Heterogenous Response of Credit Conditions[☆]

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Abstract

I document substantial heterogeneity in the response of credit conditions to changes in the risk-free rate. An increase in the risk-free rate increases interest rates and decreases the number of approved loans for all borrowers. However, riskier borrowers get larger increases in interest rates and smaller decreases in the number of approved loans. These results support the predictions from standard models of consumer credit. They also have important implications for the response of macroeconomic aggregates. I show that he predicted response of aggregate borrowing is overestimated by about 20% when heterogeneity is ignored.

Keywords: Monetary Policy, Interest Rates, Credit, Heterogeneity

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1. Introduction

How do credit conditions respond to changes in lenders' cost of funds? I shed light on this question by empirically investigating the effect of a change in the risk-free rate on loan interest rates and on the number of approved loans. I document that there is significant heterogeneity in the adjustment of these two margins across borrowers, and that the heterogeneity is relevant for the response of macroeconomic aggregates.

My motivation stems from the growing literature of micro-based macroeconomic models of consumer credit, most of which are based on the seminal work of Chatterjee et al. (2007) and Livshits et al. (2007).[1] These models feature a pricing equation that yields three standard predictions in asset pricing theory: (i) interest rates are increasing in borrowers' default probability, (ii) interest rates are increasing in lenders' cost of funds, and (iii) changes in lenders' cost of funds lead to larger changes in interest rates for riskier borrowers.

My first contribution is to empirically investigate this last prediction. I document that interest rates increase three times more for the riskiest borrowers following an increase in the cost of funds. This result is also consistent with the evidence from the empirical literature on the risk-taking channel of monetary policy, although this literature examines the question mostly in the context of bank lending to firms.[2]

My second contribution is to document that changes in lenders' cost of

[1]For a recent survey on the topic see Tertilt and Exler (2020).

[2]See for instance Jiménez et al. (2014), Ioannidou et al. (2015), Dell'Ariccia et al. (2017), Paligorova and Santos (2017).

funds also affect the extensive margin. I find that the total number of approved loans decreases following an increase in the cost of funds, and that the decrease is largest for the safest borrowers. This result agrees with the prediction from models of consumer credit that incorporate an extensive margin, such as Livshits et al. (2016). Although these models typically abstract from heterogeneity across borrowers, the differences I document are consistent with the predictions from several monetary policy transmission mechanisms. An increase in the risk-free rate may decrease the credit quality of the pool of borrowers through the balance-sheet channel of monetary policy (Bernanke and Gertler (1995)). Similarly, the risk-taking channel predicts that an increase in the risk-free rate leads to a tightening in lending standards as investors have more incentive to screen out bad borrowers (Dell'Ariccia and Marquez (2006)). For a fix pool of loan applicants, these two effects imply that fewer applicants qualify as safe (and hence loans to "safe" borrowers decrease). Of course, the pool of loan applicants may also change. However, and to the extent that safer borrowers are less borrowing-constrained than riskier ones, an increase in the risk-free rate also disproportionately discourages safer borrowers from applying to loans.

My last contribution is to show that the heterogeneous response in credit conditions has important macroeconomic implications. I document that the riskiest borrowers are also the least responsive to changes in interest rates and hold the largest loan amounts. The negative correlation between the marginal propensities to lend and borrow, and between the number of approved loans and the loan amounts, dampens the response of aggregate borrowing.

The first half of my study is based on a regression discontinuity design.

I use daily data from Lending Club to identify dates on which there were changes in Lending Club's loan interest rates.[3] From hereon, I refer to these dates as discontinuity dates. Three features of the data allow me to precisely identify these dates. First, Lending Club groups borrowers into different risk categories – each category is associated with a *unique* interest rate. Second, changes in interest rates are instantaneous. Third, loan interest rates change sporadically over time.

I argue that, in a subset of these discontinuity dates, the adjustments in interest rates are driven by changes in Lending Club's idiosyncratic factors and/or changes in aggregate economic conditions. I use the effective Fed Funds Rate (FFR) to identify this subset for two reasons. First, changes in the FFR are a proxy for changes in aggregate economic conditions, specifically, those related to lenders' cost of funds. Second, the FFR changes instantaneously and sporadically over time, which allows me to precisely identify a subset of 14 (out of 23) discontinuity dates.[4]

In principle, Lending Club's interest rates could depend on four sets of factors: lenders' characteristics, borrowers' characteristics, idiosyncratic Lending Club factors, and aggregate economic conditions. However, Lending's Club institutional setting implies that: (i) interest rates are not a function of

[3]Lending Club was the largest peer-to-peer lending platform in the U.S. from 2008 to 2021.

[4]Note that I am not implying that the FFR changes are unanticipated shocks. I am just stating that the instantaneous and sporadic nature of the FFR changes allows me to accurately identify the dates on which those changes happened. I actually provide some evidence that suggest some of these changes had an unanticipated component, while others didn't.

lenders' characteristics, and (ii) interest rates depend on borrowers' characteristics only through borrowers' default risk. To see this, note that Lending Club does not hold any financial stake in the loans. All loans are funded by institutional and retail investors. At any point in time, Lending Club simply assesses the risk of a borrower and assigns the corresponding interest rate. In practice then, Lending Club's interest rates are a function of borrowers' default risk, idiosyncratic Lending Club factors, and aggregate economic conditions. If borrowers' default risk does not change on the subset of discontinuity dates with changes in the FFR, then the changes in interest rates on these dates must be driven by changes in Lending Club's idiosyncratic factors and/or changes in aggregate economic conditions.

Lending Club's detailed information on loan repayment status allows me to construct a measure of default risk. Consider a loan issued at date t. If the loan matured prior to March 31$^{\text{st}}$, 2019 (the date I obtained the data), I observe whether that loan ended up in default or fully repaid. If the loan did not mature, I observe if it is late on its payments. This allows me to use the ex-post default rate (δ_t) as a measure of the default probability. Importantly, δ_t measures the fraction of loans *issued at time* t that end up in default, and not the fraction of loans in default at time t. In other words, δ_t captures current *and* future default risk over the entire life of the loan.

I show that the default probability remains unchanged on *and* following the 14 discontinuity dates on which there are changes in the FFR. Note that the default probability remains unchanged even if interest rates change. This is because borrowers internalize the changes in interest rates and choose to borrow different amounts.[5] Consider for example the dates with an increase in the FFR. I show that overall borrowing (from Lending Club and other sources) decreases on these dates, while total income remains unchanged. The resulting decrease in the debt-to-income ratio then offsets the higher interest rates. Importantly, this is consistent with an *economy-wide* increase in the cost of funds.

I use the 9 discontinuity dates on which there are no changes in the FFR to provide further evidence that the Lending Club data is consistent with the pricing equation of the standard models of consumer credit. If default risk and the cost of funds are the major drivers of Lending Club's interest rates, then one would expect to see changes in the probability of default in the discontinuity dates on which there are no changes in the FFR. I corroborate that this is indeed the case.

The second half of my study uses the Lending Club data on the subset of 14 discontinuity dates with changes in the FFR to estimate the heterogeneity across groups of borrowers in: the marginal propensity to lend (MPL), the marginal propensity to borrow (MPB), and the extensive margin adjustment (EMA). I define the MPL as the change in loan interest rate given a 1% change in the FFR, the MPB as the change in loan amount given a 1% change in the loan interest rate, and the EMA as the change in the number of approved loans given a 1% change in the FFR.

The definitions for the MPL and MPB follow from Lending Club's origination process. This process ensures that Lending Club sets the loan interest

[5] This is also a property of the standard models of consumer debt and default.

rates, while borrowers' choose the loan amounts. The definition of the EMA abstracts from who is responsible for the change in the number of approved loans. I show that the *aggregate* number of total loan applications (approved and rejected) does not change on the discontinuity dates. Although this indicates that total loan demand remains unchanged, it is consistent with two possible scenarios. On one hand, Lending Club could have changed the approval rates for the different groups of borrowers. On the other, the composition of the pool of loan applicants could have changed – there could be more (less) relatively risky borrowers, and less (more) relatively safe ones. Looking at the response of approved and rejected loans for each group of borrowers would shed light on the mechanism, but unfortunately I can't conduct this analysis due to data limitations.[6]

I estimate the heterogeneity in the MPL (EMA) across different groups of borrowers by regressing the change in loan interest rates (number of approved loans) on the change in the FFR. I don't include any controls for changes in borrower characteristics in my baseline specifications. My research design ensures that there are no changes in the probability of default for the different groups of borrowers on the contractionary discontinuity dates. As discussed earlier, this implies that the changes in interest rates must be driven by changes in aggregate economic conditions (or in Lending Club's idiosyncratic factors). It also implies that the changes in the number of approved loans are not driven by changes in the (risk) composition of borrowers within each group. I show, nonetheless, that my results are robust to controlling for

[6]My borrower groups are based on Lending Club's risk categories, which are assigned only to approved loans.

changes in the probability of default and in several other borrower characteristics.

I estimate the heterogeneity in the MPB in an analogous fashion – I regress the change in the loan amount on the change in loan interest rate for each group of borrowers. My baseline specification controls only for changes in borrowers' overall debt holdings (specifically, debt-to-income ratio and revolving credit balance). By construction, there is a change in cost of funds (proxied by the FFR) on the contractionary discontinuity dates. I show that, as standard economic theory predicts, borrowers adjust their overall debt holdings (not only on the loan amount requested to Lending Club) in response to this economy-wide change in the cost of funds. Although the changes in economic conditions can affect borrowers' behavior via income and other characteristics, these changes are unlikely to operate at a daily frequency. Again, I show that my results are robust to adding a wide set of controls for changes in other borrower characteristics.

An important limitation of my MPL and EMA regressions is that I don't include any controls for Lending Club's idiosyncratic factors, such as transaction costs or markups. If these factors are correlated with changes in the FFR, then my estimates would reflect the response of interest rates (number of approved loans) to changes in the aggregate cost of funds *and* in these factors. Of course, one can argue that these factors are also part of lenders' cost of funds. The issue is really related to the generalizability of my estimates. If other lenders' transaction costs and markups are not correlated with the FFR in the same fashion as Lending Club's, then my results would not apply to those lenders. However, note that this issue (i) is not unique to using Lending Club's data, (ii) is only relevant if the behavior of other lenders differs substantially from Lending Club's, and (iii) is attenuated if one believes that most of the response is driven by changes in the aggregate cost of funds.

My estimates suggest that the MPL is positive and increasing in the default risk – it is three times larger for the riskiest borrowers compared to the least risky ones. The MPB is negative and non-monotonic in the default risk. The magnitude of the MPB is largest for medium-risk borrowers, and it decreases as borrowers get either riskier or safer. This actually matches the quantitative performance of many default models. In these models, the lowest-risk borrowers tend not to be sensitive, and the highest-risk borrowers tend to be priced out even under the best of circumstances. Lastly, the EMA is negative and increasing in the default risk – the number of approved loans decreases the most for the least risky borrowers.

