be identified by comparing a selected to an unselected group. To this end, I exploit the introduction in the interest rate schedules, which provides both groups.[3] Those who are offered a notched schedule have the option to self-select into one group: bunchers or non-bunchers (i.e., selected group). Whereas, those whose loan requests came before the introduction of the notches are part of the unselected group, since they do not have the bunching option. Therefore, it is possible to identify the effect of selection induced by the notch on repayment by comparing observationally equivalent borrowers (i.e., same creditworthiness, similar credit contracts, and around the same thresholds) but differing in the option to bunch (i.e., face or not face a notched interest rate menu).[4]

There are three primary findings. First, contrary to the benchmark model prediction, I find substantial heterogeneity in sensitivities to interest rate changes across broad credit-rating groups. In particular, for borrowers with the highest creditworthiness (Grade-A) the elasticity is 0.25, while for borrowers with the lowest creditworthiness (Grades-C-E), it is only 0.04. In addition, I find that the fraction of unresponsive borrowers is 40% for borrowers with the

private sector prices, mortgages, among others.

[2]This empirical approach is related to the regression discontinuity design which also exploits notched incentives, but in settings where the variable that determines the treatment (running variable) is not subject to manipulation. Whereas the bunching approach considers the opposite case, in which the running variable is a direct choice.

[3]In addition, the introduction of the notched schedules is plausibly exogenous since it was not advertised in advance on the LC website.

[4]Supporting the empirical design for this section, there are no significant differences in pre-treatment characteristics or the contract conditions (i.e., interest rate and maturity term).

highest creditworthiness, while it is 92% for those in the lowest category. Finally, I estimate the elasticity if borrowers would have responded as the benchmark model predicts, and I find that this counterfactual elasticity is 0.36.

The second finding is related to why some borrowers fail to reduce their financing costs by bunching below the loan amount thresholds. First, I test whether more sophisticated borrowers are less likely to make optimization errors.[5] Supporting this hypothesis, I find that borrowers with high incomes, who live in highly educated neighborhoods, whose occupations require at least a bachelor's degree and have high FICO scores, as proxies for sophistication, are more likely to bunch below the notches. Consistent with these results, I also find that residence in a state in which high schools offer mandatory personal finance education increases the probability of minimizing financing costs.

I also explore whether other channels, such as adjustment costs, information availability, or liquidity constraints explain the heterogeneity in responsiveness. Regarding adjustment costs, borrowers could enter different amount combinations before submitting their final application without impacting their credit scores. Thus, it seems unlikely that adjustment costs drive the heterogeneity in responsiveness. In terms of information availability, the interest rate schedule was publicly available through the LC website and was labeled as "Interest Rates and How We Set Them." In addition, LC also provided borrowers six different alternatives to the loan amount entered, along with their respective interest rates (three above and three below). Therefore, borrowers potentially could have noticed the notches even without reading the rules about how the interest rates were set. Finally, I find no support for the liquidity constraint hypothesis, since there are no significant differences in the distribution of liquidity constraint proxies between more and less responsive borrowers.[6]

The third finding is that the bunching decision uncovers information about the borrowers' unobserved creditworthiness. In particular, those who do not bunch are 2.89 percentage points more likely to default (16% relative to the mean), even after controlling for the complete set of 50 borrower characteristics at origination. In addition, I find that the loans applications of this group of borrowers take 20% longer to get funded. Subsequently, I exploit the lenders' heterogeneity in the setting.[7] I find that after the adoption of the notched interest rate menus,

[5]Sophistication is defined as the ability to avoid making decisions that are hard to reconcile with the standard financial literature (Campbell, 2016).

[6]In addition, to avoid the jump in interest rate, borrowers only need to request \$25 less to save an average of \$531.

[7]More than 70% of the loans facilitated through LC are funded by banks, insurance companies, hedge funds, and pension plans.

institutional lenders are 24% more likely to fund a loan requested by a buncher than by a non-buncher. This finding suggest that this set of lenders use borrowers' sub-optimal choices for screening.

This paper offers three main contributions. First, it presents new evidence of substantial heterogeneity in borrowers' credit choices. More importantly, it shows that the lack of sophistication can be the main driver of borrowers' sub-optimal choices, in a setting with low search costs and in which liquidity constraints and adjustment costs play only marginal roles. Second, this paper provides evidence that borrowers' sub-optimal decisions can be used to screen loan candidates, and institutional lenders seem to incorporate this information. Finally, this paper offers estimates of the interest rate elasticity of unsecured debt, which do not exist in the prior literature.

This paper is connected to a number of strands of literature. It relates to the work on borrowers' behavior in the credit card market (Gross and Souleles, 2002; Agarwal et al., 2014; Stango and Zinman, 2015). It complements this literature by showing that borrowers do not optimally choose their loan amounts even within the same contract. This paper also relates to the literature on credit contract choices in mortgages (Agarwal et al., 2015; Keys et al., 2016). It shows that in a context with low search and adjustment costs, more sophisticated borrowers are less likely to make dominated decisions.

Moreover, this paper contributes to the literature that documents the importance of information asymmetries in credit markets (e.g., Adams et al., 2009; Dobbie and Skiba, 2013). In particular, Karlan and Zinman (2009) design a field experiment to distinguish adverse selection from moral hazard in a developing country. In addition, Hertzberg et al. (2015) find that loan maturity can be used to screen borrowers. This paper adds to this literature by providing the first evidence that sub-optimal borrowers' decisions can be informative about their unobserved creditworthiness.

This paper also contributes to the growing literature on financial innovation. It has been documented that financial technology has democratized financial services (Morse, 2015), it has enhanced lending efficiency (Iyer et al., 2015), and it also helps borrowers obtain individualized feedback about the interest rates at which they can borrow (Liskovich and Shaton, 2017). This paper contributes to this literature by showing that less sophisticated borrowers gain fewer advantages from the benefits that innovations in financial technology provide.

By estimating that the unsecured credit demand elasticity is 0.36, and the semi-elasticity is 2.2%, this paper adds to the estimates of secured credit. Attanasio et al. (2008) find an elasticity of loan demand around zero for sub-prime auto-loans. DeFusco and Paciorek (2016) find that the semi-elasticity is between 2% and 3%, in the context of mortgages in the U.S., while Best et al. (2015) find that the elasticity is 0.55 in the U.K.

The remainder of the paper is organized as follows. Section 1 presents the conceptual framework, while Section 2 describes the institutional setting and data. Section 3 presents the empirical methodology. Section 4 discusses the potential hypotheses for the lack of responsiveness. Estimates of the impact of bunching on defaults and how lenders use borrowers' sub-optimal decisions when funding loans are presented in Section 5, while Section 6 concludes the paper.

1 Conceptual Framework

A starting point to study whether borrowers minimize their financing costs and the heterogeneity in their responses is to estimate how elastic their demand for (unsecured) credit is. The advantages of taking this approach are twofold. First, the elasticity builds the foundations to quantify how sensitive borrowers are when they face different interest rate schedules. Second, it allows quantification of the fraction of borrowers who behave sup-optimally for each loan amount threshold.

To estimate the interest rate elasticity of unsecured credit demand, I exploit bunching methods which were originally developed in the public finance literature to quantify the elasticity of taxable income.[8] The bunching approach exploits the incentives for bunching generated by discontinuities in the slope of choice sets (kinks) or in the level of choice sets (notches) to study the behavior of individuals and firms.[9]

To understand the intuition of the framework, consider a situation where the interest rate increases discretely at a loan amount threshold. This notch introduces an incentive to move from a region above the cutoff to a point just below it, thereby creating a hole in the loan amount distribution above the cutoff and excess bunching below it.[10] One of the key aspects is that the notch is associated with a region of strictly dominated choice above the threshold.

[8] Bunching is the opposite case of the Regression Discontinuity Design in which the assignment variable is subject to manipulation.

[9] Notches have been implemented in a variety of settings, such as pension plans, fuel economy policy, student evaluation, and mortgages. For example, the U.K. case documented in Best et al. (2015) is an interesting example in which private banks offer a notched interest schedule to borrowers.

[10] The difference between a kink and a notch, is that in the latter, the average interest rate jumps discontinuously, while in a kink, the marginal price changes discontinuously, but the average price is continuous (i.e., borrowers pay the higher interest rate on the entire balance of the loan).

Thus, in a frictionless framework, agents can move below the cutoff by decreasing the loan amount demanded. Therefore, if borrowers value future consumption, then the dominated region should be completely empty, which implies that for empirical purposes, any observed density mass in the dominated region may be used to measure frictions.[11]

1.1 Baseline Model

To formalize the prediction of a borrower's behavior in the presence of interest notches and to motivate the empirical application, I develop a two-period model of borrower credit choice. This model is based on the public finance literature on behavioral responses to kinks and notches (Saez, 2010; Chetty et al., 2011; Kleven and Waseem, 2013; DeFusco and Paciorek, 2016).

I start by analyzing the impact of a linear interest rate schedule at the intensive margin (i.e., how much debt to demand). In the model, borrowers live for two periods and maximize their lifetime utility. In the second period, the borrower consumes all of his remaining wealth. I assume that the borrower's preferences are given by a constant relative risk aversion utility function, $u(c_t) = \frac{\epsilon}{1-\epsilon} c_t^{\frac{\epsilon-1}{\epsilon}}$, and that $0 \leq \epsilon < \infty$. Suppose the borrower has to purchase an asset s, that has no returns, and takes a loan b in the first period.

$$max_{\{c_t\}_{t=0}^{1}} \sum_{t=0}^{1} \beta^t u\left(c_t\right)$$

$$\begin{aligned}
&s.t.\ c_0 + s \leq y_0 + b \\
&c_1 \leq y_1 + s - (1+r)b \\
&c_t \geq 0,\ \forall t = 0, 1
\end{aligned}$$

where c denotes units of a numeraire consumption good, y is the borrower's income, r is the loan's interest rate, and $\beta \in (1, 0)$ is the discount factor . The maximization of utility yields the loan demand:

$$b = \frac{y_1 + s - (y_0 - s)\left[\beta(1+r)\right]^{\epsilon}}{1 + r + \left[\beta(1+r)\right]^{\epsilon}} \tag{1}$$

Assume that the heterogeneity in the model is driven by the discount factor, and that there is a smooth distribution of β in the population captured by a distribution function $F(\beta)$ and a

[11]Implementing the increasing interest rate schedule as a step function may not be second-best efficient. The key assumptions that make kinks preferable to notches is that the underlying fundamentals are continuous; agents are sophisticated optimizers; and the available policy instruments are unconstrained (Kleven, 2016). However, if any of those assumptions do not hold, notches may become optimal. In particular, in cases in which agents are not sophisticated optimizers, discrete categories are found to be simpler, more intuitive, and more salient than a continuum, which makes notches more desirable and easier to implement.

density function $f(\beta)$. Then the combination of the discount factor distribution and the loan demand function yields a distribution of loan amounts $K_0(b)$, and the the density function $k_0(b)$. Therefore, given a smooth interest rate schedule (no notches), the discount factor distribution converts into the loan amount distribution. For illustrative purposes, I also assume that y_t and ϵ are constant across borrowers. This assumption is not crucial and can be relaxed.

Suppose that a notch is introduced at the loan amount b^*. Loans above this amount are subject to a higher interest rate leading to the new interest rate schedule $r(b) = r + \triangle r \mathbb{1}(b > b^*)$, where $\mathbb{1}(\cdot)$ is an indicator function for being above the cutoff, and $\triangle r$ is the interest rate notch.

Figure 1 illustrates the implications of a notched interest rate schedule in a budget set diagram (Panel A) and a density distribution diagram (Panel B). In the presence of a smooth interest rate schedule, the intertemporal budget set is given by the line with slope equal $-(1+r)$. The introduction of an interest rate notch creates a discontinuity at the consumption threshold c_0^*. Thus, for consumption levels higher than c_0^*, the interest rate jumps discretely $(r + \triangle r)$, which creates a discontinuity in the slope of the choice set and consequently, a discrete drop in future consumption.

In Figure 1 Panel A, Borrower A is the household demanding the smallest pre-notch loan amount, whose combination of future and present consumption is A^*, irrespective of whether the notch exists. Borrower B, the marginal bunching individual, is the one demanding the highest pre-notch loan amount whose consumption localizes at B^*. When the notch is introduced, Borrower B is exactly indifferent between c_0^* and the best interior point c_0^I . As Figure 1 Panel B depicts, when confronted with a linear interest rate schedule (i.e., without any notch), this borrower would choose a loan amount of $b^* + \triangle b$. However, with the notched schedule, Borrower B is indifferent between positioning at b^* and the best interior point b^I. Thus, in the absence of optimization frictions, any borrower with a pre-notch loan amount in the interval $(b^*,\, b^* + \triangle b)$ will bunch at b^*. Moreover, no borrower will choose a loan amount between b^* and b^I in the notched schedule case.

Contrary to kinks, notches might create an interval of strictly dominated choice (Kleven and Waseem, 2013; Best et al., 2015; Kleven, 2016). If borrowers are perfectly impatient ($\beta = 0$), demanding a loan just above the notch will be optimal. However, for borrowers who value future consumption ($\beta > 0$), the interval $(b^*,\, b^* + \triangle b^D]$ is the "strictly dominated region," in which it is possible to increase consumption by reducing the loan amount demanded.

In Figure 1 Panel B, the dashed line shows the counterfactual density of loan amounts in the absence of the notch, $k_0(b)$, while the solid line depicts the density in the presence of it,

$k_1(b)$. The post-notch density shows a mass of borrowers locating at b^* in addition to a missing mass of individuals immediately to the right of it. Intuitively, the excess bunching depends on the width of the hole, $\triangle b$, which is a function of the elasticity, ϵ. Therefore, in a frictionless world there would be an empty hole in the interval $(b^*, b^* + \triangle b^D]$.

The determination of the elasticity requires the estimate of the loan response $\triangle b$ to an increase in the interest rate. Denoting excess bunching at the notch by B, the number of borrowers bunching at b^* is given by:

$$B = \int_{b^*}^{b^*+\triangle b} k_0(b)db \approx k_0(b^*)\triangle b \tag{2}$$

where the approximation assumes that the counterfactual density, $k_0(b)$, is roughly constant on the bunching segment $(b^*, b^* + \triangle b)$. This approximation underlies existing bunching estimators, but I account for potential curvature in the counterfactual density when estimating the loan amount response from bunching. Given estimates of the amount of bunching, $\hat{B}$, and the counterfactual density, $k_0(b^*)$, I solve for $\triangle b$, the behavioral response to the interest rate notched schedule. This behavioral response represents the reduction in loan size of the marginal bunching individual. Scaling this response by the proportional change in the interest rate yields an estimate of the interest rate elasticity of unsecured credit demand, ϵ.[12]

1.2 Optimization Frictions

The bunching literature provides the conceptual framework for the explicit study of optimization errors or frictions such as adjustment costs, misconception, inattention, and inertia. Since the dominated region should be empty in a frictionless world, the observed density mass in this region can be used to measure attenuation bias from frictions.

To extend the model, I follow Kleven and Waseem (2013) who develop an approach based on the presence of strictly dominated regions above notches. These regions are used to estimate the fraction of non-optimizing agents, while being agnostic about the specific sources of frictions. Therefore, it is possible to adjust $\hat{B}$, for the magnitude of the optimization frictions in order to provide an estimate closer to the structural elasticity.

Similar to Best et al. (2015), I follow a parametric version of Kleven and Waseem (2013) to characterize the strictly dominated region in my setting. The intuition is that even with a

[12] The bunching estimation in Equation 2 assumes that the elasticities and income are constant across borrowers. However, the model can be extended to consider heterogeneity in elasticities (Kleven and Waseem, 2013).

zero elasticity, the jump in the interest rate should lead borrowers to reduce the loan amount demanded today, which creates a region in which they are better off demanding a loan amount b^* rather than locating within the interval $(b^*,\, b^* + \triangle b^D]$.

I assume that borrowers choose consumption according to the standard Euler equation $c_1 = [\beta(1+r)]^{\epsilon} c_0$, and that they value future consumption, $\beta > 0$. Therefore, as $\epsilon \to 0$, then $c_0 = c_1$. This implies that the lifetime utility converges to Leontief preferences, in which $U = min\{c_0, c_1\}$. Furthermore, bunching at the notch requires that $c_0^I < c_0^N$, which leads to forgoing current consumption for future consumption, $c_0^N < c_1^N$. Hence, evaluating these conditions gives the following dominated range:

$$\left(b^*, \left(1 + \frac{\triangle r}{2+r}\right) b^*\right) \tag{3}$$

where r is the interest rate pre-notch, and $\triangle r$ is the jump in the interest rate.

Finally, the frictionless response can be identified using the estimate of the share of non-optimizing borrowers, a^*. This is the ratio of the observed density mass in the strictly dominated region to the counterfactual density distribution in that region (Kleven and Waseem, 2013). Therefore, the bunching-adjusted estimate is defined as $\frac{B}{1-a^*}$. This approach combines the two moments of the observed distribution: bunching B and the hole in the dominated range $(1-a^*)$, to estimate the behavioral response not attenuated by frictions.

2 Market and Lender Overview

Peer-to-peer (P2P) lending can be seen as the household credit implementation of crowdfunding (Morse, 2015). In P2P lending, individuals post their borrowing needs and personal profiles on a P2P platform (e.g., loan purpose, FICO score, home ownership, income, location, employment status, etc.). Individual and institutional investors can then view, select, and fund consumer loans through the platform. As of June 2017, the Lending Club (LC) is the world's largest P2P lender based upon their issued loan volume and revenue, with more than $26 billion in loans since inception in 2007, followed by Prosper with more than $9 billion in loans.[13] LC offers (unsecured) loans for amounts between $1,000 and $35,000 (in $25 increments), for 36 and 60

[13]LC was co-founded by Renaud Laplanche and John Donovan. Since its inception, LC has received 13 funding rounds by venture and private equity investors and has also sold stakes to Google and to Peter J. Thomson (Thomson-Reuters founder). In August 2014, Lending Club filed for an IPO with the SEC. The offering took place in December 2014 and raised almost $900 million.

month maturities.[14]

2.1 Borrowing Process

Between December 2012 and October 2013, LC offered publicly available notched interest schedules, which implied that the loan interest rates featured discrete jumps (notches) at specific thresholds for the loan amount entered.[15] LC used to publish a pre-specified rule about how the interest rates were set on their website (see Appendix Table 1).[16] This information was available on Lending Club's page titled "Interest Rates and How We Set Them."[17]

To obtain a loan from LC, borrowers must have a FICO score over 660, a monthly debt to income ratio (DTI) below 30%, more than one year of continuous employment, and a minimum credit history of 36 months. Only 13.65% of individuals seeking loans on this marketplace meet the credit criteria required to post their loan requests. In 92.37% of the loan requests rejected, the loan applicant had a FICO score lower than 660. Finally, 99% of the approved loans are fully funded.