These results have important implications for the response of macroeconomic aggregates to changes in the FFR. The negative correlation between the EMA and the average loan amount dampens the response of aggregate borrowing. In simple terms, the number of approved loans changes the most for the the borrowers that request the lowest loan amounts. The intensive margin plays a less significant role. The non-monotonicity of the marginal propensity to borrow implies that the MPL and MPB are positively correlated for low to mid-risk borrowers, and negatively correlated for mid to high-risk borrowers. The former amplifies the response of aggregate borrowing, and the later dampens it. Overall, these two opposing effects cancel each other out.

My estimates predict a decrease in aggregate borrowing of \$629 (per capita) in response to a 2.1 b.p. increase in the FFR. The magnitude of the predicted decrease increases to \$758 when the heterogeneity in the MPL, MPB, and EMA is ignored. I am not the first to point out that heterogeneity in the marginal propensities to lend and borrow dampens the response of aggregate borrowing. Agarwal et al. (2018) find a similar result. In their case, however, the dampening is entirely driven by the negative correlation between the MPL and MPB.

Three final comments on the generalizability of my results. First, I show that the credit outcomes in the Lending Club data are strongly correlated with several other standard measures of aggregate consumer lending. These measures include credit card originations reported by the Consumer Financial Protection Bureau, and total consumer loans by commercial banks from the Federal Reserve's H.8 release. I interpret these as evidence that there is a *common* set of factors driving the changes in lending for both, Lending Club and more traditional lenders such as commercial banks.

Second, I compare the borrowers' risk distribution across several different datasets and conclude that both tails of the borrowers' risk distribution are missing from the Lending Club data.[7] This implies that my estimates for the response of aggregate borrowing are not representative. However, my aim is to quantify the dampening effect of heterogeneity on the response of aggregate borrowing, and not the magnitude of the aggregate response per

[7]These datasets include the Survey of Consumer Finances, the Credit Card Metrics dataset assembled by the U.S. Office of the Comptroller of the Currency, and data collected by the Fair Isaac Corporation on all borrowers in the U.S.

se. Missing both tails of the risk distribution simply implies that my results should be viewed as a lower bound.[8] Note that this is also consistent with the results from other studies. For example, Agarwal et al. (2018) estimate a much larger effect of heterogeneity – they find that the response of aggregate borrowing is two times larger when heterogeneity is ignored (while I find it is only about 20% larger).

Third, my research design considers only dates with changes in loan interest rates. There are several dates on which there are changes in the FFR without changes in loan interest rates. Thus my MPL and EMA estimates should be viewed as conditional estimates – they capture the effect of a change in the FFR on loan interest rates (number of approved loans) conditional on loan interest rates changing. I focus on the conditional estimates given that I want to jointly estimate the MPL, EMA, *and* MPB. Note that although the results for the EMA need not generalize, the insights about the heterogeneity in the MPL extend to the unconditional case. This follows by noting that the magnitude of the unconditional MPL estimates is scaled by the same factor for all grades.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 reviews the testable implications from the standard models of consumer credit that motivate the paper. Section 4 discusses how Lending Club's origination process defines a mapping that resembles the pricing equation implied by the standard models of consumer default, provides a basic summary of the Lending Club data and compares it with

[8]The dampening effect is driven by the negative correlation (across the borrowers' risk distribution) between the EMA and the average loan amount.

data from other more standard sources, and describes how I identify the discontinuity dates. Section 5 introduces my empirical framework. Section 6 validates my research design. Section 7 presents my estimates and examines the macroeconomic implications of these results. Section 8 concludes.

2. Related Literature

My work fits within three strands of literature. First, the literature that uses peer-to-peer lending data to study a variety of topics within economics and finance. Second, the literature that studies the effect of monetary policy on credit conditions. Third, the literature that quantifies the effect of credit supply shocks on borrowing and spending.

Several studies have taken advantage of the detailed loan-level information on contract terms and borrower characteristics available from peer-to-peer lending platforms.[9] However, to the best of my knowledge, none of them study the heterogeneous response of loan contract terms to changes in the risk-free rate.

There is a vast literature that investigates the effect of monetary policy on credit conditions. Some examples include Kashyap et al. (1993), Kashyap and Stein (1994), Kishan and Opieda (2000), Maddaloni and Peydró (2011, 2013), Jiménez et al. (2012), Ciccarelli et al. (2015), and Argudo (2023). These papers estimate the changes in loan supply that result from changes in banks' cost of funds. Although they are similar in spirit to mine, they abstract from quantifying changes in the actual contract terms (such as changes

[9] Some examples include Paravisini et al. (2016), Hertzberg et al. (2018), Tang (2019), and Ravina (2019).

in interest rates). The studies that do quantify changes in contract terms often focus on bond interest rates and/or stock prices. For example, Kuttner (2001), Gürkaynak et al. (2005), Hanson and Stein (2015), Abrahams et al. (2015), Gertler and Karadi (2015), Gilchrist et al. (2015), Nakamura and Steinsson (2018), and Crump et al. (2018). A recent exception is Argudo (2021) – they study the response of Commercial and Industrial loans contracts terms to monetary policy shocks, but abstract from any heterogeneity across borrowers. There are several studies that do consider heterogeneity across borrowers, particularly those that study the risk-taking channel of monetary policy such as Jiménez et al. (2014), Ioannidou et al. (2015), Dell'Ariccia et al. (2017), Paligorova and Santos (2017). However, all of these studies examine the change in credit conditions across borrowers in the context of bank lending to *firms*.

My study is most closely related to the literature that quantifies the effect of credit supply shocks on borrowing and spending such as Gross and Souleles (2002), Agarwal et al. (2018), Gross et al. (2020), and Aydin (2021). These studies differ from mine in that they focus on credit cards and exploit variation in credit card limits, whereas I focus on unsecured non-revolving debt and exploit variation in interest rates. The scope of my study is very similar to Agarwal et al. (2018). They examine how banks change credit card limits across borrowers in response to a change in the cost of funds (MPL), and how borrowers change credit card volume in response to a change in their credit limit (MPB). They find that the MPL and MPB are negatively correlated, which dampens the response of aggregate borrowing. However, my study differs in at least four ways. First, we use different datasets. Second, our aims are different. Their main goal is to show that heterogeneity has important implications for the response of macroeconomic aggregates. Mine is to test some predictions from the standard models of consumer credit. I show that these predictions matter for the response of macroeconomic aggregates as a corollary. Third, they find that the MPB is increasing in borrowers' risk. Meanwhile, I find that the MPB is non-monotone. Lastly, and perhaps most importantly, Agarwal et al. (2018) abstract completely from the extensive margin. Their results are driven by the negative correlation between the marginal propensities to lend and borrow. In contrast, my results are mostly driven by the extensive margin. The intensive margin plays a less significant role because of the non-monotonicity of the marginal propensity to borrow.

3. Theoretical Background

My empirical study is motivated by the growing literature of micro-based macroeconomic models of consumer debt and default. In what follows, I review two key predictions from these models pertaining the response of credit conditions to a change in the risk-free rate.

3.1. Intensive Margin: Changes in Interest Rates

Most modern micro-based macroeconomic models of consumer credit are based on the seminal work of Chatterjee et al. (2007) and Livshits et al. (2007). In these models, the loan pricing equation takes the form:

$$r(\boldsymbol{x}, \boldsymbol{S}) = \frac{1 + i(\boldsymbol{S})}{1 - \delta(B(r; \boldsymbol{x}, \boldsymbol{S}); \boldsymbol{x}, \boldsymbol{S})} - 1, \tag{1}$$

where r denotes the loan interest rate, B the loan amount, δ the borrower's default probability, $\boldsymbol{x}$ a vector of borrower characteristics, i the risk-free rate, and $\boldsymbol{S}$ a vector that summarizes the state of the economy. Equation (1) is the result of a zero profit condition for perfectly competitive, deep pocketed, risk neutral, rational lenders. It has two important implications. First, interest rates are increasing in the probability of default. Second, changes in the risk-free rate lead to larger changes in interest rates for riskier borrowers (provided that the probability of default remains unchanged).

In this study I focus on the latter – the former is a standard prediction of most asset pricing models and has been extensively studied. I first show that the data defines a relationship between the probability of default and interest rate as in equation (1). I then argue that my empirical framework ensures that the changes in interest rates are not driven by the probability of default (i.e. the probability of default remains fixed). Lastly, I estimate the change in interest rates across different groups of borrowers to assess if it is larger for riskier borrowers.

It is worth pointing out that some recent work has developed models of consumer credit that feature more complex pricing equations. For example, Dempsey and Ionescu (2022) develop a model where equation (1) has additional terms, all of which depend on the probability of default. Chatterjee et al. (forthcoming) add asymmetric information into the model from Chatterjee et al. (2007), so that lenders observe a noisy signal of a borrowers' type instead of their probability of default. Nonetheless, in both cases the the pricing equation still implies that changes in the risk-free rate lead to larger changes in interest rates for riskier borrowers.

3.2. Extensive Margin: Changes in the Number of Loans

Livshits et al. (2016) develop a model of consumer credit that incorporates adjustments in the extensive margin. They use the model to study the effect of financial innovations (including lower lenders' cost of funds) on unsecured consumer loans. The model features a continuum of two-period lived risk-neutral borrowers who can get a low or high endowment in the second period. The borrowers differ in their probability (σ) of receiving the high endowment realization.[10] Lenders offer loan contracts, but they must pay a fixed cost for each contract. A contract specifies an interest rate, a borrowing limit, and the set of eligible borrowers. The number and terms of lending contracts are determined endogenously due to free entry into the credit market.

Finitely many loan contracts are offered in equilibrium. The number of contracts offered (N) is given by:

$$N = \left\lfloor \frac{(y_h - y_l)\left(\frac{1}{1+i} - \beta\left(1 + \sqrt{\frac{2\chi(1+i)}{\gamma y_h}}\right)\right)}{\left[\frac{y_h}{1+i} - \beta(y_h - y_l)\right]\sqrt{\frac{2\chi(1+i)}{\gamma y_h}}} \right\rfloor, \tag{2}$$

where y_h and y_l are the high and low endowments realizations, respectively, β is the discount factor, i is the risk-free rate, γ is the borrowers' cost of bankruptcy (given as the fraction of endowment lost in the second period), and χ is the lenders' fixed cost of extending a contract. Each contract ($n \leq N$) serves borrowers with probabilities σ in the interval $\left[\underline{\sigma}_n, \underline{\sigma}_{n-1}\right)$, where

$$\underline{\sigma}_n = 1 - n\sqrt{\frac{2\chi(1+i)}{\gamma y_h}}, \text{ for } n \geq 0. \tag{3}$$

Equations (2) and (3) imply that there are two opposing forces driving the response of the extensive margin to an increase in the risk-free rate. On one

[10] Livshits et al. (2016) also consider the case where σ is just a noisy signal of borrowers' default risk. Adding asymmetric information does not change the relationship between the extensive margin and the risk free rate implied by equations (2) and (3).

hand, the number of contracts offered decreases. On the other, the measure of borrowers served by each contract increases. As Livshits et al. (2016) show, the former effect dominates and the total measure of approved loans decreases in response to an increase in the risk-free rate.

The interest rate for contract n is given by $r_n = \frac{1+i}{\underline{\sigma}_n} - 1$, which is clearly in the form of the standard loan pricing equation depicted in (1). In this context, $\underline{\sigma}_n$ can be interpreted as the probability of repayment. Given that my empirical framework ensures that the probability of repayment remains fixed as loan interest rates change, one should interpret my extensive margin results as a test of the prediction from equation (2). In other words, I focus on the change in the number of loan contracts offered in response to an increase in the risk-free rate, while holding the measure of borrowers served by each contract fixed.

4. Data

I use data from Lending Club, the main peer-to-peer lending platform in the U.S. until 2021.[11] Lending Club connected investors with borrowers looking for loans between \$1,000 and \$40,000 at 3 or 5 year maturities. The Securities and Exchange Commission (SEC) considered Lending Club loans individual securities. As a result, Lending Club was required to disclose detailed information on loan contract terms and borrower characteristics.[12]

[11] In February 2021 Lending Club became a Bank Holding Company after acquiring Radius Bancorp, Inc.

[12] One can access the Lending Club data directly from the SEC filings using the online engine EDGAR and Lending Club's company identifier (*CIK*=1409970).

The data also includes information on loan applications that were rejected. I focus on the period January 1st, 2013 to March 31st, 2019. Although the Lending Club data is available from 2008 onwards, I restrict the sample period because the number of daily observations is scarce prior to 2013.[13] The sample period ends in March of 2019, which is when I started working on this project.

In what follows, I first discuss Lending Club's origination process and how it defines a monotonic mapping from risk to interest rates. I then present some basic summary statistics of the Lending Club data, and compare it with data from other more standard sources. I conclude the section explaining how I identify the discontinuity dates for my research design.

4.1. Risk Categories, Default Risk, and Interest Rates

Lending Club's origination process defines a monotonic mapping from risk to interest rates similar to the one from equation (1). Lending Club does not hold any financial stake in the loans – the loans are funded directly by institutional and retail investors. Lending Club just assesses the risk of a borrower and assigns the corresponding interest rate.

The origination process starts with a potential borrower applying for a loan online. The borrower chooses the desired loan amount, specifies its purpose, and provides some personal information including date of birth, income, name, and address. Lending Club determines if the borrower is

[13] Lending's Club total origination volume in 2012 was \$0.6 Billion, about 3.5 times smaller than the volume in 2013. The total origination volume for the period 2008 - 2011 was even smaller.

eligible for the loan using this personal information.[14] Conditional on the borrower being eligible, Lending Club assigns the borrower to an initial risk category via a proprietary algorithm that uses information on the borrower's credit report. The borrower receives a contingent offer that specifies the term, monthly payment, and APR for the loan. If the borrower accepts the offer, some additional information is collected (homeownership status, employment status, SSN), a hard credit check is run, and the borrower has the option to make some final adjustments to the desired loan amount and maturity. Once those adjustments are made, Lending Club assigns the borrower to a final risk category. The borrower then gets the formal loan contract and decides whether or not to accept it.

Lending Club uses 35 final risk categories – each is denoted by a two-character alpha-numeric label, g_i, where $g \in \{A, B, C, D, E, F, G\}$ and $i \in \{1, 2, 3, 4, 5\}$. From here on, I will refer to g_i as the loan *sub-grade* and to g as the loan *grade*. Figure 1 presents the average default rate (Panel A) and interest rate (Panel B) for each of the 35 sub-grades over the entire sample period. Panel A shows that default rate is increasing in the sub-grade: borrowers with sub-grade A_1 are the least risky, while borrowers with G_5 are the most risky. Panel B shows that the mapping from sub-grades (probability of default) to interest rates defined by Lending Club's origination process resembles the relationship predicted by equation (1).

Finally, note that the standard models of consumer credit rely on the assumption of lenders who are: (i) perfectly competitive, (ii) deep-pocketed,

[14]For example, loans are only given to borrowers with FICO scores of 660 and above.

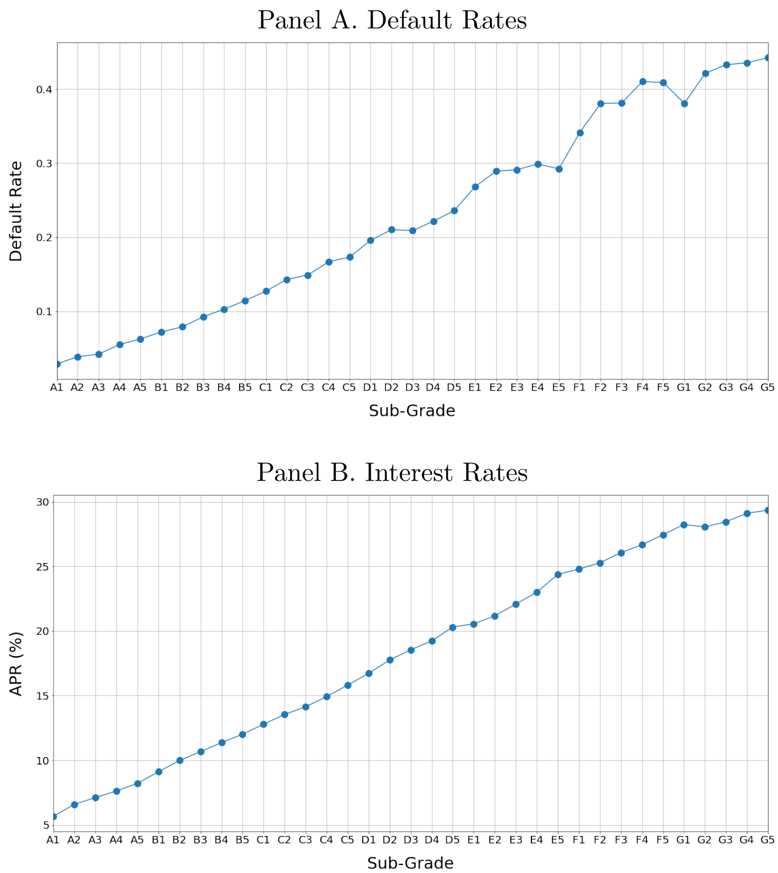

Fig. 1. Average Default and Loan Rates by Sub-Grade.

and (iii) risk neutral. One might be worried about the extent to which these features are captured by Lending Club investors, even if Lending Club's origination process resembles the mapping implied by equation (1). To address this concern, note that Lending Club investors are price takers and simply choose which loans to fund and how much of each loan to fund. Each individual investor might not be deep-pocketed, but this assumption holds in the aggregate. Any given loan can be funded by multiple investors, and any retail or *institutional* investor can fund a loan in Lending Club (they just need to create an account).[15] Investors might not be risk neutral. However, in the standard models of consumer credit, this assumption mainly ensures that the pricing equation is not a function of lenders' characteristics. This is also true in the Lending Club setting – a borrower's risk category (and hence interest rate) is determined by Lending Club's proprietary algorithm that uses the information from the borrower's credit report.

4.2. Summary Statistics

Table 1 presents summary statistics (by grade) for selected loan contract terms and borrower characteristics. I consider only grades A through E in my empirical study – the number of daily observations for grades F and G is relatively scarce, rendering them inadequate for a regression discontinuity design.[16] I include the summary statistics for grades F and G in Table 1 to show that the following remarks hold for *all* of the risk categories.

Loan interest rates and default rates are increasing in the loan grade. The average interest rate for grade E (grade A) borrowers is 22% (7%), and their default rate is about 29% (5%). The loan amount and loan maturity are also larger for riskier borrowers. The average loan amount for grade E (grade A) borrowers is \$17,341 (\$14,971) with a maturity of 51 months (37 months).

Borrower characteristics across risk types also vary as standard economic theory predicts. The debt-to-income ratio and the revolving credit utilization are larger for riskier borrowers. Grade E (grade A) borrowers have an average debt-to-income ratio of 22% (17%) and an average revolving credit

[15] In the data all of the approved loans end up being completely funded.

[16] Grades F and G make up less than 2.5% of the total sample.

Table 1. Summary Statistics for the Lending Club Data

	Loan Characteristics by Grade						
	A	B	C	D	E	F	G
Loan Rate (APR, %)	7.12	10.67	14.18	18.28	22.05	25.75	28.50
	(0.98)	(1.22)	(1.26)	(1.76)	(2.69)	(2.74)	(2.27)
Loan Amount ($)	14,971	14,453	15,196	15,822	17,341	18,984	20,368
	(9,302)	(9,127)	(9,281)	(9,312)	(9,377)	(9,148)	(8,988)
Maturity (Months)	37.48	40.95	44.68	46.53	50.78	54.96	56.05
	(5.77)	(9.71)	(11.53)	(11.91)	(11.67)	(9.78)	(8.90)
Default Rate (%)	4.71	9.31	15.10	21.21	28.65	37.59	41.43
Number of Loans (% of Total)	19.69	29.19	28.80	14.29	5.81	1.72	0.50
Number of Loans (per Day)	196.89	291.83	287.93	142.90	58.19	17.93	5.73
Loans Used for Refinancing (%)	81.45	81.74	79.96	77.15	75.99	73.5	69.54
	Borrower Characteristics by Grade						
	A	B	C	D	E	F	G
Annual Income ($)	90,989	79,713	74,849	71,436	71,574	71,694	73,907
	(92,220)	(172,628)	(74,671)	(71,933)	(63,787)	(48,105)	(49,601)
Debt-to-Income (%)	16.55	18.21	19.75	21.24	21.89	22.03	22.82
	(12.92)	(14.12)	(15.17)	(15.99)	(16.37)	(14.22)	(20.78)
Fico Score	728	700	689	684	683	681	680
	(37)	(31)	(25)	(22)	(21)	(20)	(20)
Revolving Credit Balance ($)	18,580	16,725	16,275	15,794	16,398	16,168	16,593
	(27,739)	(22,899)	(21,214)	(20,820)	(21,682)	(19,358)	(20,245)
Revolving Credit Utilization (%)	37.20	48.45	54.05	56.91	58.55	59.25	58.30
	(22.68)	(23.87)	(23.73)	(23.78)	(24.05)	(24.30)	(24.66)
Number of Open Accounts	12.03	11.56	11.56	11.60	11.81	12.03	12.25
	(5.75)	(5.62)	(5.67)	(5.72)	(5.77)	(5.82)	(6.03)

Notes. Table shows averages for some loan and borrower characteristics (by grade) over the sample period 01/01/2013 to 03/31/2019. The total number of observations is $N = 2,278,544$. Standard deviations are given in parenthesis.

card utilization of 59% (37%). Income, FICO score, and revolving credit balance are smaller for riskier borrowers. Grade E (grade A) borrowers have an average annual income of $71,574 ($90,989), an average FICO score of 683 (728), and an average revolving credit balance of $16,398 ($18,580).