In order to request a loan, individuals must provide their income, purpose of the loan, loan amount, and other personal information that is used by LC to formulate their credit profiles (see Figure 2). LC combines a statistical model with random audits to identify borrowers for verification.[18] Once an applicant has passed the initial credit screening criteria, the applicant is then assessed by LC's proprietary scoring models. The initial (base risk) sub-grade scoring model provides the applicant with an initial rank between 1 and 25 mainly based on the borrower's FICO score (i.e., sub-grades from A1 to E5, see Appendix Table 1 Panels A and B). The interest rate charged to borrowers at that time is the result of the "LC base rate," which is based on the initial sub-grade, plus the "adjustment for risk volatility" which depends only on the loan amounts and maturity terms chosen.[19] Panels C and D depict the publicly available risk modifier schedules. Borrowers are also offered alternative amounts with their respective interest rates (see Figure 2). Finally, before submitting the loan application, borrowers can adjust their loan amounts and maturity terms and see the rates with different combinations as

[14] LC's current loan amount limit is $40,000.

[15] In private conversations, LC's representatives stated that these schedules were introduced to make the process easier and more transparent for borrowers and lenders.

[16] LC offered similar schedules up to March 2015, but I focus on this period since all the conditions to set the interest rates were the same.

[17] I take snapshots of LC's "Interest Rates and How We Set Them" from the Internet Archive.

[18] Around 71% of the loans are verified. Personal information is verified through pay stubs, W2 tax records, and in some cases, LC also calls employers.

[19] The LC base rate was the same for each initial sub-grade and was 5.05% for the entire period.

many times as needed without affecting their credit scores.

Furthermore, borrowers within the same initial sub-grade bucket have very similar risk profiles as assessed by LC's lending model, while their interest rates change only with their loan amount and maturity term. For example, as Appendix Table 1 shows, if a borrower is assigned an initial sub-grade of A3 and requests a $25,000 loan with a 36-month maturity, then the loan amount modifier will be "2" and the loan term modifier "0." His sub-grade will fall two notches to A5, and his interest rate will be 8.9%. However, if the same borrower asks for $25 less, or $24,975 rather than $25,000, there would be no loan amount modifier, and the interest rate would be 7.62%. Finally, the initial sub-grade is not observable in the data, but it can be reconstructed from the final sub-grades by subtracting the loan amounts and maturity modifications. For instance, a borrower with a (final) sub-grade of B5 who requests $20,000 for 36 months has a loan amount modifier of 1 with no maturity modifier. Therefore, this borrower must have been assigned the initial sub-grade of B4.

Finally, loan applications are posted on LC's website for 14 day cycles until they are funded. Loans are formally issued if they attract enough investors who commit to funding at least 60% of the loan amount requested.[20] All the loans have fixed interest rates and can be prepaid without penalty. LC charges a one-time fee once the loan is granted and a 1% fee is charged to investors on each monthly payment received.[21]

2.2 Interest Rate Changes at the Thresholds

Since the interest rate depends only on the initial sub-grade, maturity term, and loan amount, it is possible to extract the effect of the first two factors in order to isolate the impact of loan amount on the interest rate. I estimate the size of the interest rate notch using a two stage procedure. In the first stage, the nominal interest rate for each borrower is regressed on a vector of borrower sub-grade dummies and a vector of borrower loan term dummies. In the second stage, the regression residuals resulting from the first stage are regressed on loan amount, a vector of dummies for each threshold, and an interaction variable between loan amount and each threshold dummy. These interactions allow for different slopes on either side of the cutoffs.

Figure 3 presents graphical evidence of the discontinuity in interest rates at each threshold. Each dot represents the sample average in a $1,000-bin of the interest rate residuals obtained from the first stage (i.e., the portion of the interest rate that is not affected by maturity term

[20] In the sample, 11.52% of the loan requests required more than 14 days to be funded.

[21] The one-time fee charged to borrowers is based on the initial sub-grade, and it is a percentage of the loan amount. For example, an A1 borrower will pay 1.1% at origination.

and initial sub-grade), plus a constant given by the regression residuals of the interest rate at the $1,000 loan amount, resulting from the first stage. The solid line represents the fitted values from the second stage.

The figure shows that the interest rate evolves as a step function with sharp jumps (or drops) at different loan amount thresholds. For every grade, the interest rate features a drop at the $5,000 threshold, which was meant to reduce the fixed cost and encourage borrowers to request loan amounts at least $5,000 or higher. In particular for Initial Grade-A borrowers, those with the highest creditworthiness, the interest rate jumps up at $25,000, $30,000, and $35,000. In the case of borrowers initially classified as B, there is an extra jump at the $20,000 threshold. For borrowers with the lowest credit worthiness, there is also an extra jump at $15,000. For Grade-A borrowers, these interest rate changes are larger at the $25,000 and $30,000 thresholds, whereas for Grade-B borrowers, the largest jump is at $25,000 (see Appendix Table 2). Finally, in the case of borrowers initially classified as C-E, the largest jump is at the $15,000 cutoff.

Figure 4 depicts the histograms of the observed loan amount distribution by initial grade. It is worth noting that the histograms are based on the initial grades, since in that way, it is possible to isolate the loan amount choice from the maturity term choice, while final grades do not allow for this comparison since they are based on both. The vertical axis indicates the fraction of loans in each $1,000-bin, for instance [24000, 25000), while the horizontal axis shows the loan amount. The first histogram exhibits excess mass below the $25,000 and also $30,000 cutoffs for initial Grade-A borrowers. There is also a peak at the $5,000 threshold. Contrary to what the frictionless model predicts, there is some density mass to the right of the thresholds (and to the left of the $5,000 threshold). There are also peaks at $10,000, $15,000, and $20,000 (where there are no interest rate notches), which is consistent with borrowers rounding the loan amount requested.

For Grade-B borrowers, there is excess mass only below the $25,000 and (at) the $5,000 threshold, some below the $30,000, and no bunching below the $20,000 or $35,000 thresholds. Interestingly, Grades-C-E borrowers register very limited bunching below the different cutoffs. Contrary to the findings in other settings, such as taxes and mortgages (Saez, 2010; Chetty et al., 2011; Best et al., 2015; DeFusco and Paciorek, 2016), Figure 4 depicts that for unsecured consumer loans, there is heterogeneity in sensitivities.

One concern is that the pattern that Figure 4 depicts would have happened even in the absence of the notches. To address this concern, Figure 5 presents the histograms of the observed loan amount distribution between November 2011 to November 2012, before the introduction of the notches. As the figures show, there is no excess mass below the $25,000 or $30,000 amounts. On the contrary, there is excess mass at each threshold, which is consistent with borrowers rounding the loan amount requested, regardless of their initial grade.

2.3 Data and Summary Statistics

The main sample period includes all loans requested between December 2012 and October 2013. Before this, LC used to set interest rates following a different assignment rule and between November 2013 and February 2015, the notched schedule suffered recurrent changes. Therefore, this study uses mainly this period to avoid any changes in the interest rate rule assignment.

The source of data is LC. It is publicly available and is comprised of self-reported borrower characteristics (e.g., income, loan purpose, employer) and individual pre-origination characteristics pulled from credit agencies (FICO score, credit account information, etc.). In terms of loan performance, LC updates the loan status quarterly, which includes the next payment due date, last payment made by the borrower, as well as the last FICO score pulled from the borrower's credit report (along with the respective date).[22]

However, there is information in the loan listings that LC does not make available directly in its database. Therefore, I complement this dataset by scraping and parsing each loan listing. In this way, I am able to extract information about the number of lenders who funded each loan, the exact date and time when the loan was submitted and subsequently issued, and the borrower's employer and job title.

I construct various measures of borrowers' educational attainment, as proxy for sophistication. The first measure is the proportion of adults (over age 25) with at least a college degree at the 3-digit zip-code level.[23] To this end, I use the proportion of the 2010 population with college education or better from the 2010 Census. The second proxy for financial sophistication is based on the borrower's employer. Until August 2013, LC required loan applicants to provide the name of their employer. After that period, LC started to ask for borrowers' job title. Thus, the second measure is based on the borrower's job title. The Bureau of Labor Statistics (BLS) in its Occupational Outlook Handbook provides the type of occupations that require a bachelor's degree as entry level education. Following this classification, each borrower in the main

[22] The FICO score post-origination is updated regularly except for borrowers who have fully paid their loans or who have been charged off. The most recent FICO score and repayment information for those loans which are not fully paid corresponds to June 2017.

[23] LC only reports the first 3 digits of each borrower's zip-code

sample is manually classified into two groups: those with a job title whose entry level education is at least bachelor's degree; and those whose entry level is lower than a bachelor's degree (e.g., associate degree, some college no-degree and high school diploma). The third proxy is related to the potential financial knowledge that borrowers may have, based on their employer. I also manually classify borrowers into two groups: borrowers working for a firm classified in the Financial Services Industry according to the SIC definition; and borrowers working for any other industry.[24]

Descriptive statistics are reported in Table 1. In terms of the pre-origination characteristics, the average borrower in the main sample has an income of $72,482.39, a FICO score of 697, a credit card utilization of 67%, and has participated in credit markets for 16 years. In particular, Grade-A borrowers have an average income of $94,442, a FICO score of 733, and have been in the credit markets an average of 18 years.[25] In terms of liabilities, their DTI ratio is 15%, and credit card utilization is at 47%. About 55% prepay their loans around 11 months before maturity, and the default rate is 6%.

Borrowers classified as Grade-B have an average annual income of $72,000, almost $10,000 more than for Grades-C-E borrowers. Their FICO score is around 700, 22 points more than borrowers classified within the lowest creditworthiness bucket. Similar to Grade-A borrowers, they have been in credit markets around 16 years but have a higher average DTI ratio (around 17%), and credit card utilization (67% for B and 76% for C or lower). The average default rate is almost eight percentage points lower for these borrowers (12%) than for Grades-C-E borrowers (20%).

Relative to the average household member in the U.S., from Survey of Consumer Finances in 2013, the before-tax personal income for all individuals over the age of 25 is $32,800 (in 2013 USD), while the overall household income in the same period is $84,100.[26] In terms of financial characteristics, the average DTI ratio among responders is 16.9%, and the average credit score is 687, based on Experian's reports for the same period,

[24]Based on the SIC, the Financial Service Industry comprises: depository institutions, non-depositary credit institutions, brokers, dealers, exchanges, and investment offices.

[25]The income reported is the personal income for the individual household member, not at the household level.

[26] Interestingly, among all survey respondents, 43% relied on the Internet as a source for information used to make borrowing decisions in 2013.

2.4 Cost of Non-Bunching

This section provides some estimates of the average cost of demanding a loan amount at the threshold. Table 3 Panel A reports the cost of non-bunching. Overall, the present value of the average cost of non-bunching is $531. In particular, Grade-A borrowers asking for exactly $25,000 pay an average of $21 more monthly than those borrowing $24,975. In comparison, the group of Grades-C-E borrowers facing the same threshold, pay an average of $10 extra in monthly interest for borrowing just $25 more. The results are similar across grades and thresholds, implying that borrowers can save substantially just by borrowing $25 less.

3 Empirical Methodology

3.1 Bunching Estimation

Section 2.2 provides suggestive evidence that there is heterogeneity in responsiveness across borrowers. In order to account for the differences in interest rates at the notches and to estimate the fraction of borrowers who do not behave optimally relative to the benchmark model, I use bunching methods to estimate unsecured credit demand elasticity.

The basic idea in the empirical approach is that the width of the bunching segment is determined by the interest rate notch and the elasticity, ϵ. Therefore, it is possible to uncover the elasticity given knowledge of $\triangle b$ and the proportional change in the interest rate, which are observable. Empirically, the responsiveness to the interest rate notches can be measured by comparing the observed distribution and an estimated counterfactual distribution. Thus, through this comparison, it is possible to measure the excess bunching (B) and missing mass (M), which are key parameters for the estimation. This study follows the approach developed by Kleven and Waseem (2013), who propose a non-parametric method that does not depend on any specific functional form for utility.

In this setting for the $15,000 threshold onwards, the interest rate jumps at round numbers that can be seen as focal points. This feature may lead some borrowers not to move below the thresholds simply because they are choosing a round number, and not because their structural elasticity is low. To overcome this challenge, I estimate the counterfactual distribution following two different procedures. In the first approach, I am able to use the period before the introduction of the notched schedule to construct the counterfactual distribution for all but the $5,000 cutoff, since for this specific threshold the interest rate also dropped in the pre-period.

In the second procedure, I construct the counterfactual distribution, following the standard methodology, by fitting a polynomial excluding the data around the cutoff, and adding an extra set of fixed effects to account for rounding (Kleven and Waseem, 2013).

In order to define the loan amount bins, I first take the logarithms of the loan amount. Subsequently, I set the threshold to zero where the jump occurs, given the respective grade.[27] Then, I define the bins for these standardized loan amounts as $j \in [l, u]$, where l and u are the lower and upper levels of the region affected by bunching responses, the area featuring either bunching or a hole, and will in general be an asymmetrical range around the threshold.

As previously mentioned, in the first procedure, the loans issued between November 2011 and November 2012 are used as a counterfactual distribution. To account for any difference in the number of loans issued between both periods, I take the fraction of loans instead of the raw number, in an estimation window of 10% around each threshold. The assumption is that even if the mode of the distribution could vary between periods, the proportion of loans around thresholds must be similar. As support that this counterfactual is suitable, Appendix Figure 1 shows that there is a substantial overlapping between the empirical distribution and the counterfactual distribution for the $5,000 threshold, which was in place in both periods. Then, I compute the total loans requested 10% above and below each cutoff (T) for the observed and counterfactual distributions. Subsequently, to obtain the fraction of loans per bin in the observed (c_j) and counterfactual distribution ($\hat{c}_j$), I count the number of loans in each bin, and I divide it by its respective T.

In the second procedure, the counterfactual distribution is constructed following Kleven and Waseem (2013). First, I count the number of loans in each bin (c_j). Second, to control for rounding at the thresholds, I use excess mass at similar round numbers at which the interest rate does not change. For example, for Grade-A borrowers, excess mass at $10,000, $15,000 and $20,000 can be used as counterfactuals for the $25,000, $30,000 and $35,000 thresholds. Then, grouping individuals into the small loan amount bins j, the counterfactual distribution is obtained from a regression of the following form:

$$c_j = \sum_{i=0}^{p} \beta_i (b_j)^i + \sum_{k=l}^{u} \gamma_k \mathbb{1}(b_k = b_j) + \sum_{r \in R} \rho_r \mathbb{1}(b_j = r) + \varepsilon_j \tag{4}$$

where b_j is the standardized loan amount in bin j, p is the order of the polynomial, $R = \{10,000,\ 15,000,\ 20,000\}$ for Grade-A borrowers, $R = \{10,000,\ 15,000\}$ for Grade-B borrowers and $R = \{10,000\}$ for Grades-C-E borrowers. The counterfactual bin counts are obtained as

[27] Using logs allows one to define the deviations from the thresholds in percentage terms.

the predicted values from Equation 4 omitting the contribution of the dummies in the excluded region but not the contribution of the round-number indicators:

$$\hat{c}_j = \sum_{i=0}^{p} \hat{\beta}_i (b_j)^i + \sum_{r \in R} \rho_r \mathbb{1}(b_j = r) * \mathbb{1}(b_j = 0) \tag{5}$$

Excess bunching is estimated as the difference between the observed and counterfactual bin counts within and to the left of the excluded region:

$$\hat{B} = \sum_{l \leq j < 0} (c_j - \hat{c}_j) \tag{6}$$

and the missing mass due to bunching is:

$$\hat{M} = \sum_{j=0}^{u} (c_j - \hat{c}_j) \tag{7}$$

This procedure relies on specifying the excluded region $[b_l, b_u]$. The lower bound of the excluded region (b_l) is determined visually.[28] However, in contrast to the case of kinks, where the excluded region is determined visually, the missing mass above notches is more diffuse making it difficult to visually determine the upper bound (b_u). To deal with this issue, Kleven and Waseem (2013) develop an approach based on the condition that, absent extensive margin responses, excess mass below the notch must be equal to the missing mass above the notch. Hence, by setting $\hat{B}=\hat{M}$, it is possible to find b_u. I estimate Equation 7 by choosing the upper bound that minimizes the difference between $\hat{B}$ and $\hat{M}$.[29]

The parameter of interest to estimate the borrowing elasticity is the average behavioral response of the marginal bunching borrower $\Delta\hat{b}$ as measured by the amount of bunching scaled by the counterfactual density distribution below the threshold. Following the conceptual framework, the parameter is calculated as:

$$\Delta\hat{b} = \frac{\hat{B}}{\hat{k_0}(b^*)} \tag{8}$$

The denominator represents the estimated counterfactual density, defined as $\hat{k_0}(b^*) = \sum_{l \leq j < 0} \hat{c}_j / |\frac{b_0 - b_l}{l}|$, where the denominator is the bin-width. Therefore, as the ratio of bunched to counterfactual loans increases, the higher the effect of the notch on loan amounts demanded.

[28] It allows for some overshooting by bunching households.

[29] b_u is also the most natural definition of the "point of convergence" between the counterfactual and the observed distribution.

There are two key identifying assumptions: First, the loan size distribution that would exist in the absence of notches does not depict bunching below the thresholds. Figure 5 provides support for this assumption, by showing that borrowers do not bunch in the period before the introduction of the notches. This assumption also implies that the threshold does not serve as a reference point, in which case, bunching confounds the incentive effect with a reference-point effect (Best et al., 2015). In this setting, the only threshold that may be susceptible to reference point (or rounding) is the $5,000, which is not included in the analysis.

The second assumption concerns the shape of the counterfactual distribution in the second approach (i.e., fitting a high order polynomial). Behavioral responses are typically very local in the case of kinks but less so in the case of notches, which require extrapolation for a larger range, that is more difficult in settings with multiple notches. However, following the bunching literature, I perform a sensitivity analysis with respect to the order of the polynomial p and the bin-width. Appendix Table 3 shows the robustness of the estimates.

3.2 Elasticity Estimates

The empirical approach for notches is less straightforward than for kinks, since the behavioral response is driven by a jump in the average interest rate rather than a jump in the marginal rate (Best et al., 2015). Consequently, I calculate the elasticity using an estimate of the implicit marginal interest rate, rather than the jump in the interest rate (Kleven and Waseem, 2013; DeFusco and Paciorek, 2016).