4.3. Comparison of Lending Club Data With Other Data

Table 2 presents the yearly volume of loans originated by Lending Club and Prosper, which were the two largest peer-to-peer lending platforms in the U.S. during the sample period. Note that Lending Club's origination volume was always at least twice as large as Prosper's, an indication of how dominant Lending Club was in the peer-to-peer lending market.

Table 2 also includes data on credit card originations from the Consumer Financial Protection Bureau (CFPB). The origination volume of the two largest peer-to-peer platforms accounted for at most 4% of credit card originations in any given year. The small market share of peer-to-peer lending raises two important concerns. First, to what extent are credit outcomes in the Lending Club data representative of credit outcomes from more traditional sources of credit? Second, are the borrowers that use Lending Club systematically different from those who resort to more traditional sources of credit? I next address these two concerns.

Figure 2 presents the monthly number (Panel A) and volume (Panel B) of originations for Lending Club loans and credit cards. The trends from these monthly time series are consistent with the yearly trends implied by Table 2. Lending's Club origination volume was steadily increasing from 2013 to 2019. The origination volume of Lending Club doubled every year until 2015,

Table 2. Origination Volume (Billions of $)

	Peer-to-Peer Lending		
	Lending Club	Prosper	Credit Cards
2019	12.3	2.7	419.9†
2018	10.9	2.8	406.3
2017	9.0	2.9	406.8
2016	8.7	2.2	416.4
2015	8.4	3.7	380.7
2014	4.4	2.2‡	335.3
2013	2.1	0.6‡	296.6

Notes. The data for Lending Club and Prosper was obtained from the 10K reports filed with the SEC. The credit card data comes from the CFPB Consumer Credit Panel. †Data for 2019 is only available through April. The number corresponds to an estimate using the monthly average over the first four months. ‡Prior to 2014, Prosper provides only the total cumulative volume of loans originated since 2009.

Table 3. Correlation With Measures of Aggregate Borrowing

Credit Card Originations		Lending by Commercial Banks	
Number	Volume	Consumer Loans	Revolving Credit
0.70	0.80	0.79	0.73

Notes. The correlation is computed using monthly data over the period January 2013 to March 2019. The credit card data comes from the CFPB Consumer Credit Panel. The data on lending by commercial banks comes from the Federal Reserve Economic Database (FRED).

and then consistently grew at a rate between $4\% - 13\%$ from 2016 to 2019.[17]

[17]The sharp decline in Lending Club loan originations in May-June of 2016 came after

Credit card originations also grew consistently from 2013 to 2016 (always at a rate smaller than Lending Club's), but remained relatively constant between 2016 and 2019. In addition to having similar trends, the two time series track each other closely in term of monthly variation. That is, despite the large difference in scales, there is a strong correlation between Lending Club loans and credit card originations. Table 3 quantifies this correlation. It also shows that Lending Club's loan volume is strongly correlated with two other standard measures of aggregate consumer lending: consumer loans and revolving credit by all commercial banks.

Figures 3 and 4 address the question related to the types of borrowers that use Lending Club. Figure 3 compares the FICO score distribution implied by the Lending Club data with the FICO score distributions from Agarwal et al. (2018) (Panel A) and from the FICO Blog (Panel B). The former is based on the Credit Card Metrics dataset assembled by the U.S. Office of the Comptroller of the Currency, and the latter is based on data collected by the Fair Isaac Corporation on all borrowers in the U.S.[18] The figure suggests that borrowers at both tails of the FICO score distribution are underrepresented in the Lending Club data. Figure 4 compares the distribution of Lending

the resignation of its founder and then CEO, Renaud Laplanche. The resignation was the result of an internal loan review (called for by the Lending Club Board) that found irregularities in $22 million worth of loans associated with one specific buyer. It is worth pointing out that the irregularities were non-credit and non-pricing in nature.

[18]The FICO Blog is an online blog maintained by the Fair Isaac Corporation. The blog pertaining the FICO score distribution in the U.S. can be accessed via the following URL: https://www.fico.com/blogs/average-us-ficor-score-716-indicating-improvement-consumer-credit-behaviors-despite-pandemic.

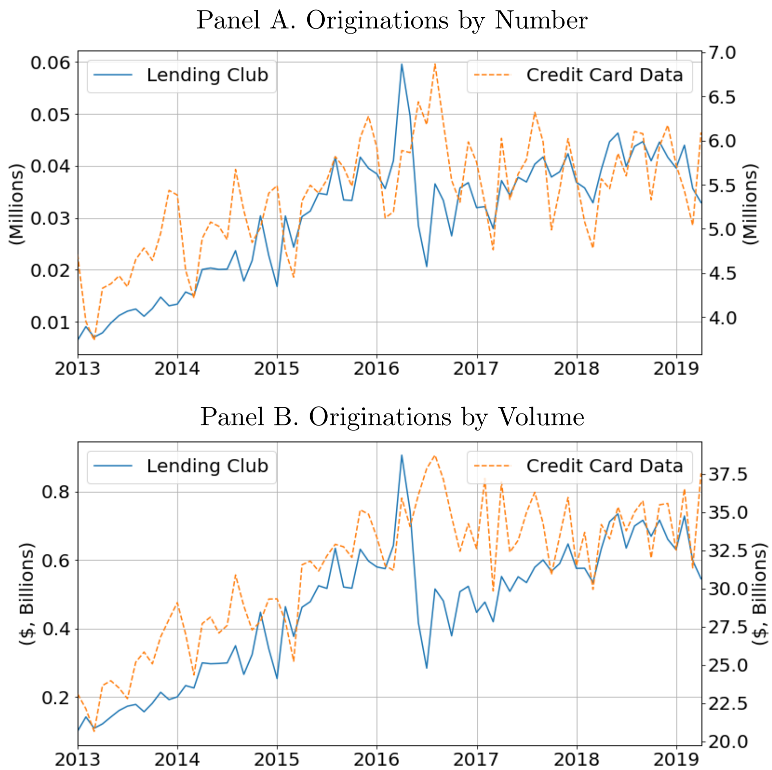

Fig. 2. Comparison of Monthly Lending Club and Credit Card Originations. Panel A compares the number of originations. Panel B compares the volume. The scale for the Lending Club originations is on the left y-axis, while the scale for the credit card data is on the right y-axis. The credit card data comes from the CFPB Consumer Credit Panel.

Club interest rates with the distribution of credit card interest rates from Tertilt and Exler (2020). Again, the figure suggests that (very) low and high risk borrowers are underrepresented in the Lending Club data.

The evidence from Figures 2 - 4 suggests that: (i) a *common* set of factors drives changes in lending for both, Lending Club and more traditional lenders such as commercial banks, and (ii) both tails of the borrowers' risk distribution are underrepresented in the Lending Club data. The former

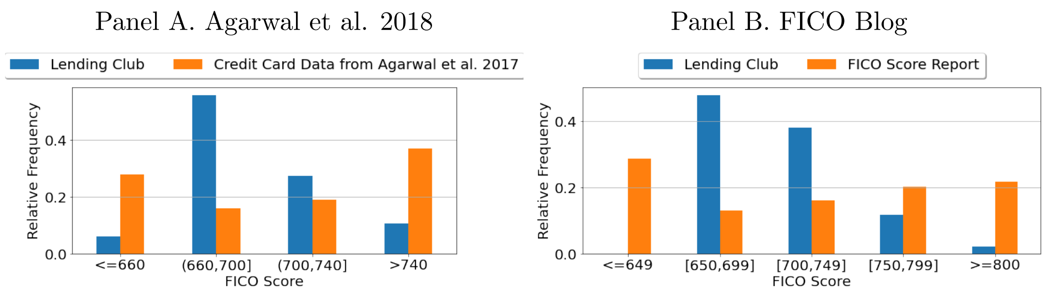

Fig. 3. Histogram of FICO Scores. Panel A compares the FICO score distribution computed by Agarwal et al. (2018) (which is based on proprietary Credit Card Data), with the FICO score distribution implied by the Lending Club Data. Panel B compares the FICO score distribution in the U.S. as of April 2018 reported by FICO, with the corresponding FICO score distribution implied by the Lending Club Data.

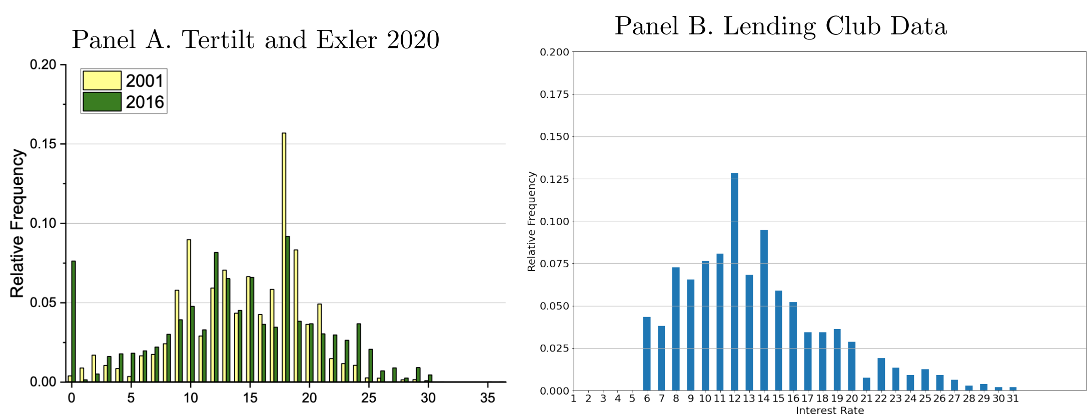

Fig. 4. Histogram of Interest Rates. Panel A presents the distribution of interest rates computed by Tertilt and Exler (2020) using data for 2016 from the Survey of Consumer Finances. Panel B presents the distribution of interest rates across all loans approved by Lending Club in 2016.

should attenuate concerns about the generalizability of my results. The latter implies that my estimates for the response of aggregate borrowing could be biased. However, I am not interested in quantifying the response of aggregate borrowing per se, but rather the dampening effect of heterogeneity on this response. Missing both tails of the risk distribution implies that my results should be viewed as a lower bound. This is because the dampening effect is driven by the negative correlation (across the borrowers' risk distribution) between the EMA and the average loan amounts.