Let $r^*(b)$ denote the implicit marginal interest rate facing the marginal bunching individual when demanding $b > b^*$. Then, the marginal cost of demanding b is $(b - b^*)\, r^*(b) = b\,(r + \triangle r) - b^* r$, which can be rewritten as

$$r^*(b) = r + \Delta r + \Delta r \, \frac{b^*}{b - b^*}$$

Consequently, the marginal interest rate depends not only on the interest rate jump at the notch but also on the ratio between the size of the loan at the notch and the amount demanded above it. Therefore, for loans slightly above the threshold, the marginal interest rate is substantially large, which captures the fact that the higher interest rate is applied to the full balance of the loan. Finally, the elasticity of unsecured credit demand is

$$\epsilon = \frac{\triangle \hat{b}}{\frac{r^*(b^* + \triangle \hat{b}) - r}{(1+r)}} \tag{9}$$

where the numerator represents the approximate percentage change in unsecured credit demand induced by the interest rate notch (since it is in logs), while the denominator measures the percentage change in interest rates.[30]

Figure 6 depicts the histograms of the observed loan amount distribution along with the counterfactual distribution estimated from the period before the introduction of the notches, described in Section 3.1. The horizontal axis shows the difference between the log of loan amount and the log of the thresholds. Therefore, zero represents the notch, and each bin represents roughly a 0.5% incremental deviation from the threshold. b_l is set visually and depends on where the excess bunch begins, whereas b_u is chosen such that it minimizes the difference between $\hat{B}$ and $\hat{M}$. The vertical axis indicates the fraction of loans in each bin. The solid black line plots the observed loan amount distribution, while the solid gray line represents the counterfactual distribution. The vertical dashed lines represent the lower (b_l) and upper (b_u) limits of the excluded region, whereas the shaded gray area delimits the dominated region, defined as in Equation 3.

Table 2 reports the average change in the interest rate ($\triangle r$), the percentage change in the loan amount demanded ($\triangle \hat{b}$), the dominated region in U.S. dollars ($\triangle \hat{b}^D$), the proportion of borrowers in the dominated region (a^*), the elasticity (ϵ), and the elasticity adjusted for frictions (ϵ_{adj}). Specifically, Panel A reports the estimates for the pooled sample (except the $5,000 threshold), Panel B by initial grade, and Panel C by initial grade and threshold.[31] Standard errors are calculated using the delta method.

Overall, borrowers are willing to reduce the loan amount demanded by 2.29% ($\triangle \hat{b}$) to avoid the interest jump of 1.04 percentage points. Following Equation 3, the dominated region on average extends to $119 (0.51%). That is, the range in which, even with a zero elasticity, borrowers are better off bunching below the notch than locating within it.

Furthermore, the fraction of non-optimizers (a^*) is obtained as the cumulated observed bin counts in the dominated range as a fraction of the cumulated counterfactual bin counts in the same region. Overall, the share of unresponsive borrowers is 73.18%. Interestingly, this share of unresponsive borrowers is substantially larger for Grades-C-E borrowers (91.60%) relative to Grade-A borrowers (40.70%).

In addition, the overall observed elasticity is significantly low, around 0.1. However, the estimates by grades along with the fraction of non-optimizers reveal that there is substantial heterogeneity in responses across borrowers' creditworthiness. In particular, the elasticity is

[30]For $\triangle \hat{b}$ in percentage terms, $r^*(b)$ can be written as $r^*(b^* + \triangle \hat{b}) = r + \Delta r + \frac{\Delta r}{\triangle \hat{b}}$.

[31]The $5,000 threshold is excluded since the interest rate also drops in the counterfactual period.

0.25 for Grade-A borrowers, whereas for Grades-C-E, the estimate is 0.04.

The elasticity adjusted by frictions is 0.36 for the pooled sample. This estimate measures the loan amount response to the interest rate changes if borrowers would have responded as the frictionless model predicts. Interestingly, the estimates are statistically similar across grades, suggesting that the heterogeneity observed can be explained by the different exposures to optimization frictions. Finally, the preceding approach allows the quantification of these frictions, while being agnostic about the sources of them. Therefore, to complement this analysis, I provide potential explanations in the next section.

As robustness, I also follow the standard procedure to construct the counterfactual distribution, by fitting a high-order polynomial and controlling for rounding at the notched thresholds. Appendix Figure 2 depicts the empirical and counterfactual distributions, and Appendix Table 3 presents the elasticity estimates. The results are qualitatively similar to the estimates in Table 2. There is heterogeneity across grades in terms of borrowers' response. However, after the frictions are accounted for, borrowers' sensitivities to interest rate changes are similar.

Relative to other estimates in the literature, DeFusco and Paciorek (2016) and Best et al. (2015) use bunching methods to estimate the elasticity of borrowing to the interest rate in the U.S. and the U.K. mortgage markets, respectively. DeFusco and Paciorek (2016) find that the interest rate semi-elasticity of mortgage demand in the U.S. is between 2% and 3%. To make the results in Table 2 comparable, I also estimate the semi-elasticity. In untabulated results, I find that the interest rate semi-elasticity for unsecured loans is 2.2%. Furthermore, Best et al. (2015) find that the reduced-form elasticity in the U.K. mortgage market is around 0.55. Finally, using different approaches Attanasio et al. (2008) find that the elasticity for sub-prime auto-loans is close to zero, while Bhutta and Keys (2016) estimate that the semi-elasticity for equity extraction in the U.S. market is between 18% and 47%.

Finally, the density graphs (Figure 4) and the share of non-optimizers a^* show that there is a non-trivial number of loans just above the notch. The standard interpretation of incomplete holes above thresholds is the presence of optimization frictions, such as liquidity constraints, adjustment costs, inattention or misperception (Best et al., 2015). Potential explanations for the excess mass will be discussed in the next section.

4 Hypotheses for the Lack of Bunching

The excess mass at the thresholds uncovers optimization frictions, whose magnitude is captured by a^*. For example, the low elasticities have been attributed to adjustment costs (in the mortgage market), liquidity constraints (sub-prime credit market), information availability and misperception (welfare programs). This section examines the potential hypotheses for the lack of responsiveness.

4.1 Information Availability

One explanation for the lack of bunching is that the interest rate schedule in the setting is not salient enough. However, there are some arguments that do not support this hypothesis. First, the interest rate schedule was publicly available through the LC website at that time and labeled as "Interest Rates and How We Set Them."

Second, LC also provided borrowers six different alternatives to the loan amount requested (three above and three below), which tend to be in \$1,000 increments (see Figure 2). In addition, borrowers could also try different amount combinations before submitting their final application without impacting their credit scores.[32] Therefore, borrowers could have noticed the notch even without reading rules about how the interest rates were set.

Third, some blogs specialized in P2P lending, such as "Lend Academy," "LendingMemo" and "Credit Karma" provided information about the optimal loan amounts to request. They also warned borrowers to avoid round numbers.

Finally, if the schedules were not salient enough, then no bunching across groups could be observed. However, Figure 4 along with the estimates in Table 2 show that some borrowers are more responsive than others, which seems to be correlated to the borrower's initial grade profile.

4.2 Liquidity Constraints

It is conceivable that some borrowers stay above the notches due to liquidity constraints that prevent them from borrowing less. To assess the potential role of liquidity constraints, I compare the debt to income (DTI) distribution among bunchers and non-bunchers as a standard proxy (e.g., Best et al., 2015; Gross et al., 2014). If liquidity constraints represent an important reason

[32] This feature of the setting also rules out the adjustment cost hypothesis as potential explanation for the lack of bunching.

for not bunching below the thresholds, then the DTI ratio is expected to be larger among those located just above notches than among those located just below. Figure 7 therefore compares the DTI distributions for bunchers (within $1,000 below the notches) and non-bunchers (within $1,000 above the notches). Figure 7 shows that the two DTI distributions are similar and that the p-value of the Kolmogorov–Smirnov test does not reject the null hypothesis that both samples are the same, further supporting the argument that liquidity constraints do not play a central role in the lack of responsiveness.

4.3 Sophistication

The household finance literature defines sophistication as the ability to avoid making decisions that are hard to reconcile with standard financial theory and that have been labeled as financial mistakes (e.g., Calvet et al., 2009). Therefore, keeping constant other frictions (e.g., liquidity constraints and adjustment costs), those borrowers who do not bunch are predicted to be less sophisticated. In particular, the reduced form elasticity estimates in Table 2 show that a non-trivial number of borrowers make sub-optimal choices, and that the proportion of unresponsive borrowers varies across groups. Therefore, in this section, I explore whether this heterogeneity in the bunching decision can be explained by a borrower's sophistication level.

It is worth noting that the non-bunching decision can be due to not reading the small print (i.e., limited attention) or not understanding the contract terms (i.e, misperception). Interestingly, around 92% of the loans requested within the dominated region are exactly at the thresholds. This is presumably caused by borrowers using some heuristic, such as rounding, to determine how much to borrow. This fact points toward limited attention or misperception.[33] However, given data constraints, disentangling between the two channels is challenging due to data limitation.[34]

From the financial literacy literature, among the standard proxies for sophistication are educational attainment, income, wealth, and FICO score (Calvet et al., 2009; Lusardi and Mitchell, 2014; Andersen et al., 2015; Agarwal et al., 2015). LC reports income and FICO score at origination. However, they do not collect data about borrowers' wealth or educational

[33]Limited attention deters individuals from acquiring and using readily available information when making financial decisions. Broadly, limited attention refers to the incomplete consideration of elements and prices in the individual's choice set (Stango and Zinman, 2014).

[34]The data about what sub-domains each borrower visits in the web-site and the time expended in each of them is not available. An alternative could be the traffic data of the sub-domains that contains the information about how the interest rates are set. Unfortunately, since the former sub-domain disappeared in March 2015, the traffic data is no longer available.

attainment.

To partially overcome this hurdle, as described in Section 2.3, I compute three different proxies for educational attainment or financial knowledge. The first measure is the proportion of adults with at least a college degree at the 3-digit zip-code level ($Percentage\, College\, Degree\, (3-ZIP)$). The second measure is based on the borrower's occupation, for which there is data available between August 2013 and October 2013. In particular, whether the borrower's job entry level education is at least a bachelor's degree, according to the Bureau of Labor Statistics ($College\, Degree$). Finally, the third proxy is based on the borrower's employer, for which LC provides data between December 2012 and August 2013. That is, whether the borrower works for a firm classified in the Financial Service Industry ($Financial\, Services\, Industry$).

To test for the sophistication hypothesis, the following specification is estimated:

$$bunching_i = \lambda_{sgt} + \mu_m + \varphi_l + \psi' \mathbf{X}_i + \varepsilon_i \tag{10}$$

where $bunching_i$ (at loan level i) is an indicator variable equal to one, if a loan amount is located at a maximum of \$1,000 below the threshold and equal to zero at or at a maximum of \$1,000 above the threshold, excluding the \$5,000 cutoff.[35] X_i comprises a vector of pre-treatment characteristics pulled from the borrower's credit report at the time the loan is requested, in particular, $Ln\, Annual\, Income$, $FICO$ score, and $Proportion\, College\, Degree\, (3-ZIP)$ as the main proxy for educational attainment, since it is the only measure available for the complete period of analysis. $College\, Degree$ and $Finance\, Industry$ are also included, for the period in which the data is available.

I also include threshold (s) by initial sub grade (g) by month of origination (t) fixed effects, along with term (m) and state (l) fixed effects, to compare borrowers at the same threshold, with the same creditworthiness, and whose loans are originated in the same month. In addition, some indebtedness proxies are included to further test the liquidity constraint along with the sophistication hypothesis. Moreover, I also incorporate an indicator variable whether $Debt\, Consolidation$ is declared as the purpose of the loan. Finally, $Other\, Controls$ includes a dummy variable for home ownership to control for any collateral effect, and the (ln) of the number of months since the first borrower's credit account was opened as proxy for age.

Table 4 presents the results. Column 1 reports the estimates for the entire sample using $Proportion\, College\, Degree\, (3-ZIP)$ as the main proxy for educational attainment, while

[35]The \$5,000 threshold is a special case in which the interest rate drops just at the cutoff. This cutoff is excluded from the analysis, since any bunching at \$5,000 can be attributed to borrower bunching due to the notch or to borrowers rounding, which might lead to confounding effects.

Columns 2 and 3 present the estimates with the alternative measures for sophistication. Panel B presents the results by grade. The estimates support the hypothesis that more sophisticated borrowers are more likely to bunch below the threshold. Specifically, the estimates in Table 4 Column 1 show that a one standard deviation increase in $Ln\,Annual\,Income$ increases the probability of bunching by 6.18 percentage points (10.49% relative to the mean). In terms of FICO score, a one standard deviation increase in this variable increases the probability of bunching by 0.74 percentage points (1.25% relative to the mean). There is also a positive correlation for the proportion of adults with at least a college degree education living in the borrower neighborhood. A one standard deviation increase in $Proportion\,College\,Degree\,(3-ZIP)$ increases the probability of bunching by 4.62 percentage points (7.84% relative to the mean).

Column 2 reports the estimates for the $College\,Degree$ measure. The estimate shows that having an occupation that requires at least a bachelor's degree increases the probability of bunching by 3.37 percentage points (5.84% relative to the mean). In addition, Column 3 reports that working in the finance industry seems to increase the probability of bunching by 2.96%. Finally, Columns 4-6 support the hypothesis that there is a positive correlation between sophistication and the bunching decision across grades.

Moreover, the estimates for liquidity constraint proxies support the findings in the previous section by showing no significant differences between bunchers and non-bunchers. Finally, there is a positive relation between declaring debt consolidation as the main purpose of the loan and the probability of bunching, which is consistent with optimizing behavior to reduce borrowing costs.

To provide further support to the previous results, I also tests whether residence in a state in which high schools offer mandatory personal finance education increases the probability of bunching. Column 1 of Panel B presents the results. Consistent with the sophistication hypothesis, borrowers who reside in these states are 2.87 percentage points more likely to bunch.

One concern is that FICO score might also be a proxy for financing constraints. Column 2 of Panel B reports the results excluding this variable. As a robustness check, Column 3 presents the estimates for a more restrictive bandwidth: loans between at the most $250 below the threshold and within the dominated region above the cutoff. The results are qualitatively similar to those in the main specification. A wider bandwidth is previously chosen to allow for some overshooting among bunching households. It could be that some borrowers do not read how the interests are set, but through quoting for different loan amount combinations, they realize that the notch exists. Furthermore, Column 4 presents the estimates for the complete sample, including the $5,000 threshold. The estimates in these three specifications are qualitatively similar to the results in Column 1 of Panel A. Finally, a falsification of the main test is to estimate a similar specification at pseudo thresholds. Column 5 of Panel B shows that there are no significant effects when the cutoffs are set $3,000 lower than the originals (i.e, $12,000, $17,000, $22,000, $27,000, and $32,000).

Furthermore, the setting also provides an arbitrage opportunity at the $5,000 threshold, in which the interest rate drops an average of 0.798 percentage points, which I exploit to further tests the sophistication hypothesis. Therefore, even if a borrower requires, for example, $4,975, it is optimal to request $5,000 rather than $25 less. To test whether borrowers who exploit this opportunity are more sophisticated, I select the loans smaller than $5,000 that would have had a lower installment if the loan amount requested had been exactly $5,000 instead. I estimate a similar specification as in equation (10). For this test, the dependent variable is an indicator equal to one if the loan amount is exactly $5,000 and zero if the loan amount is below $5,000 *and* the installment would have been lower (net of fees) if the loan application would have been for $5,000 instead. I find that on average borrowers asking for $4,669 and higher would have been better off if they would have requested $5,000 instead. Appendix Table 4 presents the results. In line with the results in Table 4, borrowers with higher incomes, FICO scores, and residence in educated neighborhoods are more likely to take advantage of this arbitrage opportunity.[36]

Overall, the results in Table 4 along with those in Appendix Table 4 support that the sophistication hypothesis explains the heterogeneity in response to the notches, rather than the liquidity constraints hypothesis.

[36] One caveat of this analysis is that borrowers at the $5,000 threshold could just be rounders. However, based on previous findings, rounders (when facing notches) tend to be less sophisticated, which would go against finding results.

5 Implications of Borrowers' Decisions in Credit Markets

5.1 Screening on Borrowers' Credit Contract Decisions

There is a growing body of literature that documents the importance of information asymmetries in credit markets and how that may lead to credit rationing (e.g., Adams et al., 2009; Dobbie and Skiba, 2013). Theories have shown that information frictions can create inefficiencies in terms of underinvestment (Hubbard, 1998), thus any mechanism that alleviates these asymmetries is beneficial in credit markets. Stiglitz and Weiss (1981) first shed light on the relevance of credit rationing in markets with imperfect information, and they propose that the loan amounts chosen by borrowers may be used as a screening device. Moreover, there are models in which maturity can be used as a screening tool (Flannery, 1986).[37] This section explores whether borrowers' decisions are informative about their unobserved creditworthiness.

A starting point is to compare default rates between non-bunchers and bunchers. Panel A of Appendix Table 5 reports the estimates. Borrowers who self-select into the non-bunching group are 4.21 percentage points more likely to default, relative to those who bunch below the thresholds. However, the interest rates that the bunchers face are lower than non-bunchers. Therefore, the difference in repayment could be capturing both the selection and the repayment burden effects (i.e., the higher default rate is due to the higher interest rates paid by non-bunchers and not to selection on unobservables). In addition, as a placebo, I test whether borrowers who request a loan amount at a maximum of $1,000 above the threshold during the period before the introduction of the notches (i.e., November 2011 and November 2012) are more likely to default than those who request a loan amount at a maximum of $1,000 below the cutoffs during the same period. Panel B reports the estimates. Interestingly, in the absent of the notches, there is no differences in terms of probability of repayment across borrowers. These results suggest that the notch may induce selection among borrowers that captures information about their unobserved creditworthiness.

To study whether the non-bunching decision captures unobservable characteristics that may impact the probability of repayment, I follow Karlan and Zinman (2009) who develop a procedure to identify selection on unobservables. They show that to identify any selection effect on default rates, it is necessary to compare a selected group relative to an unselected

[37] More recently, Hertzberg et al. (2015) have developed a stylized model of consumer credit choice finding that better borrowers can separate themselves by choosing shorter maturity loans.

group, thus any difference in repayment comes from selection on unobservables. To this end, it is necessary to find the ideal control group.

To further motivate the empirical strategy, consider the ideal experiment in this case. Suppose there are two groups of borrowers assigned randomly to either Group T or C. Both groups have similar credit profiles and face the same credit contract (i.e., maturity term and interest rate). Group T is offered a public notched interest rate schedule in which the interest rate jumps at X amount (e.g., \$25,000), while group C is offered a non-notched interest rate menu. Borrowers from Group T who decide to request a loan amount X (or $X+\varepsilon$) are selected on non-bunching, since they could have taken a loan amount $X-\varepsilon$ and have avoided the jump in the interest rate at the notch, but chose not to. Group C is the unselected group (i.e., with no option to bunch). Thus, any difference in repayment between the two groups must be due to the selection induced by the notch (i.e., selection on unobservables).

This empirical exercise tries to resemble the ideal experiment by taking advantage of LC's change of interest rate schedules. Between November 2011 and November 2012, LC offered a different interest rate schedule based on a loan amount guidance limit. Crucially, the introduction of the notch reduced the interest rate for loan amounts below the cutoff, while the interest rate for amounts at or above the threshold remained unchanged (i.e., no differences in repayment burdens between the control and the treatment group). Thus, I exploit the introduction of the notches by comparing borrowers who self-select as non-bunchers (whose loans were issued between December 2012 and October 2013) to borrowers around the same thresholds in the previous interest schedule, who were not offered a notched interest option (see Figure 8 Panel A). Important for the analysis, the change of interest schedule was not announced on LC's website in advance (i.e., the change was unexpected). Borrowers could only notice the new notched menu once they quoted for a loan or checked the "Interest Rates and How We Set Them" section.

The research design in this section relies on two identifying assumptions. First, borrowers before and after the introduction of the notch are equivalent based on observable and unobservable characteristics. One concern is that time-of-origination-varying differences in creditworthiness could have made borrowers who were exposed to the notched menu different from borrowers who were not. Table 5 provides partial evidence against this concern, since there are no significant differences on observable characteristics between those borrowers who requested a loan before the introduction of the notch and those after. Second, the control and the treatment groups face similar credit contracts.[38] Panel B of Table 5 provides support for this assumption, since there are no statistically significant differences in interest rates between the control and the treatment groups. This test supports the notion that the only distinction is the introduction of the notches.

I estimate the following specification:

$$default_i = \lambda_{s\,f} + \gamma_t + \mu_m + \varphi_l + \alpha\, non\text{-}bunching_i + \theta' \mathbf{X}_i + \varepsilon_i \tag{11}$$

where i indexes borrowers; t is the quarter of origination; $default$ is an indicator variable equal to 1 if the loan was charged-off (as of June 2017); *non-bunching* is a dummy variable equal to one if the loan amount requested is located at the threshold or at a maximum of \$1,000 above in the period from December 2012 to October 2013, and zero if the loan amount is at a maximum of \$1,000 below the threshold and at the most \$1,000 above the same threshold during the period November 2011 to November 2012 (see Figure 8 Panel A); and X_i is a vector of controls that includes a set of variables that LC reports and that lenders observe at origination. The specification includes 4-bin FICO range (f) by threshold (s) fixed effects, and term (m), state (l) and quarter of origination (t) fixed effects to compare borrowers at the same threshold with the same creditworthiness at the same quarter of origination. Since initial sub-grades are defined in a different fashion during the control period relative to the main sample period, 4-bin FICO is used instead, allowing comparison of borrowers with similar risk profiles. In addition, quarter of origination is used instead of month of origination fixed effects to avoid perfect multicolineality with the *non bunching* indicator. Standard errors are clustered at 4-bin FICO by threshold level to account for serial correlation. Finally, the \$5,000 dollar threshold is excluded since the previous interest rate menus also offered a drop in the interest rate at this cutoff.

The parameter of interest is α, which captures the selection effect of being a non-buncher (i.e., a non-sophisticated borrower) on the probability of repayment. Table 6 presents the estimates. For the entire sample, Column 1 shows that those who self-select into the non-bunchers group are 3.21 percentage points more likely to default (17.54% relative to the mean).[39] Subsequently, I include control variables to determine to what extent the estimates are sensitive

[38] The \$15,000 threshold was excluded, since borrowers around this cutoff were affected by an staggered change in maturity term introduced by LC (Hertzberg et al., 2015).

[39] In untabulated results, I also estimate the effect of *bunching* on default with respect to the unselected group. Borrowers who bunch below the thresholds after the introduction of the notch are less likely to default than the unselected group. However, since the interest rates that the bunchers and the control group face are different, the results can be driven not only by the selection effect but also by differences in repayment burden.

to the inclusion of observable borrower characteristics. Column 2 shows that the estimate is economically and statistically significant (2.89 percentage points), even when the complete set of borrower characteristics at origination (50 variables) is included. Columns 3-5 report the estimates by grades. Grade-A borrowers who do not bunch are 1.32 percentage points more likely to default, while the estimate is 4.76 percentage points for Grades-C-E borrowers.

One potential concern is that possible time-of-origination shocks could have affected borrowers in the control and treatment groups in different manners, which is not completely absorbed by the quarter of origination fixed effects. However, it is plausible to assume that those potential shocks are less likely in subsequent months. To address this concern, Column 1 of Panel B presents the estimates for Equation 11 for the sub-sample of loans originated between October 2012 and January 2013 (i.e., two months before and after the introduction of the notches). Those borrowers who self-select into the non-bunching group are 2.31 percentage points more likely to default (13.14% relative to the mean), which is qualitatively similar to the main result. In addition, Column 2 presents the results for a more restrictive bandwidth: loans between at a maximum of $250 below the threshold and within the dominated region above the cutoff, and the results are also qualitatively similar to the main specification.

Another concern is that these results might be driven by censoring, since 7% of the loans issued in the main period have not yet matured. To address this concern, Column 3 presents the estimates for the sub-sample of 36-month loans (100% of these loans issued after the introduction of the notch have matured). The estimate shows that the effect of bunching on default is qualitatively similar to that reported in Panel A.

It is also possible that non-bunchers decide ex-ante to default on their loans, which might explain the difference in terms of default rates. If this is true, then non-bunchers should default on their loans right after their loan is granted, otherwise they will be paying a larger installment than what they would have paid by bunching. To address this concern, I exclude borrowers who defaulted at period zero (i.e., never paid an installment). The findings in Column 4 do not provide support for this concern by showing that the estimate is still large and significant.

A potential concern is that LC could have changed the rejection criteria when the notches were introduced. Fortunately, LC provides the application date, loan amount, loan title, DTI ratio, FICO score, and employment length for rejected loans. Thus, to address this concern, I test whether the loans rejected are different in terms of observables (i.e., FICO score, DTI ratio, and employment length) before and after the introduction of the change in schedules. Column 1 of Table 7 presents the results. The sub-sample comprises loan applications rejected in the period from November 2011 to October 2013. The dependent variable is an indicator equal to one if the application date is after December 2012 and zero otherwise. The estimates are substantially small and statistically indistinguishable from zero for the three rejection criteria (joint F-test=0.66).

Another concern is that LC might have used the bunching decision to reject or approve some applications. To partially address this concern, I test weather applying for a loan amount just below the notches (i.e., bunching to avoid the jump in the interest rate) leads to rejection. I test this hypothesis on the sub-sample of loan applicants that satisfies the three conditions required by lending club and for which the data is available: the FICO score is higher than 660, the DTI ratio is lower than 30%, and the employment length is longer than one year. Column 2 of Table 7 presents the results. Demanding a loan amount below the notch does not lead to an arbitrary rejection, which implies that bunching does not increase the probability of been rejected.

Overall, these findings suggest that the non-bunching decision could provide additional unobservable information to lenders about the probability of borrower default, which could potentially alleviate information asymmetries. Therefore, it is of interest to study whether lenders, in this case investors who also know how the interest rates are set, exploit the borrower's sub-optimal decision when lending in this market.

5.2 Borrowers' Credit Contract Decisions and Lenders' Behavior

The results in the previous section suggest that borrowers' decisions uncover unobservable information about their creditworthiness. Subsequently, I exploit the heterogeneity of lenders in the setting to study whether institutional investors, who are the most sophisticated lenders in this market, exploit borrowers' bunching decisions when screening loan candidates.

The loans facilitated through LC are funded directly by a wide range of investors, including retail investors, banks, insurance companies, hedge funds, pension plans, and university endowments. At the early stages, most of the loans facilitated by LC were funded by retail investors. However, the typical lender profile has changed from an individual to an institutional investor. For instance, smaller banks have increased their participation in this market in order to help streamline their small loan operations and to facilitate loans that would have otherwise been unprofitable for them. As of November 2015, the rough breakdown of investors is 20% retail , 35% financial institutions, and 45% funds.

Around 30% of the loans are randomly set aside for institutional lenders. Within this pool of loans institutional lenders have certain amount of time to fund whole loans. After this period, those loans not funded are available to retail lender. Since the number of lenders who fund each loan is observable, it is plausible to identify investors who fund entire loans (within this pool) as institutional lenders. Using this proxy for institutional lenders, I test whether the non-bunching decision impacts the probability of being funded by a sole lender. I estimate a difference-in-differences specification that exploits the introduction of the notch in December 2012, in which the treatment group includes borrowers who request a loan amount at the threshold or above (non-bunchers), and the control group includes the borrowers who demand an amount below the cutoff (bunchers). The identifying assumption in this analysis is that in the absence of the shock (i.e., the introduction of the notch), the difference in the probability of being funded by an institutional investor between non-bunchers and bunchers would have followed the same trend. I estimate the following specification:

$$sole\,lender_i = \lambda_{sf} + \gamma_t + \mu_m + \varphi_l + \beta_1\, non\text{-}bunching_i + \beta_2\, non\text{-}bunching_i \,\mathrm{x}\, post_t + \theta' \mathbf{X}_i + \varepsilon_i \quad (12)$$

where i indexes loan; t is the month of origination; *sole lender* is a dummy variable equal to one if the loan is funded by only a single lender and zero if it is funded by more than one lender; $non\text{-}bunching_i$ is an indicator equal to one if the loan amount requested is located at or a maximum of $1,000 above the threshold and equal to zero at a maximum of $1,000 below; and *post* is an indicator variable equal to one if the loan was originated between December 2012 and October 2013 and equal to zero for the period between November 2011 and November 2012.[40] The model also includes a set of control variables (X), 4-bin FICO range (f) by threshold (s) fixed effects, and term (m), state (l), and month of origination (t) fixed effects. The standard errors are clustered at 4-bin FICO by threshold.

Panel A of Table 8 summarizes the results. Non-bunching reduces the probability of receiving funding from a sole lender by 11.14 percentage points, which represents a 23.41% decrease relative to the mean. In addition, there is heterogeneity in the estimates across initial grades. The effect is larger for the set of borrowers with (initial) Grades-C-E (26.53% relative to the mean) and Grade B (22.47% relative to the mean), while, for initial Grade A borrowers, the estimates are imprecise. These findings suggest that non-bunching significantly reduces the probability of being funded by institutional investors.[41]

[40] The sample is restricted only to loans initially listed as "whole," since only for this pool it is possible to differentiate between institutional and retail lenders.

[41] In untabulated results, I test whether there are differences in the Internal Rate of Return (IRR) for each

To partially test for the identifying assumption of this analysis, Panel B provides estimates of a subset of the models in Panel A, augmented with leads and lags of the introduction of the notches. To test for pre-trends, I add indicator variables for Months 1 and 2 before adoption, Months 0–3 after adoption, and Month 4 onward. Of these seven indicator variables, the first six are equal to one only in the relevant month, while the final variable is equal to one in each month, starting with the fourth month of adoption. The coefficients on the adoption leads are not significantly different from zero, showing little evidence of an anticipatory response. In the month of adoption, $non\,bunching$ decreases substantially by seven percentage points, after which this estimate fluctuates between 5.73 and 11.51 percentage points over the subsequent three months; then it averages 12.11 percentage points in Month 4 onward.

Finally, to complement the previous findings, I also test whether the average number of lenders funding each loan in the non-bunching group changes after the adoption of the new interest rate menus. The prediction is that if lenders are incorporating the information about unobserved creditworthiness that the non-bunching decisions uncover, then lenders will be less willing to invest higher stakes in those loans. Therefore, the average number of investors funding each loan from the non-bunching group should increase after the introduction of the notches. Table 8 Panel C Column 1 presents the estimates. As expected, the average number of lenders funding these specific loans increased 21.67% after December 2012, which means that lenders tend to fund a smaller fraction of the loans (funds committed divided by loan amount) when the borrower is a non-buncher rather than a buncher.

To further complement the results, I also test whether the time taken to get funded varies between bunchers and non-bunchers after the introduction of the notch. As mentioned, loan requests are listed on the marketplace for at least 14 days, which is the first round. In Table 8 Panel C Column 2, I test whether the probability of being funded after the first round differs between groups. $After\,First\,Round$ is an indicator variable equal to one if the loan is funded after 14 days and zero otherwise. The positive point estimate indicates that non-bunchers have a probability of being funded after the first round 3.35 percentage points higher than the probability for bunchers (24.96% relative to the mean). Finally, Column 3 presents the estimates for the time taken to get funded for the sub-sample of loans with non-verified incomes (since, any verification may lead to delays). The loans requested by non-bunchers take 19.39% more to be funded (around 1.41 days) relative to bunchers' loans for this sub-sample.

Overall, the findings suggest that intermediaries could screen loan applicants based on

loan, as a proxy of profitability, between bunchers and non-bunchers. I find no significant difference between groups.

their responses to notched interest rate schedules, and that there is a potential match between sophisticated lenders and sophisticated borrowers in credit markets.

5.3 Additional Robustness Checks

The previous results provide suggestive evidence that borrowers' sub-optimal decisions might capture some private information that affects the probability of repayment. This section presents more support for this hypothesis using an alternative specification.

In this section, the selected and unselected groups are redefined. Panel B of Figure 8 depicts an alternative empirical design. The selected group (i.e., treatment group) is comprised of borrowers who self-select as bunchers by requesting loan amounts at a maximum of \$1,000 below the threshold, excluding the \$5,000 cutoff. The unselected group (i.e., control group) includes the borrowers who demand between \$2,000 and \$1,025 below the cutoff. The identifying assumptions are that both groups the unselected and the selected (i.e., bunchers and no-bunchers) are observationally equivalent, and that the unselected group and the bunchers face the same contract. Appendix Table 6 presents supporting evidence for these assumptions.The intuition is that those who bunch self-select on unobservables, while those in the unselected group choose their loan amount demands independent of the notch. Thus, if the identifying assumptions hold any difference in repayment should be explained by the selection effect induced by the notch.

Column 1 of Table 9 presents the estimates for a specification similar to Equation 11 but with the new definition of the treatment and control groups, while Column 2 shows that the results are robust to the inclusion of the complete vector of characteristics at origination. The negative point estimate indicates that borrowers who select on bunching by taking a loan just below the notch have a default rate 2.13 percentage points lower than the default rate of the non-selected borrowers (12.64% relative to the mean). The results suggest that the bunching choice captures information that cannot be predicted by observable characteristics available to lenders at origination, which provide support to the results reported in the previous section.

To further test whether sophisticated lenders use the information provided by the bunching decision, I estimate a similar specification as in Equation 12, in which *Bunching* is an indicator variable equal to one if the loan amount is at a maximum of \$1,000 below the threshold and equal to zero for loans between \$2,000 and \$1,025 below the cutoff. Columns 3 and 4 of Table 9 report the results. Borrowers who self-select on bunching are 9.5 percentage points more likely to be funded by an institutional investor than the non-selected borrowers after the introduction of the notch (28.37% relative to the mean). These results support the previous findings that lenders exploit the private information revealed by borrowers' decisions, and that the effect is robust to the inclusion of the entire set of characteristics publicly available to lenders at origination.

6 Conclusion

By exploiting a new source of quasi-experimental variation in interest rates, this paper studies borrowers' choices of loan amounts within a credit contract and whether their sub-optimal decisions are informative about their unobserved creditworthiness. Surprisingly, there is substantial heterogeneity in responses to interest rate changes across borrowers, whose response to the notching is correlated to their credit worthiness. Moreover, this heterogeneity can be explained by the sophistication level of the borrowers (i.e., education, income and FICO score), while I find no support for the hypotheses of liquidity constraints and adjustment costs affecting the bunching decision. Moreover, unresponsive borrowers are more likely to default, are less likely to receive funding from institutional lenders, and their loans take longer to get funded. The findings suggest that borrowers' sub-optimal credit decisions can be used to reduce information frictions in credit markets.

The findings are of interest for multiple reasons. First, they shed light how borrowers behave in a setting with low search costs and in which liquidity constraints and adjustment costs play only marginal roles. It also provides estimates of the cost of sub-optimal decisions. Second, the findings show that sophistication matters to households in credit markets. This supports the establishment of financial education programs to increase households' understanding of credit products. Third, the results highlight that borrowers' sub-optimal choices can be used to reduce information asymmetries in credit markets, thus supporting remedies, such as information coordination and enhanced screening strategies by policymakers and lenders.

Finally, financial technology has helped to democratize financial services. Currently, households have a wider set of financial options and must make more complex financial decisions (Campbell et al., 2011). The findings in this paper suggest that even if new technologies allow borrowers to reduce financing costs, less sophisticated borrowers take less advantage of the available benefits.

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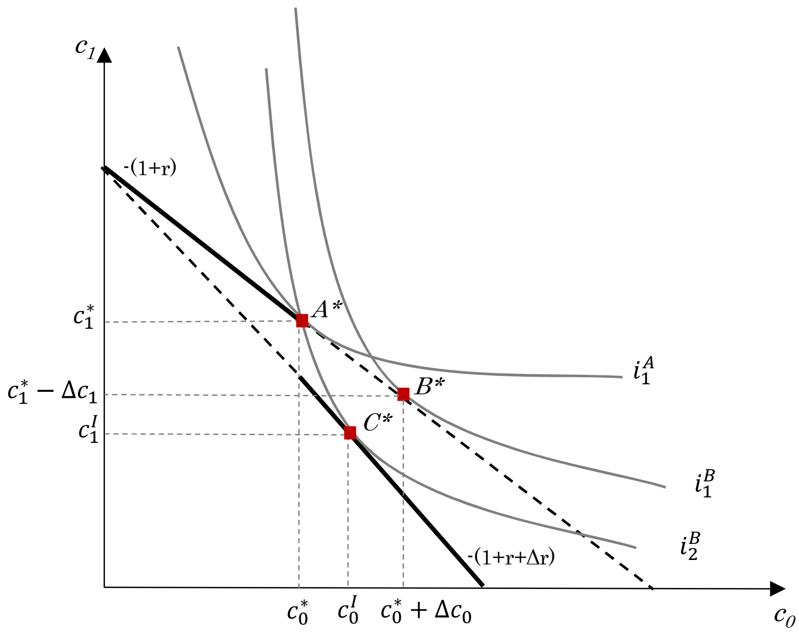
Panel A: Budget Set Diagram



Panel B: Loan Amount Density in the Presence of a Notch

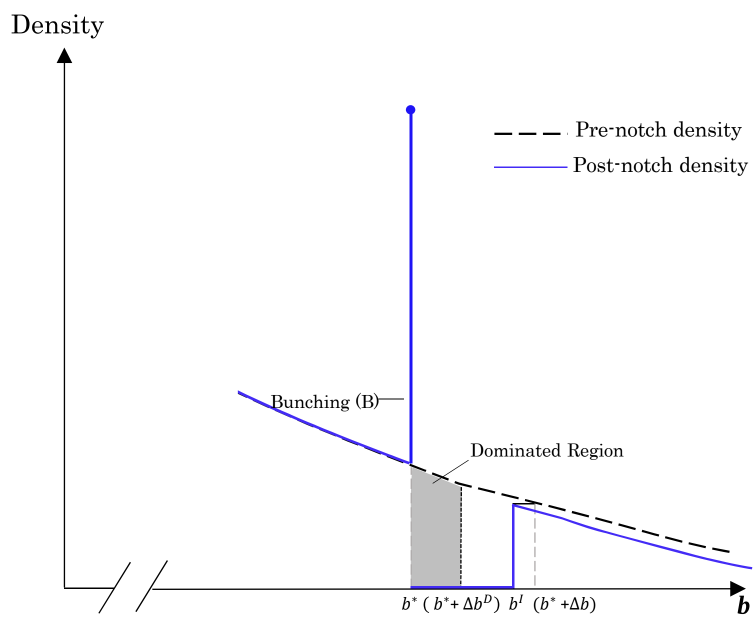


Figure 1 Borrowers' Responses to Interest Rate Notches

This figure shows the effect of a notch on the loan amount demanded. Panel A depicts the effect of an increase in the interest rate from r to $r + \triangle r$ at c_0^*. The solid black line describes the budget constraint with slope $-(1+r)$ below c_0^* and slope $-(1+r+\triangle r)$ above c_0^*. The indifference curve i_1^A corresponds to the individual A, who demands the lowest pre-notch loan amount. i_1^B is the indifference curve for the individual B, the marginal bunching borrower, who has the highest pre-notch loan demand and would have chosen $c_0^* + \triangle c_0$ in the absence of the notch. This borrower is indifferent between bunching at the notch c_0^*, and the interior point c_I^*, when facing a notch. Panel B shows the corresponding post-notch density distribution. The notch leads borrowers with counterfactual loan amounts between b^* and $b^* + \triangle b$ to bunch at the threshold. This behavior generates a discontinuity in the loan amount density, characterized by both a spike in the density of loans at the cutoff and a region of missing mass immediately to the right. For borrowers who value future consumption ($\beta > 0$), the shaded area is the "dominated region," in which it is possible to increase consumption by reducing the loan amount demanded.