4.4. Discontinuity Dates

There are three key features of the Lending Club data that allow me to precisely identify the discontinuity dates. First, borrowers within a sub-grade all get the same interest rate. Second, the changes in interest rates happen instantaneously. If the interest rate changes for some sub-grade at date t_0, then all borrowers in that sub-grade get interest rate r_0 on dates $t \leq t_0$, and rate r_1 on dates $t > t_0$. Third, the changes in interest rates happen sporadically. Loans are observed at a daily frequency and the shortest time interval within rate changes is 30 days.

I identify 23 discontinuity dates. Denote this set by $\mathbb{T}_0$. Using the FFR as a proxy for lenders' cost of funds, I find a subset ($\tilde{\mathbb{T}}_0 \subseteq \mathbb{T}_0$) of 14 discontinuity dates on which there is a change in the lenders' cost of funds within a 5-day window of the change in interest rates. Importantly, I am able to precisely identify $\tilde{\mathbb{T}}_0$ given that the FFR also changes instantaneously and sporadically over time.

Table A.1 in Appendix A lists the dates in $\tilde{\mathbb{T}}_0$. The table includes information on the start and end dates of a Federal Open Market Committee

(FOMC) meeting if it took place within a 7-day window around the discontinuity date. The last column presents the surprise in the three months ahead fed funds futures (FF_3). I compute this surprise using the monthly time series constructed by Jarociński and Karaki (2020), which covers the period Jan. 1990 to Dec. 2016. The surprise reported on the table is the average between the two months leading up to the discontinuity date.

There are eight contractionary discontinuity dates and six expansionary ones. All of the latter occurred between 2013 to 2015, a period where the Federal Reserve kept interest rates near the zero lower bound. Not surprisingly then, the changes in Lending Club's interest rates on these dates seem to be mostly associated with anticipated changes in the FFR. The Federal Reserve started raising interest rates in late 2015, and kept consistently increasing them until mid 2019. Note that all but one of the contractionary dates happened during this period. Importantly, the surprise in the FF_3 for these contractionary dates is non-zero – an indication that there was some unanticipated component to the changes in the FFR.

5. Methodology

Let $\mathbb{G}$ denote the set of grades, $\mathbb{S}$ the set of all sub-grades, $\mathbb{S}_g = \{g_1, ..., g_5\}$ the set of sub-grades of grade g, $\mathbb{T}_0$ the set of discontinuity dates identified in Section 4.4, and $\mathbb{Y}$ the set of variables of interest (loan contract terms, borrower characteristics, number of rejected and approved loans, and probability of default).

5.1. Changes Around Discontinuity Dates

Define the average change in $y \in \mathbb{Y}$ for sub-grade $s \in \mathbb{S}$ at date $t_0 \in \mathbb{T}_0$ as $\Delta y_{s,t_0} = \lim_{t \downarrow t_0} \mathbb{E}[y|t,s] - \lim_{t \uparrow t_0} \mathbb{E}[y|t,s]$.

Consider first the intensive margin variables. I estimate $\Delta y_{s,t_0}$ using the locally linear regression

$$y_{i,t} = \alpha + \gamma \mathbb{1}_{\mathbb{T}_{\bar{t}_0}} + \epsilon_{i,t}, \;\; t \in \left\{ \mathbb{T}_{\underline{t}_0} \cup \mathbb{T}_{\bar{t}_0} \right\} \tag{4}$$

where the subscript refers to the i^{th} observation with sub-grade equal to s at time t, $\mathbb{T}_{\underline{t}_0} \equiv \{t : t_0 - b \leq t < t_0\}$, $\mathbb{T}_{\bar{t}_0} \equiv \{t : t_0 \leq t < t_0 + b\}$, b is the bandwidth (in days) around date t_0, $\mathbb{1}_{\mathbb{T}_{\bar{t}_0}}$ is an indicator function for observations to the right of the discontinuity date t_0, and γ is the coefficient that estimates $\Delta y_{s,t_0}$.[19] My results are robust to alternative specifications that include first and second degree polynomials on the distance from the discontinuity date, even when allowing for different slopes and curvatures on either side of the discontinuity.

Consider next the three extensive margin variables: number of approved loans (N^A), number of rejected loans (N^R), and number of loans that end up in default (N^D). I estimate $\Delta N^x_{s,t_0}$ using local averages

$$\Delta N^x_{s,t_0} = \frac{1}{b} \sum_{t \in \mathbb{T}_{\bar{t}_0}} \mathbb{1}^x_{\{s,t\}} - \frac{1}{b} \sum_{t \in \mathbb{T}_{\underline{t}_0}} \mathbb{1}^x_{\{s,t\}}, \tag{5}$$

where $\mathbb{1}^x_{\{s,t\}}$ is an indicator function that is equal to one for observations of sub-grade s at time t that got the loan ($x = A$), that got the loan and ended

[19]For a few discontinuities, there is a very small number of observations post-t_0 that still get the "old" interest rate. The indicator function $\mathbb{1}_{\mathbb{T}_{\bar{t}_0}}$ in those cases is equal to one only for those observations that get the "new" interest rate post-t_0.

up defaulting on it ($x = D$), or that didn't get the loan ($x = R$).[20] For the latter, I can only estimate $\Delta N^R_{t_0}$ because there is no risk category for the rejected loans. In other words, specification (5) is independent of s.

Finally, consider the probability of default $\delta_{s,t} \equiv \frac{N^D_{s,t}}{N^A_{s,t}}$. I estimate $\Delta\delta_{s,t_0} = \lim_{t\downarrow t_0} \mathbb{E}[\delta|t,s] - \lim_{t\uparrow t_0} \mathbb{E}[\delta|t,s]$ using local averages

$$\Delta\delta_{s,t_0} = \frac{\sum_{t\in\mathbb{T}_{\bar{t}_0}} \mathbb{1}^D_{\{s,t\}}}{\sum_{t\in\mathbb{T}_{\bar{t}_0}} \mathbb{1}^A_{\{s,t\}}} - \frac{\sum_{t\in\mathbb{T}_{\underline{t}_0}} \mathbb{1}^D_{\{s,t\}}}{\sum_{t\in\mathbb{T}_{\underline{t}_0}} \mathbb{1}^A_{\{s,t\}}}. \tag{6}$$

Note that $\delta_{s,t}$ measures the fraction of loans *issued at time* t that end up in default, and not the fraction of loans in default at time t. In other words, $\delta_{s,t}$ captures default risk over the entire life of the loan (3 to 5 years), and $\Delta\delta_{s,t_0}$ captures changes in current *and* future default risk. This is important for two reasons. First, the change in interest rates at t_0 has macroeconomic implications that can affect future default risk. Second, in the standard models of consumer credit lenders are rational – their assessment of a borrower's probability of default in equation (1) reflects future default risk.

To estimate equations (4)-(6) I use a baseline bandwidth $b = 6$. This is the smallest bandwidth that ensures that there are at least 10 observations on both sides of t_0 for all discontinuities, and that at most 5% of the discontinuities for each grade $g \in \mathbb{G}$ have fewer than 30 observations at either side of t_0. These restrictions guarantee there are at least 10 observations per parameter estimated, and that there are enough observations to consider

[20]If the loan matured prior to March 31$^{\text{st}}$, 2019 (the date on which I downloaded the data), then I consider it to be in default if its status is not "Fully Paid." Otherwise, I consider it to be in default if its status is not "Current" (i.e. up to date in payments) or "Fully Paid."

alternative specifications of equation (4) that include first and second order degree polynomials. However, let me emphasize that the results are robust to using any bandwidth $b \geq 4$.[21]

5.2. Heterogeneity in the Marginal Propensities

Let Δi_{t_0} denote the change in the FFR around discontinuity date t_0. Consider the change in the loan interest rate ($\Delta r_{s,t_0}$), in the number of approved loans ($\Delta N^A_{s,t_0}$), and in the loan amount ($\Delta L_{s,t_0}$) for sub-grade s on discontinuity date t_0. Note that $\Delta r_{s,t_0}$, $\Delta N^A_{s,t_0}$ and $\Delta L_{s,t_0}$ are part of the panel $\{\Delta y_{s,t_0}\}_{y\in\mathbb{Y},s\in\mathbb{S},t_0\in\tilde{\mathbb{T}}_0}$, where the changes $\Delta y_{s,t_0}$ are computed as explained in Section 5.1.

I estimate the heterogeneity in the marginal propensity to borrow, the marginal propensity to lend, and the extensive margin adjustment using the panel $\{\Delta y_{s,t_0}\}_{y\in\mathbb{Y},s\in\mathbb{S},t_0\in\tilde{\mathbb{T}}_0}$ and the following regressions:

$$\Delta L_{s,t_0} = \alpha^L + \sum_{g\in\mathbb{G}} \mathbb{1}_{\{s\in\mathbb{S}_g\}} \beta^L_g \Delta r_{s,t_0} + X'_{s,t_0}\kappa^L + \theta_{t_0} + \nu_{s,t_0}, \tag{7}$$

$$\Delta m_{s,t_0} = \alpha^m + \sum_{g\in\mathbb{G}} \mathbb{1}_{\{s\in\mathbb{S}_g\}} \beta^m_g \Delta i_{t_0} + Z'_{s,t_0}\kappa^m + \epsilon_{s,t_0}, \tag{8}$$

where $m \in \left\{r, N^A\right\}$, X_{s,t_0} and Z_{s,t_0} are vectors of controls, θ_{t_0} are time fixed effects, and $\left\{\beta^r_g, \beta^{N^A}_g, \beta^L\right\}_{g\in\mathbb{G}}$ are the coefficients of interest.

The vector of controls X_{s,t_0} includes changes in the the loan maturity and in the following borrower characteristics: annual income, total debt-to-

[21] I conduct robustness checks for bandwidths of up to 15 days. I don't consider bandwidths of less than 4 days because then there are discontinuities that have at most 5 observations on either side of t_0, and the percent of discontinuities that have fewer than 30 observations at either side of t_0 substantially increases for some grades.

income ratio, number of open accounts, number of total accounts, revolving credit balance, revolving credit utilization, and FICO score. Including X_{s,t_0} in regression (7) controls for the correlation of changes in the in the FFR with changes in other unobserved macroeconomic variables. Changes in the macroeconomic conditions could lead to changes in the the loan amount via changes in income, total debt-to-income ratio, etc. I include changes in the loan maturity as borrowers decide jointly on the maturity and amount when requesting the loan from Lending Club. The fixed time effects control for changes in overall economic conditions that could affect borrowing. The vector of controls Z_{s,t_0} includes the same variables as $X_{s,t}$, and adds changes in the probability of default and in the total loan demand. Note that I don't include time fixed effects in specification (8). Time fixed effects control for potential changes in aggregate economic conditions, but in specification (8) those are proxied by changes in the FFR.[22]

The estimates β_g^r and β_g^{NA} quantify the change in the loan interest rate and the change in the number of approved loans, respectively, in response to a 1% change in the FFR. Meanwhile, β_g^L quantifies the change in the loan amount in response to a 1% change in the loan interest rate. I interpret β_g^L as the marginal propensity to borrow (MPB_g), β_g^r as the marginal propensity to lend (MPL_g), and β_g^{NA} as the extensive margin adjustment (EMA_g). I construct confidence intervals for the estimated coefficient using clustered standard errors by date. Conceptually, I am interested in identifying heterogeneity in the MPL, MPB, and EMA whenever there is an exogenous

[22]In other words, the time fixed effects are collinear with the changes in the FFR.

change in credit conditions. The dates that I have identified are clearly not all the dates that have exogenous changes in credit conditions. Clustering the standard errors by date allows me to generalize my conclusions.