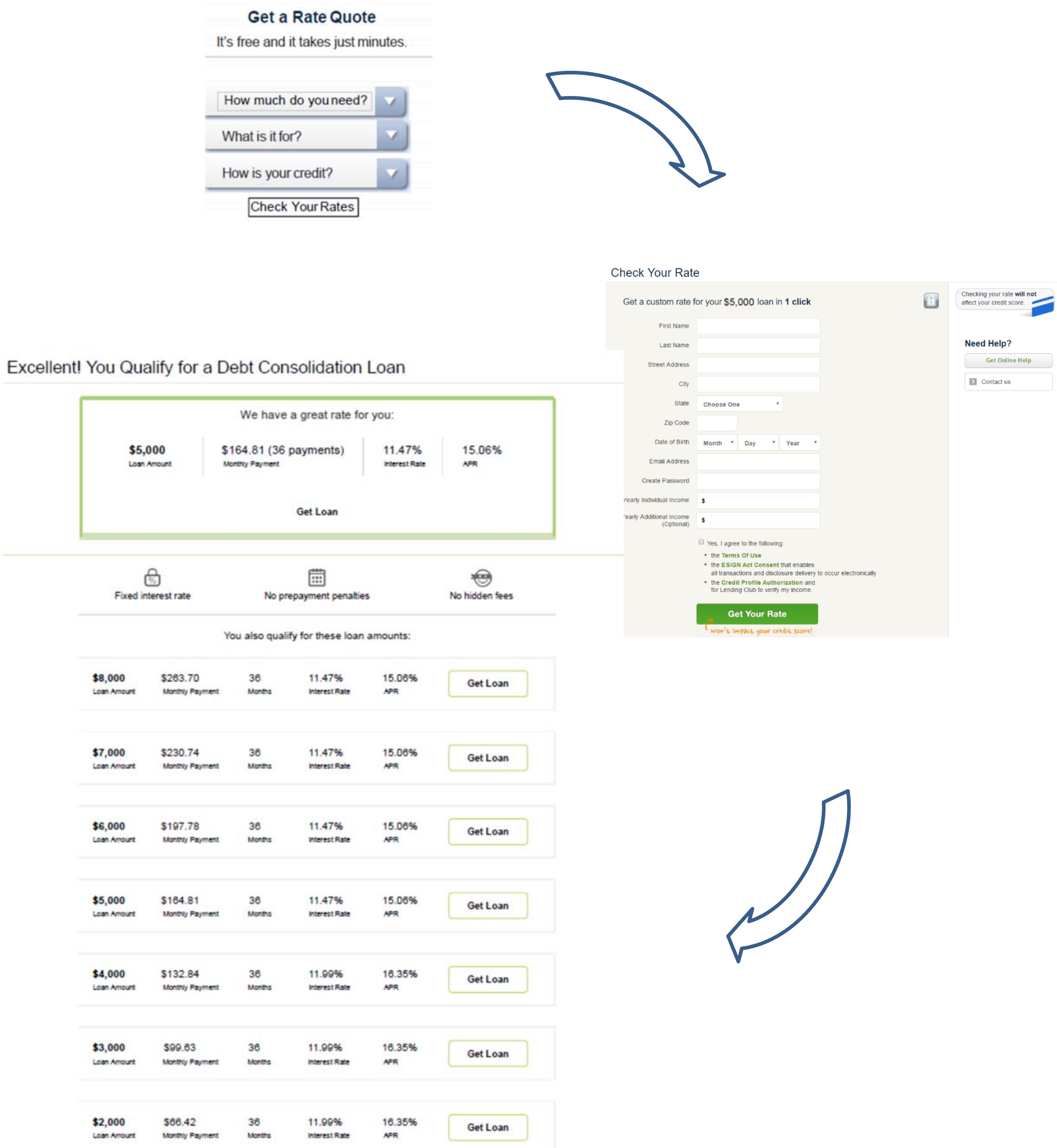
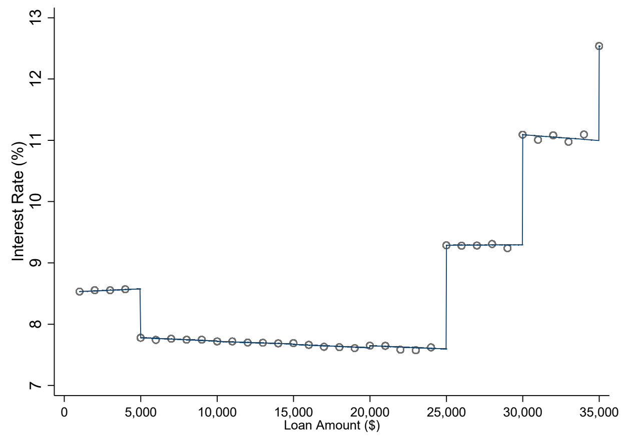


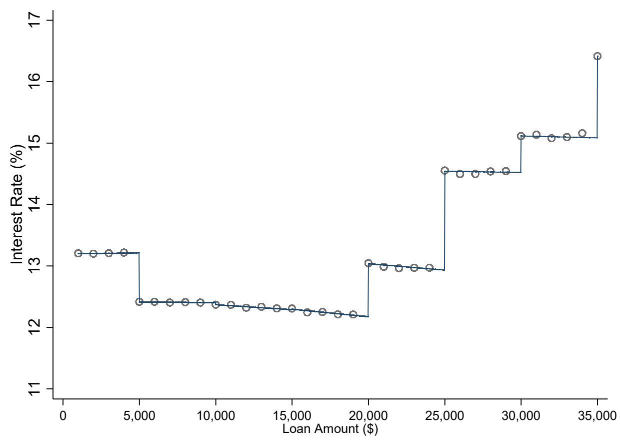
Figure 2 How Does Lending Club Work?

This figure depicts the process of a loan request through Lending Club. Loan applicants must provide the loan amount, the purpose of the loan, and other personal information that is used by Lending Club to pull their credit reports. In order to get an interest rate quote, applicants must have a FICO score over 660, a monthly debt to income ratio (DTI) below 30%, more than one year of continuous employment, and a minimum credit history of 36 months. If the applicant passes this initial credit screening criteria, he receives a quote for the amount entered along with six alternative loan amounts. Finally, borrowers can quote different loan amounts without affecting their credit scores.

Panel A: Interest Rate Relative to Loan Amount for Grade-A Borrowers



Panel B: Interest Rate Relative to Loan Amount for Grade-B Borrowers



Panel C: Interest Rate Relative to Loan Amount for Grades-C-E Borrowers

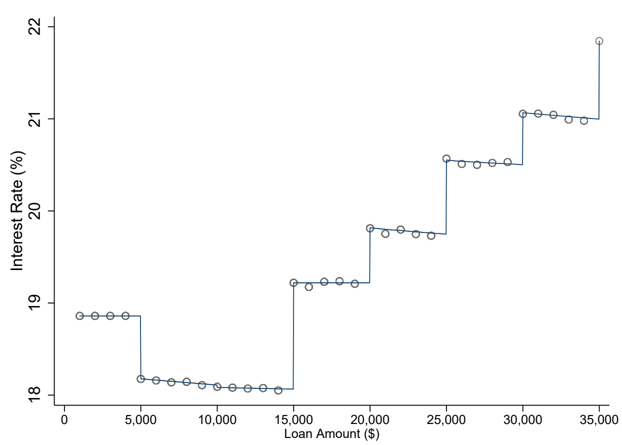
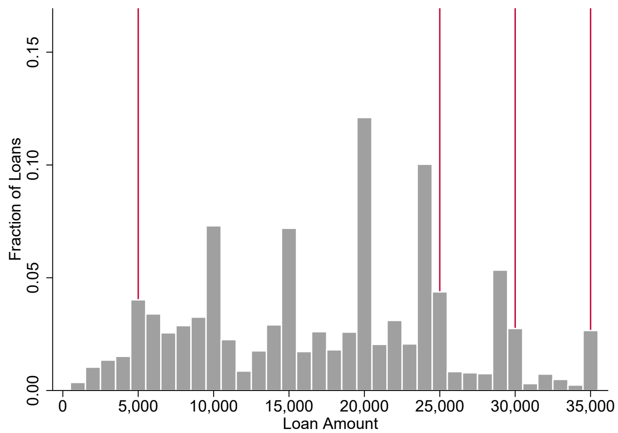


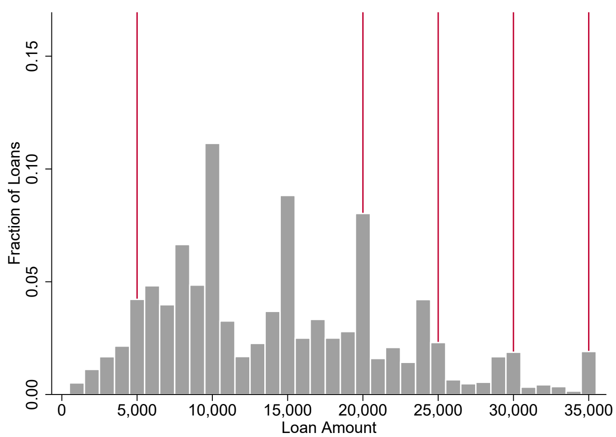
Figure 3 Interest Rate Changes at Notches by Grade

This figure plots the interest rate mean as a function of the loan amount after controlling for maturity term and initial sub-grade. Between December 2012 and October 2013, Lending Club offered publicly available notched interest schedules, in which interest rates featured discrete changes at specific loan amount thresholds. Grade-A borrowers have the highest creditworthiness based on their FICO scores, while Grades-C-E borrowers have the lowest creditworthiness. Each dot represents the average interest rate charged to borrowers within a given $1,000 bin. The solid lines are fitted values from a linear regression, allowing for changes in the slope at thresholds.

Panel A: Loan Amount Density for Grade-A Borrowers



Panel B: Loan Amount Density for Grade-B Borrowers



Panel C: Loan Amount Density for Grades-C-E Borrowers

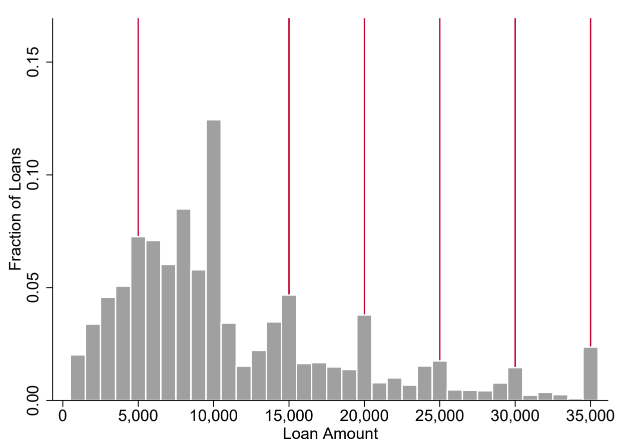
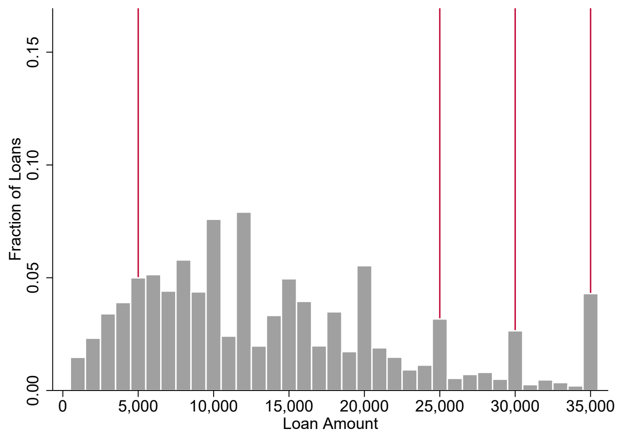


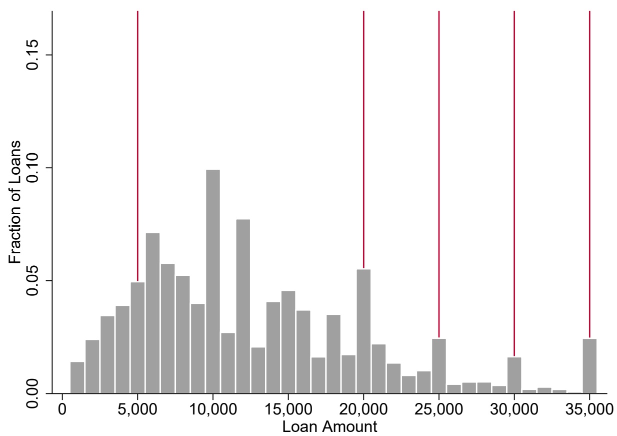
Figure 4 Loan Amount Density by Initial Grade After the Introduction of the Notches

This figure shows the loan amount distribution of all the loans originated between December 2012 and October 2013 by initial grade. The vertical axis indicates the fraction of loans in each $1,000-bin, for instance [24000, 25000), while the horizontal axis represents the loan amount. The solid red lines indicate where the interest rate changes.

Panel A: Loan Amount Density for Grade-A Borrowers



Panel B: Loan Amount Density for Grade-B Borrowers



Panel C: Loan Amount Density for Grades-C-E Borrowers

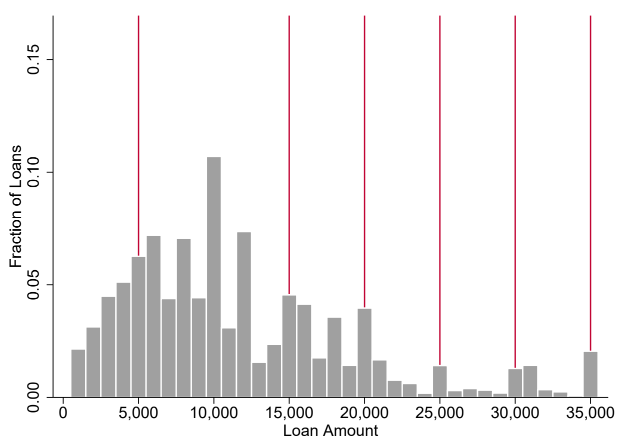
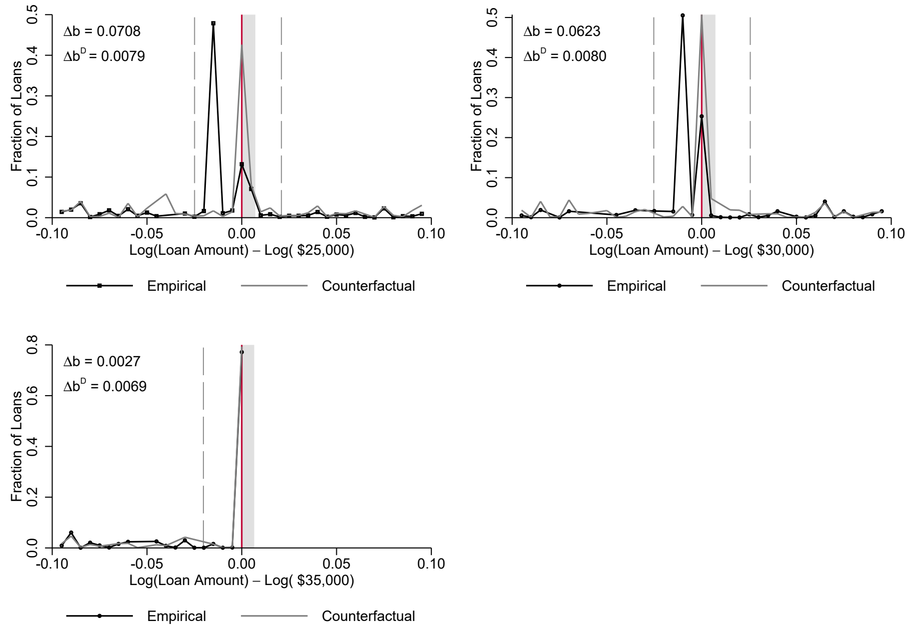


Figure 5 Loan Amount Density by Initial Grade Before the Introduction of the Notches

This figure shows the loan amount distribution of all the loans originated by grade before the introduction of the notched interest rate schedules, between November 2011 and November 2012. The vertical axis indicates the fraction of loans in each $1,000-bin, for instance [24000, 25000), while the horizontal axis represents the loan amount. The solid red lines indicate where the interest rate changes once the interest rate notches are introduced.

Panel A: Counterfactual Distributions for Grade-A Borrowers



Panel B: Counterfactual Distributions for Grade-B Borrowers

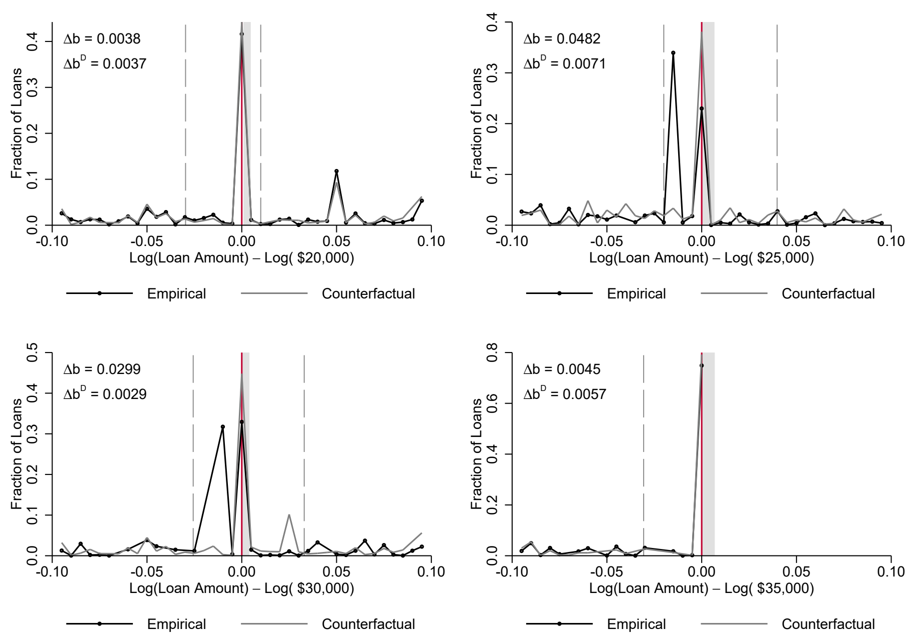


Figure 6 Bunching at Notches and Counterfactual Distributions

This figure plots the observed and counterfactual density of (log) loan amount relative to the (log) thresholds defined by Lending Club. The solid lines are the empirical densities. The gray solid lines are the estimated counterfactual densities obtained by using the proportion of loans around the same thresholds before the introduction of the notches (November 2011-November 2012). The vertical dashed lines represent the lower (b_l) and upper (b_u) limits of the excluded region, the area affected by the notch, whereas the shaded gray area delimits the dominated region. The vertical red line represents the notch in which the interest rate changes. b_l is set visually and b_u is chosen to minimize the difference between bunching and missing mass, following Kleven and Waseem (2013). $\triangle b$ denotes the estimate of the behavioral response, while $\triangle b^D$ corresponds to the dominated region. The bin-width is 0.5%.

Panel C: Counterfactual Distributions for Grades-C-E Borrowers

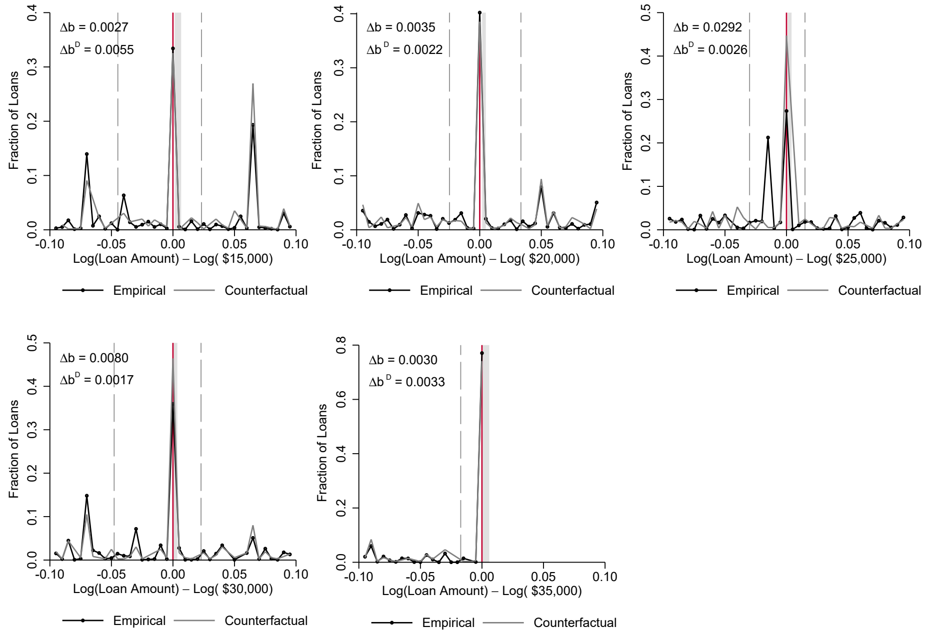


Figure 6 (continued)

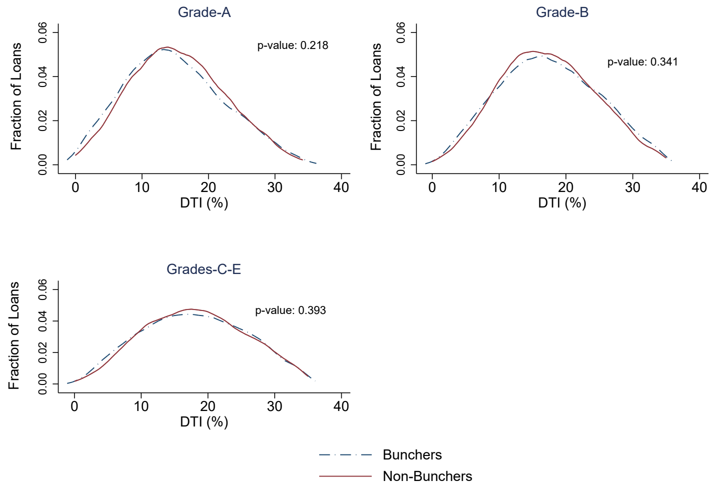
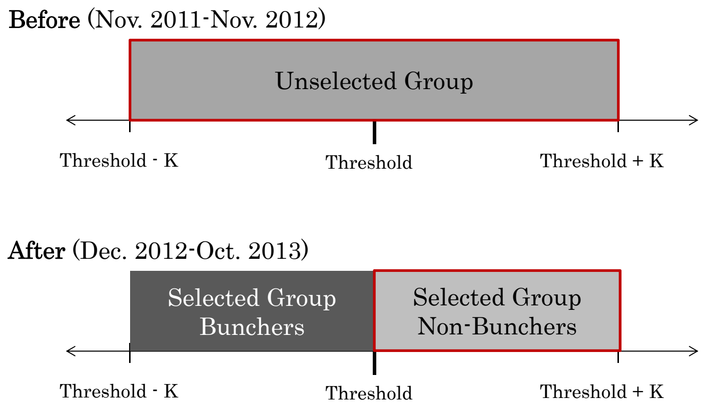


Figure 7 Liquidity Constraints Test

The figure shows the empirical distributions of the Debt to Income (DTI) ratio between bunchers, defined as those located at a maximum of \$1,000 below the notches, and non-bunchers, defined as those located at or at maximum of \$1,000 above the notches. The p-values reported correspond to the Kolmogorov-Smirnov test of the null hypothesis that the two distributions are equal.

Panel A: Main Empirical Design



Panel B: Alternative Empirical Design

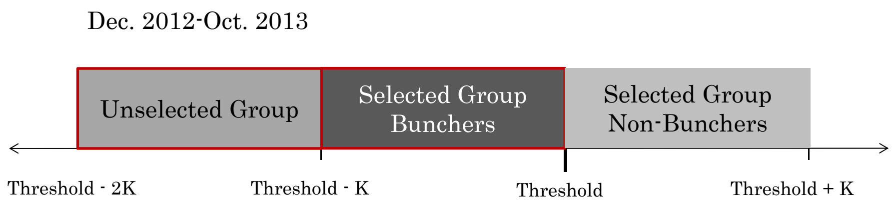


Figure 8 Empirical Designs to Identify the Effect of Selection on Loan Performance

These figures depict the empirical designs to capture the effect of selection on unobservables on default, based on Karlan and Zinman (2009). In Panel A. selection is identified by comparing the loan repayment for those who request a loan amount above the threshold after the introduction of the notch (*selected* into the non-bunching group) to the *unselected* group of borrowers who were not offered a notched interest option. Crucially, the interest rates between the *selected* and *unselected* group are not statistically different, and there are no differences in observable characteristics between individuals who request a loan before and after the introduction of the notch (as Table 5 reports). Thus, any difference in repayment between the two groups must be due to the selection induced by the notch (i.e., selection on unobservables). Panel B presents an alternative definition of the *selected* and *unselected* group.

Table 1 Summary Statistics

This table shows summary statistics of all the loans originated by Lending Club over the period December 2012 to October 2013, based on Lending Club's publicly available information and manually collected data from loan postings.

	All		Grade-A		Grade-B		Grades-C-E	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Annual Income ($)	72,482.39	55,820.74	94,441.84	72,883.93	71,863.53	57,442.52	62,975.71	39,537.27
FICO score	697.22	29.02	733.12	32.94	699.88	21.80	677.51	17.94
Maturity Term (months)	41.43	10.04	41.71	10.22	41.84	10.30	40.81	9.61
Months since first Credit Account	189.28	84.90	221.65	87.52	190.89	82.71	172.31	81.54
Default Rate (%)	14.21	35.42	6.12	23.97	12.19	32.71	20.35	40.26
Number of Open Accounts	11.07	4.60	11.78	4.77	11.17	4.49	10.63	4.60
Credit Card Utilization	66.96	25.83	46.52	25.59	67.44	23.05	76.03	25.58
Debt-to-Income (DTI %)	17.12	7.59	14.96	7.25	17.25	7.42	17.97	7.75
Total Inquiries last 6 months	0.78	1.03	0.49	0.85	0.61	0.91	1.12	1.15
Number of Credit Cards	9.07	4.81	10.60	5.13	9.35	4.68	8.04	4.56
Number of Credit Cards Inquiries last 6 months	1.76	1.51	1.36	1.31	1.55	1.38	2.18	1.62
Debt Consolidation (%)	83.41	37.12	85.04	35.67	90.27	29.64	74.67	43.49
Loan Prepayment (%)	54.70	49.76	55.87	49.87	53.24	49.89	55.87	49.65
Months Prepaid / Term (%)	47.36	25.69	44.97	25.07	46.88	25.21	49.04	26.56
Recoveries Net of Fees / PV Defaulted (%)	9.34	11.67	9.82	15.18	9.17	10.44	9.32	11.49
Time to Get Funded (days)	8.33	4.84	8.12	4.76	8.32	4.84	8.79	4.95
Number of Borrowers	106,170		18,790		47,063		40,317	

Table 2 Responsiveness of Borrowers to Interest Rate Changes

This table reports estimates of the interest rate elasticities of unsecured credit demand by grade and for a range of thresholds, as a measure for borrowers' responsiveness. The counterfactual densities are obtained by using the proportion of loans around the same thresholds before the introduction of the notches (November 2011-November 2012). Panel A presents the estimates pooling all thresholds (except for the $5,000) and grades, as well as by initial grades. $\triangle r$ is the average jump in the interest rate in percentage points. $\Delta\hat{b}$ is the percentage change in loan amount demanded, also known as behavioral response. $\Delta\hat{b}^D$corresponds to the dominated region in U.S. dollars. a^* is the fraction of non-optimizers in the dominated region. ϵ is the interest rate elasticity of unsecured credit demand, and ϵ_{adj} is the elasticity adjusted for frictions (counterfactual). Panel B shows the estimates for each threshold by initial grade. Standard errors are calculated using the delta method. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A						
Grade	$\triangle r$	$\Delta\hat{b}$	$\Delta\hat{b}^D$	a^*	ϵ	ϵ_{adj}
Overall	1.041***	0.0229***	119.02***	0.7318**	0.0972**	0.3644**
	(0.0691)	(0.0069)	(44.80)	(0.3390)	(0.0385)	(0.1603)
A	1.4811***	0.0555***	199.40***	0.4070**	0.2481***	0.4199***
	(0.0863)	(0.0171)	(73.12)	(0.1810)	(0.0836)	(0.1516)
B	1.0015***	0.0173***	114.78***	0.8377**	0.0586**	0.3589**
	(0.0593)	(0.0048)	(42.99)	(0.4069)	(0.0291)	(0.1673)
C-E	0.8013***	0.0073***	72.99***	0.9159**	0.0351**	0.3323**
	(0.0659)	(0.0023)	(28.37)	(0.4223)	(0.0167)	(0.1604)

Panel B						
Notch / Grade	A		B		C-E	
	ϵ	ϵ_{adj}	ϵ	ϵ_{adj}	ϵ	ϵ_{adj}
$15,000					0.0007**	0.2676**
					(0.0003)	(0.1302)
$20,000			0.0020**	0.3223**	0.0031**	0.3091**
			(0.0009)	(0.1568)	(0.0015)	(0.1485)
$25,000	0.3310***	0.4471***	0.1669*	0.4209*	0.1715**	0.4418**
	(0.1002)	(0.1355)	(0.0972)	(0.2259)	(0.0829)	(0.2036)
$30,000	0.2589**	0.4388**	0.1562**	0.4505**	0.0206**	0.4270**
	(0.1307)	(0.2161)	(0.0780)	(0.2220)	(0.0100)	(0.1932)
$35,000	0.0006**	0.3158**	0.0019**	0.3071**	0.0016*	0.3799*
	(0.0003)	(0.1574)	(0.0009)	(0.1545)	(0.0008)	(0.1951)

Table 3 How Much More Do Non-Bunchers Pay Relative to Bunchers?

This table shows the estimates of the average cost of demanding a loan amount at the threshold. Panel A presents the monthly cost of a loan amount just at the threshold rather than $25 below it. Panel B depicts the present value of the total cost of a loan at the cutoff. Panel C reports the marginal cost computed as the total cost (in Panel B) divided by $25.

Panel A	Monthly Cost A	Monthly Cost B	Monthly Cost C-E
$5,000	$1.59	$1.69	$1.30
$15,000			$9.35
$20,000		$8.68	$8.24
$25,000	$20.55	$12.91	$9.52
$30,000	$14.58	$10.89	$9.56
$35,000	$21.12	$13.04	$10.64
Panel B	Total Cost A	Total Cost B	Total Cost C-E
$5,000	$51.29	$51.39	$36.15
$15,000			$274.74
$20,000		$296.42	$274.28
$25,000	$773.42	$441.12	$320.24
$30,000	$517.82	$374.99	$329.28
$35,000	$720.08	$413.28	$383.47
Panel C	Marginal Cost A	Marginal Cost B	Marginal Cost C-E
$5,000	205%	206%	145%
$15,000			1099%
$20,000		1186%	1097%
$25,000	3094%	1764%	1281%
$30,000	2071%	1500%	1317%
$35,000	2880%	1653%	1534%

Table 4 Bunching and Borrowers' Characteristics

This table reports the estimates of bunching on a set of pre-origination characteristics for the period between December 2012 and October 2013. The dependent variable *Bunching* is an indicator variable equal to one if a loan amount is located at a maximum of $1,000 below the threshold and equal to zero at the threshold or a maximum of $1,000 above. The $5,000 threshold is excluded. $Percentage\,College\,Degree\,(3-ZIP)$ is the proportion of adults older than 25 with at least a college degree at the 3-digit zip-code level, according to the Census. $College\,Degree$ is an indicator variable equal to one if the borrower's job entry level education requirement is at least a bachelor's degree, according to the Bureau of Labor Statistics, and zero if it is lower. $Financial\,Services\,Industry$ is an indicator variable equal to one if the borrower works for a firm classified in the Financial Service Industry. $Debt\,Consolidation$ is a dummy variable equal to one if the borrower declares debt consolidation as the main purpose of the loan. $Financial\,Education\,Mandatory$ is an indicator variable equal to one if the borrower lives in a state in which high schools offer mandatory personal finance education. $Other\,Controls$ includes a dummy variable for home ownership and the number of months since the first borrower's account was open as proxy for age. Panel A presents the main specification in Column 1. Columns 2 and 3 report the estimates using $College\,Degree$ and $Financial\,Services\,Industry$, respectively. Columns 4-6 show the results across grades. Panel B Column 1 reports the estimates for the main specification when $Financial\,Education\,Mandatory$ is included. In Column 2, $FICO\,Score$ is excluded. Column 3 shows the results for a more restricted bandwidth: loans between a maximum of $250 below the threshold and within the dominated region (DR) above the cutoff.Column 4 considers all the loans originated, including the $5,000. For the $5,000 threshold, the dependent variable is an indicator equal to one if a loan amount is located at or at a maximum of $1,000 above and equal to zero at a maximum of $1,000 below. Column 5 reports the estimates at pseudo thresholds. Pseudo thresholds are set $3,000 below the real cutoffs (i.e, $12,000, $17,000, $22,000, $27,000, and $32,000). Threshold by initial sub-grade by month fixed effects, term and state fixed effects are included. The continuous variables are standardized. Robust standard errors are in parentheses, clustered at threshold by initial sub-grade level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Bunching					
Initial Grade	All	All	All	A	B	C-E
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Annual Income	0.0618***	0.0603***	0.0605***	0.0106*	0.0844***	0.0579***
	(0.0150)	(0.0141)	(0.0139)	(0.0061)	(0.0067)	(0.0056)
FICO score	0.0074**	0.0043*	0.0059*	0.0068*	0.0099**	0.0051***
	(0.0029)	(0.0023)	(0.0029)	(0.0036)	(0.0049)	(0.0016)
Proportion College Degree (3-Zip)	0.0462*			0.0693**	0.0557*	0.0261*
	(0.0265)			(0.0304)	(0.0312)	(0.0136)
College Degree		0.0337*				
		(0.0174)				
Financial Services Industry			0.0171**			
			(0.0075)			
Debt-to-Income	0.0027	0.0032	0.0004	0.0048	0.0013	0.0039
	(0.0025)	(0.0077)	(0.0069)	(0.0068)	(0.0041)	(0.0037)
Ln Number Inquiries Last 6 months	0.0013	0.0088	0.0085	0.0007	-0.0012	0.0057
	(0.0026)	(0.0069)	(0.0074)	(0.0067)	(0.0036)	(0.0043)
Credit Card Utilization	0.0010	0.0152	0.0189	0.0001	0.0025	0.0014
	(0.0031)	(0.0099)	(0.0120)	(0.0078)	(0.0048)	(0.0045)
Debt Consolidation	0.0138**	0.0136*	0.0117**	0.0163	0.0171*	0.0192*
	(0.0068)	(0.0080)	(0.0055)	(0.0169)	(0.0100)	(0.0102)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Threshold x Ini. Sub-Grade x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,457	6,191	30,214	5,614	16,331	14,512
R-squared	0.257	0.365	0.273	0.292	0.236	0.267

Table 4 (continued)

Panel B	Bunching				
	(1)	(2)	(3)	(4)	(5)
Ln Annual Income	0.0560***	0.0618***	0.0751***	0.0932***	0.0002
	(0.0145)	(0.0042)	(0.0045)	(0.0045)	(0.0039)
FICO Score	0.0075**		0.0041*	0.0075**	0.0005
	(0.0033)		(0.0020)	(0.0033)	(0.0026)
Proportion College Degree (3-Zip)	0.0419**	0.0411**	0.0602**	0.0288*	0.0002
	(0.0173)	(0.0201)	(0.0272)	(0.0149)	(0.0014)
Financial Education Mandatory	0.0287**				
	(0.0131)				
Debt-to-Income	0.0006	0.0029	0.0008	0.0007	0.0003
	(0.0024)	(0.0025)	(0.0033)	(0.0024)	(0.0016)
Ln Number Inquiries Last 6 Months	0.0019	0.0011	0.0040	0.0019	-0.0009
	(0.0025)	(0.0026)	(0.0032)	(0.0025)	(0.0015)
Credit Card Utilization	0.0013	0.0021	0.0041	0.0013	0.0013
	(0.0029)	(0.0029)	(0.0040)	(0.0029)	(0.0017)
Debt Consolidation	0.0191***	0.0123*	0.0135	0.0095	0.0002
	(0.0068)	(0.0066)	(0.0096)	(0.0068)	(0.0047)
Other Controls	Yes	Yes	Yes	Yes	Yes
Threshold x Ini. Sub-Grade x Month FE	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes
Sample: Loan Amount (USD)	>6,000	>6,000	>6,000	>1,000	Pseudo Thresholds
Bandwidth (USD)	1,000	1,000	[-250, DR]	1,000	1,000
Observations	36,457	36,457	25,371	44,230	17,239
R-squared	0.314	0.284	0.152	0.189	0.147