My interpretations of β_g^L and β_g^r as the marginal propensities to borrow and lend, respectively, follow from Lending Club's origination process. This process starts with a potential borrower applying for a loan online. The borrower chooses the desired loan amount, specifies its purpose, and provides some personal information including date of birth, income, name, and address. Upon submission of the application, the borrower receives a contingent offer that specifies the term, monthly payment, and APR for the loan. If the borrower accepts the offer, some additional information is collected (homeownership status, employment status, SSN) and a credit check is run. The borrower then gets the formal loan contract and decides whether or not to accept it. In a nutshell, Lending Club sets the loan interest rate while the borrower chooses the loan amount.

A final remark on my baseline specifications. I exclude the vector of controls Z_{s,t_0} from my baseline specification of regression (8). As I argue in Section 6, my research design ensures that there are no changes in the probability of default on the discontinuity dates $t_0 \in \tilde{\mathbb{T}}_0$. This implies that the changes in interest rates for the different groups of borrowers must be driven by changes in aggregate economic conditions (or in Lending Club's idiosyncratic factors). It also implies that the changes in the number of approved loans are not driven by changes in the (risk) composition of borrowers within each group. I show, nonetheless, that my MPL_g and EMA_g estimates are robust to adding the full set of controls Z_{s,t_0}.

Similarly, I control only for changes in borrowers' overall debt holdings (specifically, debt-to-income ratio and revolving credit balance) in my baseline specification of regression (7). By construction, there is a change in cost of funds (proxied by the FFR) on the discontinuity dates. Standard economic theory predicts that borrowers will adjust their overall debt holdings (not only on the loan amount requested to Lending Club) in response to this economy-wide change in the cost of funds.[23] Although the changes in economic conditions can affect borrowers' behavior via income and other characteristics, these changes are unlikely to operate at a daily frequency. Again, I show that my MPB_g estimates are robust to including the full set of controls X_{s,t_0}.

5.3. Effect on the Response of Aggregate Borrowing

Let $\Delta L^{\mathrm{agg}} \equiv \frac{\partial L/\partial \mathrm{FFR}}{\sum_{g\in\mathbb{G}} N_g}$ denote the change in aggregate borrowing given a change in the FFR (normalized by the total number of loans). Then ΔL^{agg} is given by:

$$\Delta L^{\mathrm{agg}} = \sum_{g\in\mathbb{G}} w_g \left[\mathrm{EMA}_g \cdot \left(\frac{L_g}{N_g}\right) + \mathrm{MPL}_g \cdot \mathrm{MPB}_g\right], \tag{9}$$

where $w_g \equiv \frac{N_g}{\sum\limits_{g\in\mathbb{G}} N_g}$, N_g is the number of approved loans, and L_g is the average loan amount. Equation (9) decomposes the change in aggregate borrowing into its extensive $\left(\mathrm{EMA}_g \cdot \frac{L_g}{N_g}\right)$ and intensive $(\mathrm{MPL}_g \cdot \mathrm{MPB}_g)$ margin components. The former captures the change in aggregate borrowing from the adjustment in the number of approved loans, while the latter captures the change in aggregate borrowing from changes in the requested loan amounts.

[23] Section 6 shows that this is indeed the case.

Let $x \in \left\{\text{MPL}, \text{EMA}, \text{MPB}, \frac{L}{N}\right\}$ and denote the average x across all grades by $\overline{x} \equiv \sum\limits_{g \in \mathbb{G}} w_g \cdot x_g$. Consider the counterfactual that assumes $x_g = \overline{x}$. Then equation (9) can be written as:

$$\overline{\Delta L^{\text{agg}}} = \left[\overline{\text{EMA}} \cdot \left(\overline{L/N}\right) + \overline{\text{MPL}} \cdot \overline{\text{MPB}}\right].$$

One can think of $\overline{\Delta L^{\text{agg}}}$ as the predicted response of aggregate borrowing when ignoring the heterogeneity across grades. Therefore, I measure the effect of heterogeneity using the ratio $f^{\text{damp}} \equiv \Delta L^{\text{agg}} / \overline{\Delta L^{\text{agg}}}$. I refer to this ratio as the dampening factor: $f^{\text{damp}} < 1$ (> 1) indicates that heterogeneity dampens (amplifies) the response of aggregate borrowing. Note that the closer the factor is to one, the smaller the effect of heterogeneity.

To separately assess the role of heterogeneity in the intensive and extensive margins, I define intensive (f^{damp}_{int}) and extensive (f^{damp}_{ext}) margin dampening factors as follows:

$$f^{\text{damp}}_{int} \equiv \frac{\sum_{g \in \mathbb{G}} w_g \cdot \text{MPL}_g \cdot \text{MPB}_g}{\overline{\text{MPL}} \cdot \overline{\text{MPB}}} = \sum_{g \in \mathbb{G}} w_g \cdot \widehat{\text{MPL}}_g \cdot \widehat{\text{MPB}}_g, \tag{10}$$

$$f^{\text{damp}}_{ext} \equiv \frac{\sum_{g \in \mathbb{G}} w_g \cdot \text{EMA}_g \cdot (L/N)_g}{\overline{\text{EMA}} \cdot \left(\overline{L/N}\right)} = \sum_{g \in \mathbb{G}} w_g \cdot \widehat{\text{EMA}}_g \cdot \left(\widehat{L/N}\right)_g. \tag{11}$$

Equations (10) and (11) show that f^{damp}_{int} and f^{damp}_{ext} can be written in terms of the normalized variables $\hat{x}_g \equiv x_g / \overline{x}$.

6. Validation of Research Design

Lending Club's interest rates are a function of three factors: borrowers' default risk, idiosyncratic Lending Club factors, and aggregate economic conditions. In principle, the interest rates could depend on lenders' characteristics, borrowers' characteristics, idiosyncratic Lending Club factors, and aggregate economic conditions. However, Lending Club does not hold any financial stake in the loans – all loans are funded by institutional and retail investors. Lending Club simply assesses the risk of a borrower, and assigns the corresponding interest rate. In other words, Lending's Club institutional setting implies that: (i) interest rates are not a function of lenders' characteristics, and (ii) interest rates depend on borrowers' characteristics only through borrowers' default risk.

The previous discussion has an important implication. If borrowers' default risk remains unchanged when interest rates change, then the adjustments in interest rates must be driven by changes in Lending Club's idiosyncratic factors and/or changes in aggregate economic conditions. In what follows, I show that this is indeed the case for the subset of discontinuity dates on which the FFR increases. I also show that the total number of loan applications does not change for this subset of discontinuity dates, which addresses concerns about borrowers strategically adjusting their behavior as they anticipate the change in interest rates.

6.1. Changes in Default Risk

Consider discontinuity date $t_0 \in \tilde{\mathbb{T}}_0$ and sub-grade $s \in \mathbb{S}$. Let $\mathbb{D}_{t_0} \equiv \{d : |t_0 - t| \leq 30\}$ denote the 30-day window around discontinuity date t_0 and $\hat{y}_{d,s,t_0}$ the average value of y for sub-grade s and $d \in \mathbb{D}_{t_0}$ predicted by a locally linear regression estimated separately on either side of t_0.[24] Define

[24] I use the same bandwidth b as in regressions (4)-(6).

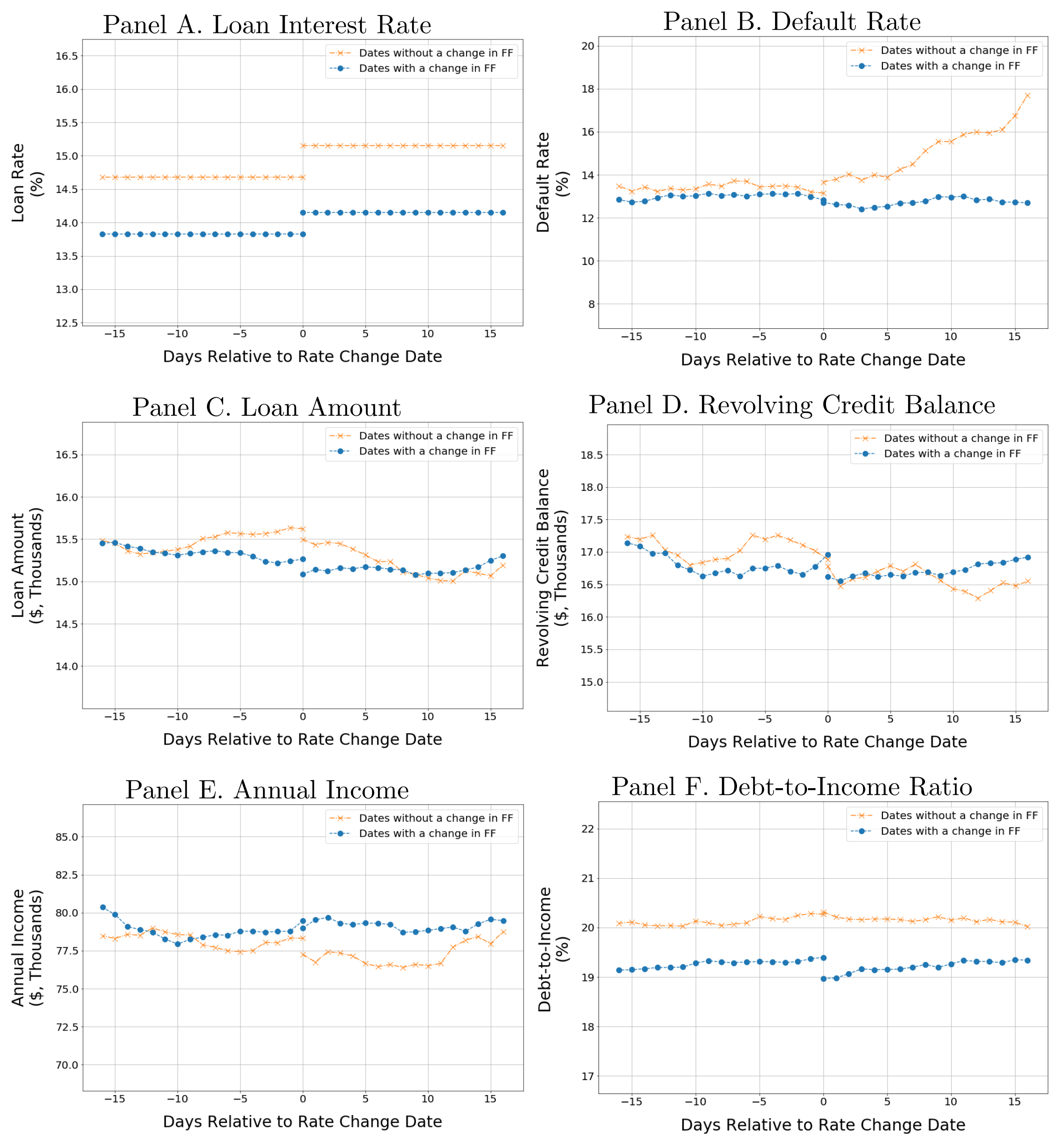

Fig. 5. Loan Interest Rate, Default Rate, Loan Amount, Revolving Credit Balance, Annual Income, and Debt-to-Income Ratio Around Contractionary Discontinuity Dates. The figure shows predicted values from locally linear regressions estimated separately on either side of the discontinuity date. The horizontal axis measures the number of days relative to the discontinuity date.

$\hat{y}_d \equiv \sum_{t_0 \in \tilde{\mathbb{T}}_{0+}, s \in \mathbb{S}} \frac{\hat{y}_{d,s,t_0}}{|\mathbb{S}| \cdot |\tilde{\mathbb{T}}_{0+}|}$ and $\hat{y}_d^{\complement} \equiv \sum_{t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}, s \in \mathbb{S}^+_{t_0}} \frac{\hat{y}_{d,s,t_0}}{|\mathbb{S}| \cdot |\tilde{\mathbb{T}}_{0+}|}$, where $\tilde{\mathbb{T}}_{0+} \subseteq \tilde{\mathbb{T}}_0$ denotes the set of discontinuity dates on which there is an increase in the FFR, $\tilde{\mathbb{T}}^{\complement}_{0+} \subseteq \mathbb{T}_0 \setminus \tilde{\mathbb{T}}_0$ the set of discontinuity dates on which there is an increase in loan interest rates (for at least one sub-grade) but no change in the FFR, and $\mathbb{S}^+_{t_0}$ the set of sub-grades for which the loan interest rate increases on date t_0.[25]

Figure 5 presents $\{\hat{y}_d\}_{\{d:|d| \leq 30\}}$ ("o" blue line) and $\left\{\hat{y}_d^{\complement}\right\}_{\{d:|d| \leq 30\}}$ ("x" orange line) for the loan interest rate, default rate, loan amount, revolving credit balance, annual income, and debt-to-income ratio. Panel A illustrates that loan interest rates increase on average for discontinuity dates $t_0 \in \tilde{\mathbb{T}}_{0+}$. Note that, by definition, they also increase for discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}$.

The increase in interest rates could be driven by an increase in borrowers's risk, changes in Lending Club's idiosyncratic factors (such as transactions costs or markups), or changes in aggregate economic conditions (such as an increase in lenders' costs of funds). Panel B shows that the default rate (my measure of borrowers' risk) remains unchanged leading up to, on, and following, the discontinuity dates on which there is an increase in the FFR. This suggests that changes in the loan interest rates on contractionary discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_{0+}$) are *not* driven by changes in borrowers's risk. Recall that I define the default rate as the fraction of loans issued at date t that end up in default, and not the fraction of loans in default at date t. Therefore, the default rate captures current and future default risk over the

[25] One can define the averages weighting each $\hat{y}_{d,s,t_0}$ by the number of observations that were used to estimate it. The conclusions that follow do not change.

entire life of the loan.

Note also that Figure 5 shows that the default probability remains unchanged *following* the change in interest rates on dates $t_0 \in \tilde{\mathbb{T}}_{0+}$. This is because borrowers internalize the changes in interest rates and choose to borrow different amounts, which is also a property of the standard models of consumer debt and default. Panels C and D show that borrowing from Lending Club and from other sources, respectively, decreases following the increase in interest rates.[26] The decrease in borrowing leads to a decrease in the debt-to-income ratio (Panel F) given that total income remains unchanged (Panel E). A lower debt-to-income ratio with higher interest rates explains why the probability of default remains unchanged. Importantly, the decrease in overall borrowing with no changes in other borrower characteristics is consistent with an *economy-wide* increase in the cost of funds.[27]

Table 4 presents the estimates of the difference in the average probability of default before and after the increase in interest rates (the averages are taken over the entire 30 day window). Panel A shows the difference for discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}$, and Panel B for $t_0 \in \tilde{\mathbb{T}}_{0+}$. These estimates corroborate the observations from Figure 5. The probability of default increases by 1.67 percentage points on discontinuity dates on which there is no change in the FFR, while it remains unchanged on dates on which the

[26] I proxy the amount borrowed from other sources using borrowers' total revolving credit balance. Using other proxies, such as the number of total revolving accounts and the number of open accounts, leads to similar conclusions.

[27] Although not show in Figure 5, FICO scores and other borrower characteristics remain unchanged on and following the discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}$.

Table 4. Difference in the Average Probability of Default

Panel A. Dates With No Change in the Federal Funds Rate

		Grade				
	All	A	B	C	D	E
Average Difference	1.67***	0.41	1.54***	1.48*	2.14**	2.77*
	(0.37)	(0.25)	(0.38)	(0.58)	(0.67)	(1.40)
Number of observations	3, 026	476	612	680	884	374

Panel B. Dates With a Change in the Federal Funds Rate

		Grade				
	All	A	B	C	D	E
Average Difference	-0.27	0.16	-0.11	-0.57	-0.33	-0.63
	(0.27)	(0.16)	(0.26)	(0.42)	(0.58)	(0.92)
Number of observations	6,256	1,360	1,360	1,360	1,360	816

Notes. Table shows the difference in the average probability of default 30 days before and 30 days after the increase in interest rates. Panel A presents the difference for the subset of discontinuity dates on which there is no change in the Federal Funds Rate ($t_0 \in \tilde{\mathbb{T}}^{\mathsf{C}}_{0+}$), while Panel B presents it for the discontinuity dates on which there is a change in the Federal Funds Rate ($t_0 \in \tilde{\mathbb{T}}_{0+}$). Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

FFR increases.[28] Importantly, Table 4 also shows that this holds true when looking at each grade individually.

Figure 5 also illustrates that the Lending Club data is consistent with the pricing equation of the standard models of consumer credit. If default risk and the cost of funds are the major drivers of Lending Club's interest rates, then one would expect to see changes in the probability of default around discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\mathsf{C}}_{0+}$. The figure shows that this is indeed the case. Furthermore, the probability of default continues to increase *after*

[28]The estimate is negative, but it's magnitude is 6 times smaller than the magnitude of the difference for dates $t_0 \in \tilde{\mathbb{T}}^{\mathsf{C}}_{0+}$ and it is not statistically significant.

the increase in interest rates. Borrowers internalize the changes in interest rates and decrease their borrowing (Panels C and D). However, unlike for discontinuity dates $t_0 \in \tilde{\mathbb{T}}_{0+}$, there is no change the debt-to-income ratio (Panel F) because borrower's income decreases as well (Panel E). The same debt-to-income ratio with higher interest rates explains the ensuing increase in the probability of default.

Appendix B presents the equivalent of Figure 5 for discontinuity dates on which there was a decrease in loan interest rates. It compares dates with a decrease in the FFR ($\tilde{\mathbb{T}}_{0-} \subseteq \tilde{\mathbb{T}}_0$), with those on which there was no change in the FFR ($\tilde{\mathbb{T}}^{\complement}_{0-} \subseteq \mathbb{T}_0 \setminus \tilde{\mathbb{T}}_0$). Note that the loan amount (or any other variable for that matter) does not change around the discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0-}$. This is likely because of the small magnitude of the average change in interest rates on these dates, which is about 15 b.p. For comparison, the magnitude of the average change in interest rates for all other discontinuity dates ($\tilde{\mathbb{T}}_{0+}$, $\tilde{\mathbb{T}}^{\complement}_{0+}$, and $\tilde{\mathbb{T}}_{0-}$) is between $30 - 50$ b.p.

The loan amount increases as expected for the expansionary discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_{0-}$), but borrowing from other sources and overall borrowing do not. Instead, overall borrowing dips sharply and then recovers on the days *leading up* to the discontinuity dates. This dip results in a persistent decrease in the the debt-to-income ratio during the 10-day period preceding the change in interest rates.[29] The previous scenario is not consistent with an *economy-wide* decrease in the cost of funds, but rather with a decrease in interest rates that is driven by changes in borrowers' default risk. Looking at

[29]Note that the debt-to-income ratio was relatively constant at around 18% 10 to 15 days prior to the discontinuity dates.

probability of default corroborates this concern – it sharply decreases (from about 17% to 16%) on the 7-day period leading up to the change in interest rates.

An additional concern regarding the expansionary discontinuity dates is that the decrease in the FFR seems to be mostly anticipated (see Section 4.4). For these reasons, my baseline results are based on the contractionary discontinuity dates.

6.2. Extensive Margin

Figure 6 presents the changes in the loan approval rate (Panel A), the number of loan applications (Panel B), and the number of approved loans (Panel C) around the discontinuity dates $t_0 \in \tilde{\mathbb{T}}_{0+}$ ("o" blue line) and $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}$ ("x" orange line). The figure shows that the number of loan applications, the number of approved loans, and (consequently) the loan approval rate remain unchanged on the discontinuity dates $t_0 \in \tilde{\mathbb{T}}^{\complement}_{0+}$.

Meanwhile, the loan approval rate decreases by about 2 percentage points following the increase in interest rates on contractionary discontinuity dates. Panels B and C illustrate that the decrease in the approval rate is entirely supply driven; the total number of loans applications remains unchanged.[30] The previous observation addresses concerns about borrowers strategically adjusting their behavior in anticipation to the increase in interest rates. It

[30] The number of loan applications and the number of approved loans exhibit a hump-shaped pattern – loan applications are largest in the middle of the week. Panels B and C in Figure 6 present the seasonally adjusted series (to make the discussion more transparent). The loan approval rate in Panel A is computed using the unadjusted series, but the graph is virtually identical when using the adjusted series.