Table 5 Differences in Characteristics and Contract Terms

This table presents the results of the tests for the identifying assumptions of the empirical design depicted in Figure 8. The first assumption is whether borrowers are observationally equivalent in terms of characteristics at origination before and after the introduction of the notches. The second assumption is whether borrowers in the treatment group (i.e., Non-Bunchers in the selected group) and control group (i.e, unselected group) face the same interest rate. *Post* is an indicator variable equal to one if the loan is originated between December 2012 and October 2013 and equal to zero for the period between November 2011 and November 2012. *Non-Bunching* (Selected v. Unselected) is an indicator variable equal to one if the loan amount is at the threshold or a maximum of $1,000 above and if the borrower asks for the loan between December 2012 and October 2013, and zero if the loan amount is located at a maximum of $1,000 above and below the same threshold and the borrower requests the loan between November 2011 and November 2012. Column 1 of Panel A presents the estimates for the main set of covariates at origination, and Column 2 shows the results for a more comprehensive set of characteristics. The p-value is for an F-test of the joint significance of the difference in characteristics at origination. Panel B provides the estimate for the difference in terms of interest rate between the loans in the non-bunching group (selected) and the unselected group. Robust standard errors are in parentheses, clustered at threshold by 4-bin FICO score. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Post	
	(1)	(2)
Ln Annual Income	0.0011	0.0015
	(0.0017)	(0.0023)
Proportion College Degree (3-Zip)	0.0180	0.0105
	(0.0164)	(0.0242)
Debt-to-Income	-0.0006	-0.0002
	(0.0013)	(0.0058)
Ln Number Inquiries Last 6 Months	0.0001	0.0004
	(0.0017)	(0.0022)
Credit Card Utilization	0.0016	0.0015
	(0.0023)	(0.0030)
Debt Consolidation	0.0029	0.0017
	(0.0031)	(0.0050)
Ln Employment length		0.0026
		(0.0018)
Home Mortgage		0.0017
		(0.0028)
Ln Open Accounts Ever		0.0001
		(0.0014)
Ln Months since Most Recent Lowest FICO		0.0003
		(0.0005)
Threshold x 4-bin FICO FE	Yes	Yes
State FE	Yes	Yes
Term FE	Yes	Yes
Quarter of Origination FE	Yes	Yes
Joint F-Test	[0.692]	[0.855]
Observations	53,107	53,107
R-squared	0.879	0.888

Panel B	Non-bunching (Selected v. Unselected)
	(1)
Interest Rates	-0.2352
	(0.3066)
Threshold x 4-bin FICO FE	Yes
State FE	Yes
Term FE	Yes
Quarter of Origination FE	Yes
Observations	46,642
R-squared	0.706

Table 6 Borrowers' Credit Decisions and Default

This table reports the default rate of borrowers who self-select into the *non-bunching* group by requesting a loan amount at the threshold or $1,000 above between December 2012 and October 2013, relative to borrowers who did not face a notched interest schedule between November 2011 and November 2012 and who asked for a loan amount $1,000 above and below the same threshold (see empirical design in Figure 8). The $5,000 threshold is excluded. The dependent variable is $Default$, a dummy equal to one if the loan is charged-off. *Non-Bunching* (Selected v. Unselected) is an indicator variable equal to one if the loan amount is at the threshold or a maximum of $1,000 above and if the borrower asks for the loan between December 2012 and October 2013, and zero if the loan amount is located at a maximum of $1,000 above and below the same threshold and the borrower requests the loan between November 2011 and November 2012. Panel A Column 1 reports the estimates without controls. Column 2 presents the estimates for the main specification, which includes a total of 50 covariates at origination. Columns 3-5 report the estimates with covariates across grades. Panel B Column 1 reports the estimates for the main specification for the period October 2012 and January 2013. Column 2 reports the estimates for a more restricted bandwidth: loans between a maximum of $250 below the threshold and within the dominated region (DR) above the cutoff. Column 3 presents the estimates for the sub-sample of 36-month loans. Column 4 presents the estimates for the main specification excluding borrowers who default just after their loans are funded (t=0). Additional covariates reported by LC at origination are also included. Threshold by 4-bin FICO score, quarter of origination, term and state fixed effects are included. The continuous variables are standardized. Robust standard errors are in parentheses, clustered at threshold by 4-bin FICO score. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A			Default		
Initial Grades	All	All	A	B	C-E
	(1)	(2)	(3)	(4)	(5)
Non-bunching (Selected v. Unselected)	0.0321***	0.0289**	0.0132*	0.0246*	0.0476**
	(0.0141)	(0.0140)	(0.0069)	(0.0141)	(0.0203)
Ln Annual Income		-0.0395***	-0.0252***	-0.0424***	-0.0515***
		(0.0030)	(0.0044)	(0.0049)	(0.0072)
Proportion College Degree (3-Zip)		-0.0041*	-0.0035	-0.0079**	-0.0007
		(0.0024)	(0.0042)	(0.0033)	(0.0049)
Debt-to-Income		0.0111***	-0.0002	0.0084**	0.0195***
		(0.0026)	(0.0041)	(0.0036)	(0.0048)
Ln Number Inquiries Last 6 Months		0.0106***	0.0120***	0.0121***	0.0076*
		(0.0022)	(0.0043)	(0.0034)	(0.0039)
Credit Card Utilization		0.0072**	0.0084*	0.0021	0.0126**
		(0.0033)	(0.0045)	(0.0051)	(0.0062)
Debt Consolidation		-0.0272***	-0.0229**	-0.0243***	-0.0319**
		(0.0059)	(0.0090)	(0.0073)	(0.0128)
Additional Controls (44 characteristics)	No	Yes	Yes	Yes	Yes
Threshold x 4-bin FICO FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes
Quarter of Origination FE	Yes	Yes	Yes	Yes	Yes
Observations	46,642	46,642	10,834	20,187	15,621
R-squared	0.041	0.058	0.042	0.043	0.037

Table 6 (continued)

Panel B	Default			
	(1)	(2)	(3)	(4)
Non-Bunching (Selected v. Unselected)	0.0231*	0.0311**	0.0245**	0.0227***
	(0.0126)	(0.0129)	(0.0123)	(0.0079)
Initial Grades	All	All	All	All
Controls (50 characteristics)	Yes	Yes	Yes	Yes
Threshold x 4-bin FICO FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Quarter of Origination FE	Yes	Yes	Yes	Yes
Loan Maturity	All	All	36-month	All
Sample Period:	Oct. 2012-Jan. 2013	Main	Main	Main
Bandwidth (USD)	1,000	[-250, DR]	1,000	1,000
Observations	5,873	33,927	38,763	44,945
R-squared	0.034	0.062	0.053	0.049

Table 7 Loan Rejections and Borrowers' Characteristics

This table reports estimates of loan rejections and borrowers' characteristics. *Bunching* is an indicator variable equal to one if a loan amount is located at a maximum of $1,000 below the threshold and equal to zero at the threshold or a maximum of $1,000 above. *Rejections Post* is an indicator variable equal to one if the loan is rejected between December 2012 and October 2013 and zero if the rejection is between November 2011 and November 2012. *Rejections* is an indicator variable equal to one if the loan is rejected between December 2012 and October 2013 *and* the borrower has a FICO score greater than 660, a DTI lower than 30%, and the employment length is longer than one year.

	Rejections Post	Rejections
	(1)	(2)
Bunching		-0.0059
		(0.0041)
FICO score	-0.0000	-0.0001
	(0.00000)	(0.00001)
DTI	-0.0000	0.0000***
	(0.00000)	(0.00000)
Ln Employment Length	0.0003	-0.0998***
	(0.00085)	(0.00229)
Observations	1,000,754	132,313
R-squared	0.01	0.347

Table 8 Borrowers' Credit Decisions and the Probability of Being Funded by an Institutional Lender

This table reports the changes on the probability of being funded by a sole lender (as a proxy for Institutional Lender) when the notched interest schedules were introduced in December 2012. *Sole Lender* is an indicator variable equal to one if the loan is funded by a single lender and zero otherwise. *Non-Bunching* is an indicator variable equal to one if the loan amount is at the threshold or a maximum of $1,000 above, and zero if the loan amount is located at a maximum of $1,000 below. The $5,000 is excluded. *Post* is an indicator variable equal to one if the loan was originated between December 2012 and October 2013, and equal to zero for the period between November 2011 and November 2012. The sample is restricted to loans initially listed as "whole," since only for this pool is possible to differentiate between institutional and retail lenders. Panel A Column 1 presents the estimates without pre-treatment covariates, while in Column 2, the complete set of controls are included. Columns 3-5 report the estimates by grade. Panel B provides estimates of a subset of the models, augmented with leads and lags of the introduction of the notches. Panel C Column 1 presents the estimates for the (ln) number of lenders funding each loan. After being approved, loan applications are posted on LC's website for at least 14 days (first round). Column 2 reports the results for the probability of being funded after the first round. Column 3 provides the estimates for the (ln) number of days taken to get funded for the sub-sample of loans with non-verified income. Threshold by 4-bin FICO score, state, term, and month of origination fixed effects are included. The continuous variables are standardized. Additional covariates reported by LC at origination are also included. Robust standard errors are in parentheses, clustered at threshold by 4-bin FICO score are included. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Sole Lender				
Initial Grades	All	All	A	B	C-E
	(1)	(2)	(3)	(4)	(5)
Non-Bunching	0.0387*	0.0355*	0.0509	0.0286*	0.0394**
	(0.0228)	(0.0186)	(0.0371)	(0.0153)	(0.0197)
Non-Bunching x Post	-0.1126***	-0.1114***	-0.1051	-0.1069**	-0.1262***
	(0.0419)	(0.0402)	(0.0817)	(0.0496)	(0.0482)
Ln Annual Income		0.0236***	0.0079	0.0174**	0.0352***
		(0.0074)	(0.0143)	(0.0081)	(0.0113)
Proportion College Degree (3-Zip)		0.1229**	0.1474	0.1057**	0.1586*
		(0.0606)	(0.1314)	(0.0525)	(0.0956)
Debt-to-Income		-0.0072	-0.0169	-0.0018	-0.0067
		(0.0060)	(0.0127)	(0.0083)	(0.0084)
Ln Number Inquiries Last 6 Months		-0.0320***	-0.0214*	-0.0286***	-0.0219***
		(0.0065)	(0.0120)	(0.0079)	(0.0076)
Credit Card Utilization		-0.0004	-0.0244	-0.0145	-0.0044
		(0.0072)	(0.0149)	(0.0097)	(0.0098)
Debt Consolidation		0.0404**	0.0303	0.0029	0.0527***
		(0.0169)	(0.0334)	(0.0267)	(0.0171)
Additional Controls (44 characteristics)	No	Yes	Yes	Yes	Yes
Threshold x 4-bin FICO FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes
Month of Origination FE	Yes	Yes	Yes	Yes	Yes
Observations	11,791	11,791	1,967	5,195	4,629
R-squared	0.115	0.131	0.115	0.101	0.166

Table 8 (continued)

Panel B	Sole Lender
	(1)
Non-Bunching$_{t-2}$	0.0347
	(0.0218)
Non-Bunching$_{t-1}$	0.0249
	(0.0152)
Non-Bunching$_0$	-0.0573**
	(0.0269)
Non-Bunching$_{t+1}$	-0.0939***
	(0.0321)
Non-Bunching$_{t+2}$	-0.1277***
	(0.0483)
Non-Bunching$_{t+3}$	-0.1016***
	(0.0310)
Non-Bunching$_{t+4\,forward}$	-0.1211**
	(0.0498)
Controls (50 characteristics)	Yes
Threshold x 4-bin FICO FE	Yes
State FE	Yes
Term FE	Yes
Month of Origination FE	Yes
Observations	11,791
R-squared	0.157

Panel C	Ln (Number of Lenders)	# of Days >14	Ln (Number of Days)
	(1)	(2)	(3)
Non-Bunching	-0.7874**	0.0166	0.0061
	(0.4608)	(0.0143)	(0.0053)
Non-Bunching x Post	0.8931***	0.0335***	0.3547***
	(0.1279)	(0.0047)	(0.0627)
Controls (50 characteristics)	Yes	Yes	Yes
Threshold x 4-bin FICO FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Term FE	Yes	Yes	Yes
Month of Origination FE	Yes	Yes	Yes
Observations	53,107	53,107	12,902
R-squared	0.145	0.052	0.043

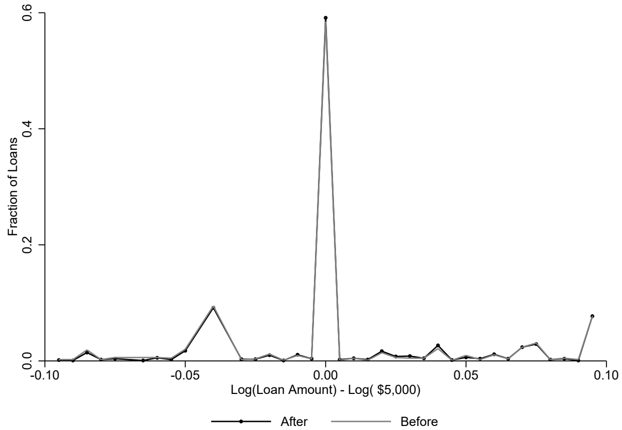
Table 9 Borrowers' Credit Decisions: Robustness Checks

This table reports the estimates for the alternative empirical design depicted in Figure 8 Panel B. *Bunching (Selected v. Unselected)* is an indicator variable equal to one for borrowers who self-select as *bunchers* by requesting a loan amount at the most $1,000 below the threshold and zero for borrowers whose loan size is between $1,025 and $2,000 below the cutoff between December 2012 and October 2013. The $5,000 threshold is excluded. In Columns 1 and 2 the dependent variable is *Default*, a dummy variable equal to one if the loan is charged-off. The dependent variable for Columns 3 and 4 is *Sole Lender*, an indicator variable equal to one if the loan is funded by a single lender (as a proxy for Institutional Lender) and zero otherwise, in the sample of loans initially listed as "whole." *Post* is an indicator variable equal to one if the loan was originated between December 2012 and October 2013 and equal to zero for the period between November 2011 and November 2012. Columns 1 and 3 report the estimates without controls. Columns 2 and 4 include a total of 50 covariates at origination. The continuous variables are standardized. Robust standard errors are in parentheses, clustered at threshold by initial grade in Columns 1 and 2, and threshold by 4-bin FICO score in Columns 3 and 4. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

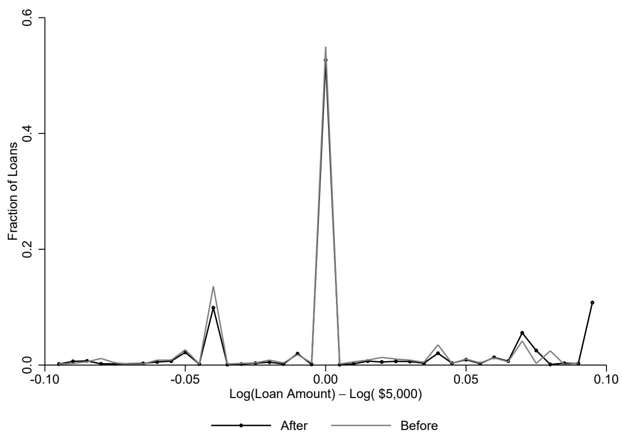
	Default		Sole Lender	
	(1)	(2)	(3)	(4)
Bunching (Selected v. Unselected)	-0.0213**	-0.0199**	0.0088	0.0095
	(0.0092)	(0.0089)	(0.0083)	(0.0082)
Bunching (Selected v. Unselected) x Post			0.0743***	0.0764***
			(0.0241)	(0.0242)
Controls (50 characteristics)	No	Yes	No	Yes
Threshold x Ini. Sub-Grade x Month FE	Yes	Yes	No	No
Threshold x 4-bin FICO FE	No	No	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month of Origination FE	No	No	Yes	Yes
Observations	22,169	22,169	6,104	6,104
R-squared	0.104	0.104	0.055	0.057

Appendix

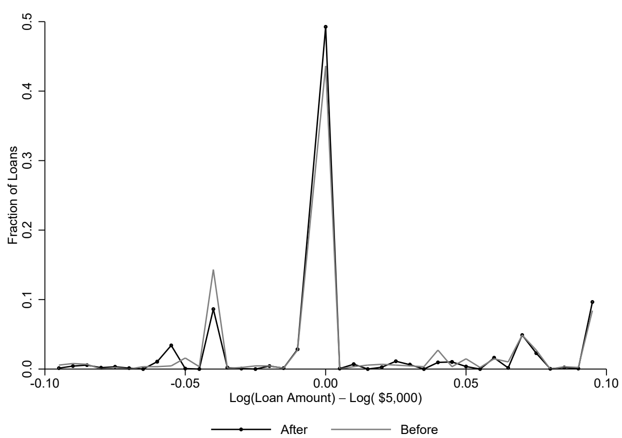
Panel A: Distributions for Grade-A Borrowers



Panel B: Distributions for Grade-B Borrowers



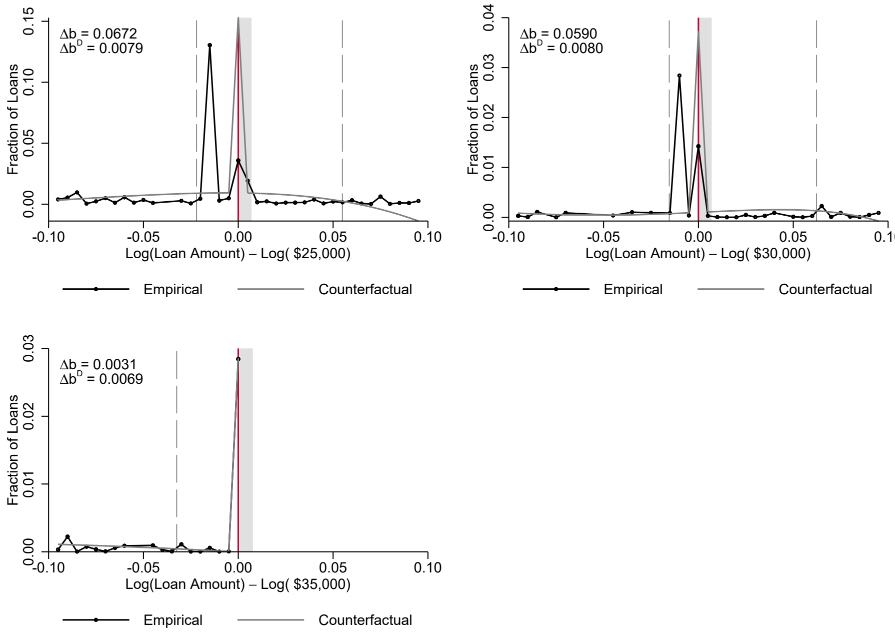
Panel C: Distributions for Grades-C-E Borrowers



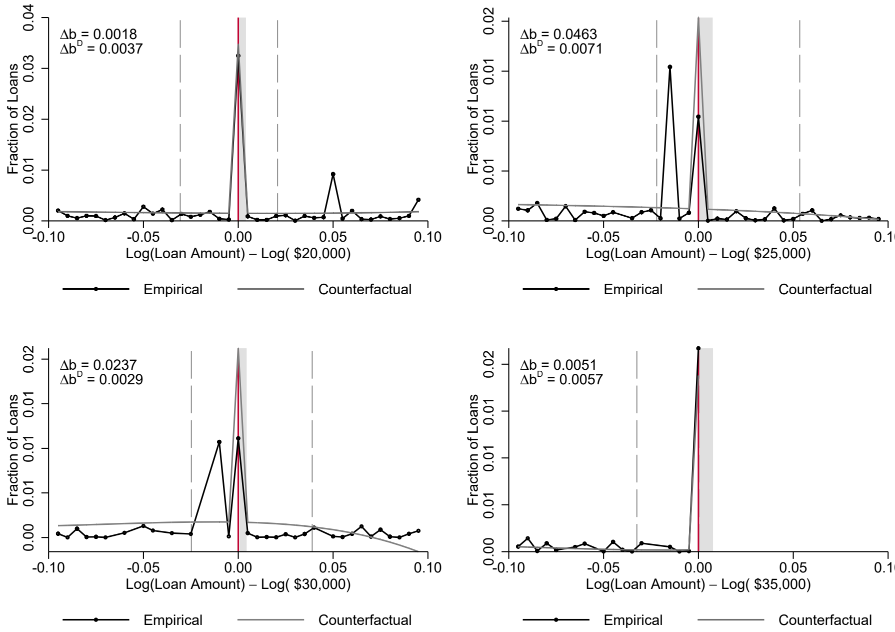
Appendix Figure 1 Loan amount Distributions by Initial Grade at the $5,000 threshold

This figure plots the empirical density ("After," between December 2012 and October 2013) and counterfactual density ("Before," between November 2011 and November 2012) around the $5,000 threshold. The estimated counterfactual densities are obtained by using the proportion of loans around the same thresholds before the introduction of the notches (November 2011-November 2012). The bin-width is 0.5%. For both periods the interest rate drops at $5,000.

Panel A: Counterfactual Distributions for Grade-A Borrowers



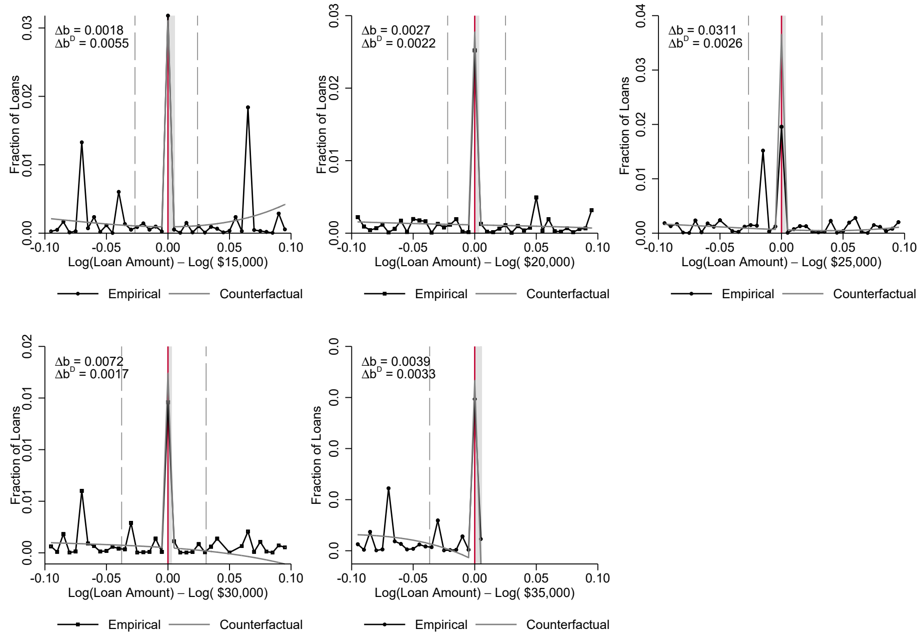
Panel B: Counterfactual Distributions for Grade-B Borrowers



Appendix Figure 2 Counterfactual Distributions Estimated by Fitting a Polynomial

These figures plot the observed and counterfactual densities of (log) loan amount relative to the (log) thresholds defined by Lending Club. The solid lines are the empirical densities. The gray solid lines are the estimated counterfactual densities obtained by fitting a 5th degree polynomial to the bin counts (bin-width 0.5%), omitting the contribution of the bins in the region marked by the vertical dashed gray lines. The vertical dashed lines represent the lower (b_l) and upper (b_u) limits of the excluded region, the area affected by the notch, whereas the shaded gray area delimits the dominated region. The vertical red lines represent the notch in which the interest rate changes. b_l is set visually, and b_u is chosen to minimize the difference between bunching and missing mass, following Kleven and Waseem (2013). $\triangle b$ denotes the estimate of the behavioral response, while $\triangle b^D$ corresponds to the dominated region. The bin-width is 0.5%.

Panel C: Counterfactual Distributions for Grades-C-E Borrowers



Appendix Figure 2 (continued)

Appendix Table 1 How Does Lending Club Set Interest Rate?

This table shows how Lending Club sets the interest rates between December 2012 and October 2013. This information was available on Lending Club's page titled "Interest Rates and How We Set Them." Panel A presents the interest rates based on the final sub-grade (i.e., after all the risk modifiers). Panel B shows the initial sub-grade rank. Panel C describes the different loan amount notches by grades, while Panel D shows the loan term modifiers. For instance, if a borrower is assigned an initial sub-grade of A3 and requests a $25,000 loan with a 36-month maturity, then the loan amount modifier will be "2" and the loan term modifier "0." His sub-grade will fall two notches from A3 to A5, and his interest rate will be 8.9%. However, if the same borrower asks for $25 less, or $24,975 rather than $25,000, there would be no loan amount modifier, and the interest rate would be 7.62%.

Panel A: Final Grades

Loan Grade	Sub-Grade	Lending Club Base Rate	Adjustment for Risk & Volatility	Interest Rate
A	1	5.05%	0.98%	6.03%
	2	5.05%	1.57%	6.62%
	3	5.05%	2.57%	7.62%
	4	5.05%	2.85%	7.90%
	5	5.05%	3.85%	8.90%
B	1	5.05%	5.11%	10.16%
	2	5.05%	6.09%	11.14%
	3	5.05%	7.07%	12.12%
	4	5.05%	8.06%	13.11%
	5	5.05%	9.04%	14.09%
C	1	5.05%	9.28%	14.33%
	2	5.05%	10.26%	15.31%
	3	5.05%	10.75%	15.80%
	4	5.05%	11.24%	16.29%
	5	5.05%	12.22%	17.27%
D	1	5.05%	12.72%	17.77%
	2	5.05%	13.44%	18.49%
	3	5.05%	13.70%	18.75%
	4	5.05%	14.00%	19.05%
	5	5.05%	14.67%	19.72%
E	1	5.05%	15.44%	20.49%
	2	5.05%	15.95%	21.00%
	3	5.05%	16.44%	21.49%
	4	5.05%	16.93%	21.98%
	5	5.05%	17.42%	22.47%
F	1	5.05%	17.90%	22.95%
	2	5.05%	18.23%	23.28%
	3	5.05%	18.58%	23.63%
	4	5.05%	18.71%	23.76%
	5	5.05%	18.78%	23.83%
G	1	5.05%	19.65%	24.70%
	2	5.05%	19.78%	24.83%
	3	5.05%	19.84%	24.89%
	4	5.05%	19.84%	24.89%
	5	5.05%	19.84%	24.89%

Appendix Table 1 (continued)

Panel B: Initial Loan Sub-Grade Assignment

Model Rank	Base Risk Sub-Grade
1	A1
2	A2
3	A3
4	A4
5	A5
6	B1
7	B2
8	B3
9	B4
10	B5
11	C1
12	C2
13	C3
14	C4
15	C5
16	D1
17	D2
18	D3
19	D4
20	D5
21	E1
22	E2
23	E3
24	E4
25	E5

Panel C: Requested Loan Amount Modifier by Base Risk Grade

Requested Loan Amount	A	B	C-E
<$5,000	-1	-1	-1
$5,000 - <$10,000	0	0	0
$10,000 - <$15,000	0	0	0
$15,000 - <$20,000	0	0	-2
$20,000 - <$25,000	0	-1	-3
$25,000 - <$30,000	-2	-3	-4
$30,000 - <$35,000	-4	-4	-5
$35,000	-6	-6	-6

Panel D: Loan Term Modifier

Loan Term (Maturity)	Loan Grade	Risk Modifier
36 months	A - E	0
60 months	A	-4
60 months	B	-5
60 months	C - E	-8

Appendix Table 2 Interest Rate Relative to Loan Amount

This table shows the jump in the interest rate (in percentage points) at each loan amount threshold by grade, estimated in a $1,000 bandwidth around each cutoff.

Jump in the Interest Rate			
Threshold	Grade-A	Grade-B	Grade-C-E
$5,000	-0.8537***	-0.8125***	-0.6974***
	(0.1292)	(0.0897)	(0.0426)
$10,000	0.0042	-0.0086	0.0247
	(0.0105)	(0.0064)	(0.0185)
$15,000	-0.0222	0.0067	1.2053***
	(0.0520)	(0.0199)	(0.0747)
$20,000	0.0401	0.8001***	0.5303***
	(0.0481)	(0.0558)	(0.0467)
$25,000	1.5237***	1.5031***	0.6782***
	(0.0667)	(0.0345)	(0.0622)
$30,000	1.5421***	0.7774***	0.4227***
	(0.1173)	(0.1035)	(0.1081)
$35,000	1.2702***	1.2239***	0.8142***
	(0.1291)	(0.1323)	(0.1246)

Appendix Table 3 Robustness of Elasticity Estimates

This table reports estimates of the interest rate elasticities of unsecured credit demand by grade and for a range of thresholds. The counterfactual densities are obtained by fitting a 5th order polynomial. Panel A presents the estimates pooling all thresholds (except for the $5,000) and grades, as well as by initial grades. $\triangle r$ is the average jump in the interest rate in percentage points. $\Delta\hat{b}$ is percentage change of the loan amount demanded, also known as the behavioral response. $\Delta\hat{b}^D$corresponds to the dominated region in U.S. dollars. a^* is the fraction of non-optimizers in the dominated region. ϵ is the interest rate elasticity of unsecured credit demand, and ϵ_{adj} is the elasticity adjusted for frictions. Panels B and C show the estimates to a different polynomial (7th order) and bin-width (0.025%), which are the two key free parameters needed for the elasticity estimation. Standard errors are calculated using the delta method. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Counterfactual: 5th Order Polynomial					
Grade	$\triangle r$	$\Delta\hat{b}$	$\Delta\hat{b}^D$	a^*	ϵ	ϵ_{adj}
Overall	1.041***	0.0229***	119.03***	0.7256**	0.0917**	0.3448**
	(0.0691)	(0.0069)	(38.20)	(0.3055)	(0.0362)	(0.1561)
A	1.4811***	0.0555***	199.40***	0.3739**	0.2464***	0.3953***
	(0.0863)	(0.0171)	(59.90)	(0.1684)	(0.0827)	(0.1427)
B	1.0015***	0.0173***	114.78***	0.8566**	0.0478**	0.3324**
	(0.0593)	(0.0048)	(37.90)	(0.4142)	(0.0232)	(0.1641)
C-E	0.8013***	0.0073***	72.99***	0.9062**	0.0305**	0.3235**
	(0.0659)	(0.0023)	(24.62)	(0.4178)	(0.0153)	(0.1581)

Panel B	Counterfactual: 7th Order Polynomial			
Grade	$\Delta\hat{b}$	a^*	ϵ	ϵ_{adj}
Overall	0.0239***	0.6986**	0.0902**	0.3142**
	(0.0072)	(0.2989)	(0.0356)	(0.1422)
A	0.0513***	0.3468**	0.2281***	0.3491***
	(0.0158)	(0.1562)	(0.0766)	(0.1261)
B	0.0184***	0.7654**	0.0469**	0.1998**
	(0.0051)	(0.3701)	(0.0227)	(0.0986)
C-E	0.0083***	0.9717**	0.0337**	0.4432**
	(0.0026)	(0.3939)	(0.0151)	(0.2167)

Panel C	Bin-with 0.025%			
Grade	$\Delta\hat{b}$	a^*	ϵ	ϵ_{adj}
Overall	0.0249**	0.7434**	0.0939**	0.3092**
	(0.0108)	(0.3559)	(0.0473)	(0.1558)
A	0.0577***	0.4139**	0.2727**	0.4097**
	(0.0218)	(0.1722)	(0.1194)	(0.1794)
B	0.0179**	0.8810**	0.0492**	0.2266**
	(0.0079)	(0.4270)	(0.0250)	(0.1156)
C-E	0.0086**	0.8505*	0.0286*	0.2383*
	(0.0040)	(0.4343)	(0.0153)	(0.1281)

Appendix Table 4 Arbitrage Strategy at the $5,000 Threshold and Borrowers' Characteristics

This table reports the estimates of the probability of exploiting the arbitrage opportunity at the $5,000 threshold, at which the interest rate drops, on a set of characteristics at origination for the period between December 2012 and October 2013. The dependent variable is an indicator equal to one if the loan amount is exactly $5,000 and zero if the loan amount is below $5,000 *and* the installment would have been lower (net of fees) if the loan application would have been for $5,000 instead. $Percentage\, College\, Degree\,(3 - ZIP)$ is the proportion of adults older than 25 with at least a college degree at the 3-digit zip-code level, according to the Census. $Debt\, Consolidation$ is a dummy variable equal to one if the borrower declares debt consolidation as the main purpose of the loan. $Other\, Controls$ includes a dummy variable for home ownership and the house price index at the 3-digit zip-code level, from the Federal Housing Finance Agency (FHFA). Threshold by initial sub-grade by month fixed effects, term, and state fixed effects are included. The continuous variables are standardized. Robust standard errors are in parentheses, clustered at threshold by initial sub-grade level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Initial Grades	Loan amount $5,000
	(1)
Ln Annual Income	0.1104***
	(0.0085)
FICO	0.0168*
	(0.0087)
Proportion College Degree (3-Zip)	0.0164*
	(0.0091)
Debt-to-Income	0.0138
	(0.0099)
Ln Number Inquiries Last 6 Months	0.0032
	(0.0081)
Credit Card Utilization	0.0007
	(0.0089)
Debt Consolidation	0.0035
	(0.0021)
Other Controls	
Threshold x Ini. Sub-Grade x Month FE	Yes
State FE	Yes
Term FE	Yes
Observations	3,470
R-squared	0.153

Appendix Table 5 Borrowers' Credit Decisions and Default

This table reports the default rate between *non-bunchers* and *bunchers* after the introduction of the notch, between December 2012 and October 2013. The dependent variable is *Default*, a dummy variable equal to one if the loan is charged-off. *Non-Bunching* is an indicator variable equal to one if the loan amount is at the threshold or a maximum of $1,000 above, and zero if the loan amount is located at a maximum of $1,000 below the same threshold. Panel A compares the default rate between *non-bunchers* and *bunchers* after the introduction (December 2012 and October 2013). Panel B compares the default rate between *non-bunchers* and *bunchers* before the introduction (November 2011 and November 2012), when the interest rates were smooth across thresholds, as a placebo test. Threshold by initial sub-grade by month of origination fixed effects, along with term and state fixed effects are included. Robust standard errors are in parentheses, clustered at threshold by initial sub-grade. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Default (1)
Non-Bunching v. Bunching	0.0421*** (0.0077)
Controls (50 characteristics)	Yes
Threshold x Ini. Sub-Grade x Month FE	Yes
Term FE	Yes
State FE	Yes
Sample Period:	Dec. 2012-Oct. 2013
Bandwidth (USD)	1,000
Observations	36,457
R-squared	0.048

Panel B	Default (1)
Non-Bunching v. Bunching	0.0086 (0.0117)
Controls (50 characteristics)	Yes
Threshold x Ini. Sub-Grade x Month FE	Yes
Term FE	Yes
State FE	Yes
Sample Period:	Nov. 2011-Nov. 2012
Bandwidth (USD)	1,000
Observations	16,651
R-squared	0.027

Appendix Table 6 Differences in Characteristics at Origination and in Contract Terms: Alternative Empirical Design

This table presents the results of the tests for the identifying assumptions of the alternative empirical design depicted in Figure 8 Panel B. *Selected Group* is an indicator variable equal to one if the loan amount is between a maximum of $1,000 below the threshold and a maximum of $1,000 above the threshold, and zero for borrowers whose loan size is between $1,025 and $2,000 below the cutoff. *Bunching* (Selected v. Unselected) is an indicator variable equal to one if the loan amount is at a maximum of $1,000 below the threshold and zero if the loan amount is located between $1,025 and $2,000 below the cutoff. Column 1 of Panel A presents the estimates for the main set of covariates at origination, and Column 2 shows the results for a more comprehensive set of characteristics. Panel B provides the estimate for the difference in terms of interest rate between the loans in the bunching group and the unselected group. The *p*-value is for an F-test of the joint significance of the difference in characteristics at origination. Robust standard errors are in parentheses, clustered at threshold by initial sub-grade level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A	Selected Group (Bunchers and Non-Bunchers)	
	(1)	(2)
Ln Annual Income	0.0043	0.0012
	(0.0036)	(0.0046)
Proportion College Degree (3-Zip)	0.0035	0.0017
	(0.0274)	(0.0370)
Debt-to-Income	-0.0039	-0.0070
	(0.0049)	(0.0074)
Ln Number Inquiries Last 6 Months	-0.0001	-0.0017
	(0.0024)	(0.0030)
Credit Card Utilization	0.0034	0.0048
	(0.0055)	(0.0073)
Debt Consolidation	-0.0082	-0.0052
	(0.0072)	(0.0117)
Ln Employment length	0.0038	0.0033
	(0.0033)	(0.0045)
Home Mortgage		0.0039
		(0.0027)
Ln Open Accounts Ever		0.0073
		(0.0079)
Ln Months since Most Recent Lowest FICO		0.0000
		(0.0000)
Threshold x Ini. Sub-Grade x Month FE	Yes	Yes
Term FE	Yes	Yes
State FE	Yes	Yes
Joint F-Test	[0.692]	[0.855]
Observations	44,281	44,281
R-squared	0.128	0.151

Panel B	Bunching (Selected v. Unselected)
	(1)
Interest Rates	0.0066
	(0.0071)
Threshold x Ini. Sub-Grade x Month FE	Yes
Term FE	Yes
State FE	Yes
Observations	22,169
R-squared	0.706