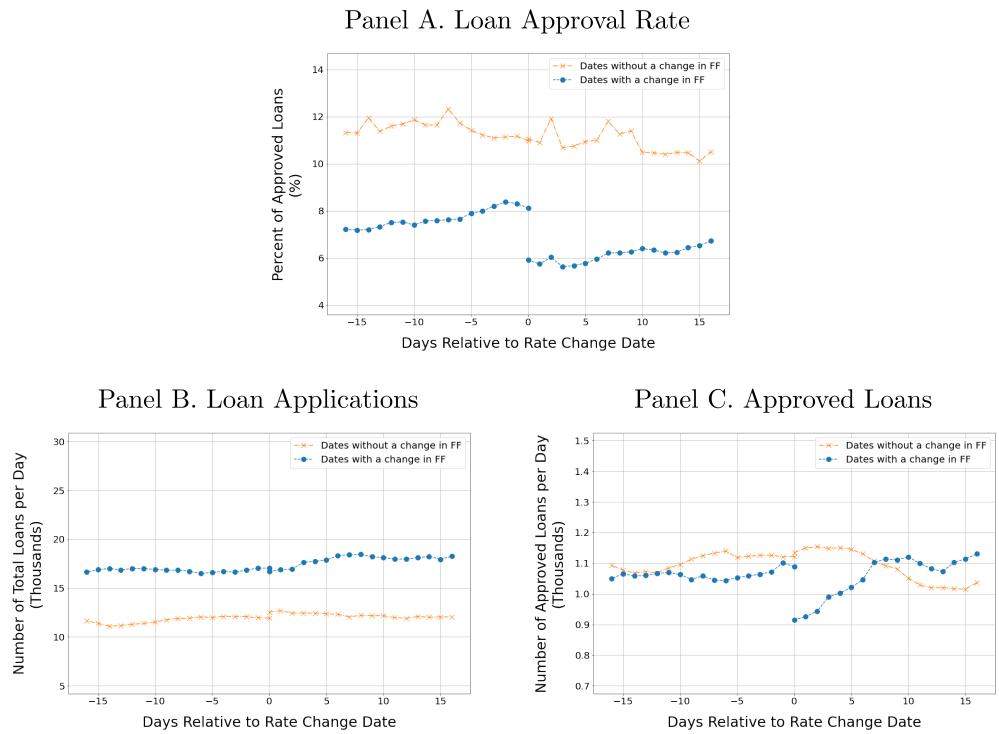

Fig. 6. Loan Applications, Approved Loans, and Loan Approval Rate Around Contractionary Discontinuity Dates. The figure shows daily averages over a b-day window around each day. The averages are estimated separately on either side of the discontinuity date. The horizontal axis measures the number of days relative to the discontinuity date.

is also consistent with the evidence presented in Section 4.4, which suggests that increases in the FFR on contractionary dates have an important unanticipated component.

Finally, note that loan demand for each risk-category could still change even if aggregate loan demand remains unchanged. For instance, this could happen if the composition of the pool of loan applicants changes – there could be more (less) relatively risky borrowers applying for loans, and less (more) relatively safe ones. Looking at the response of approved and rejected loans for each *grade* would shed light on the mechanism. Unfortunately I can't; Lending Club only assigns risk categories to the approved loans.[31] Therefore, the EMA_g that I document could be driven by changes in Lending Club's approval standards (supply) or by changes in the number of loan applicants (demand).

7. Results

Figures 5 and 6 show that, on average, loan interest rates increase by 31 b.p., loan amounts decrease by $176, and the number of daily approved loans decreases by 174 on the contractionary discontinuity dates. I next show that these averages hide a substantial amount of heterogeneity across grades, which has important implications for the response of aggregate borrowing to changes in the FFR.

7.1. Heterogeneity Across Grades

Table 5 presents the estimates of the MPL_g, MPB_g, and EMA_g from regressions (7) and (8). The MPL_g is positive for all grades and increasing in the default risk. My estimates suggest that the MPL_g for the riskiest borrowers (grade E) is three times larger than for the least risky ones (grade A). This result agrees with the prediction from the standard models of consumer credit à la Chatterjee et al. (2007) and Livshits et al. (2007). It is

[31] In theory, the rejected loan data could be mapped into the different risk categories. This requires that enough common information be given for the rejected and approved loans. However, there are only two common fields that are available for approved and rejected loans during the entire sample period: debt-to-income ratio and state of residence.

Table 5. Marginal Propensities and Extensive Margin Adjustment

	Regression Specification		
Coefficient	MPL ($x = r$)	EMA ($x = N$)	MPB ($x = L$)
β^x_A	10.19**	-337.61**	-773.31
	(3.75)	(119.70)	(669.16)
β^x_B	10.32**	-377.56***	-912.33*
	(3.63)	(113.48)	(410.50)
β^x_C	13.63***	-234.11	-1356.07**
	(3.39)	(158.58)	(427.18)
β^x_D	18.03***	-46.87	-989.72**
	(4.90)	(174.66)	(336.39)
β^x_E	30.02***	-6.65	-712.23**
	(5.06)	(181.74)	(251.63)
Number of Observations	178	178	178
Adjusted R^2	0.34	0.13	0.39

Notes. Table shows the estimates of the coefficients of interest $\left\{\beta^r_g, \beta^L_g, \beta^{N^A}_g\right\}_{g\in\mathbb{G}}$ for the baseline specification of regressions (7) and (8). The estimates are based on the sample that includes only the contractionary discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_{0+}$). Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

also consistent with the evidence from the empirical literature on the risk-taking channel of monetary policy, which suggests that banks charge risky firms higher loan spreads (compared to safe firms) when the risk-free rate increases.

The MPB_g is negative for all grades and non-monotonic in the default risk. The magnitude of the MPB_g is largest for medium-risk borrowers (grade C), and it decreases as borrowers get either riskier or safer. Note that this actually matches the quantitative performance of many default models. In these models, the lowest-risk borrowers tend not to be sensitive, and the highest-risk borrowers tend to be priced out even under the best of circumstances.

Lastly, the EMA_g is negative for all grades and increasing in the default risk – the number of approved loans changes the most for the safest borrowers. The sign agrees with the prediction from models of consumer credit that incorporate the extensive margin à la Livshits et al. (2016). Although these models typically abstract from heterogeneity across borrowers, the differences I document are consistent with the predictions from several monetary policy transmission mechanisms. An increase in the risk-free rate may decrease the credit quality of the pool of borrowers through the balance-sheet channel of monetary policy (Bernanke and Gertler (1995)). Similarly, the risk-taking channel predicts that an increase in the risk-free rates leads to a tightening in lending standards as investors have more incentive to screen out bad borrowers (Dell'Ariccia and Marquez (2006)). For a fix pool of loan applicants, these two effects imply that fewer applicants qualify as safe (and hence loans to "safe" borrowers decrease).

As stated earlier, my research design does not guarantee that loan demand remains fixed within each risk-category. This means that the composition of the pool of loan applicants may also change. However, and to the extent that safer borrowers are less borrowing-constrained than riskier ones, an increase in the risk-free rate disproportionately discourages safer borrowers from applying to loans. The summary statistics from Table 1 show that the characteristics of safer borrowers (grade A) make them less likely to be borrowing constrained than riskier borrowers (grade E): higher income, lower debt-to-income ratio, higher FICO score, and lower revolving credit utilization. The table also shows that safer borrowers are about $5-10\%$ more likely to use Lending Club loans to refinance existing debt, which would also disproportionately discourage safer borrowers from applying to loans after an increase in the risk-free rate.[32]

To illustrate the magnitude of my estimates, consider a 2.1 b.p. increase in the FFR (the average increase across contractionary dates). My point estimates imply that the least risky borrowers (grade A) would experience a 21 b.p. increase in the interest rate, a \$165 decrease in the requested loan amount, and a decrease of 7 approved loans per day. Medium-risk borrowers (grade C) would experience a 29 b.p. increase in interest rates, a \$338 decrease in the requested loan amount, and a decrease of 5 approved loans per day. The riskiest borrowers (grade E) would experience a 63 b.p. increase in interest rates, a \$449 decrease in the requested loan amount, and no change in the number of approved loans. These changes correspond to $2-6\%$ of the average values of interest rates, loan amounts, and number of approved loans over the sample period (see Table 1).

Appendix C examines the robustness of my results. Appendix C.1 shows that my estimates are robust to including the expansionary discontinuity dates in the analysis, Appendix C.2 shows that the estimates are robust to using different bandwidths in the locally linearly regressions (4)-(6), and Appendix C.3 shows that my estimates are robust to including the full set of borrower characteristics as controls in regressions (7) and (8).

[32]Lending Club asks prospective borrowers the purpose of the loan, one of the options is refinancing.

Two final comments about my MPL_g and EMA_g estimates. First, I don't control for changes in Lending Club's idiosyncratic factors (such as transaction costs or markups).[33] If these factors are correlated with changes in the FFR, then my estimates would not isolate the response of interest rates and the number of approved loans to changes in the aggregate cost of funds. Of course, one can argue that these factors are also part of Lending Club's cost of funds. The issue is really related to the generalizability of my estimates. If other lenders' transaction costs and markups are not correlated with the FFR in the same fashion as Lending Club's, then my results would not apply to those lenders. However, this issue (i) is not unique to using Lending Club's data, (ii) is only relevant if the behavior of other lenders differs substantially from Lending Club's, and (iii) is attenuated if one believes that most of the response is driven by changes in the aggregate cost of funds.

Second, one should view my MPL_g and EMA_g estimates as *conditional* estimates. My research design considers only dates with changes in Lending Club's interest rates, but there are dates on which these don't change despite changes in the FFR. Therefore, these estimates capture the effect of a change in the FFR on loan interest rates, and on the number of approved loans, conditional on loan interest rates changing. I focus on the conditional estimates given that I want to jointly estimate the MPL_g, EMA_g, *and* MPB_g. Although the results for the EMA_g need not generalize, the insights about the heterogeneity in the MPL_g extend to the unconditional case. This follows by noting that the magnitude of the unconditional MPL_g estimates is scaled

[33] I don't have information on such factors.

Table 6. Macroeconomic Implications

	Panel A. Average Loan Amount and Weight for Each Grade				
	A	B	C	D	E
Average Per Loan Amount, \$ $\left(\frac{L_g}{N_g}\right)$	80.03	49.93	58.80	120.39	465.28
Weight $\left(w_g \equiv \frac{N_g}{\sum_{g \in \mathbb{G}} N_g}\right)$	0.21	0.32	0.29	0.15	0.04

	Panel B. Response of Aggregate Borrowing		
	Change, \$		Dampening Factor
	Predicted	Counterfactual	(Predicted/Counterfactual)
Intensive Margin	-282.46	-281.16	1.00
Extensive Margin	-346.39	-476.44	0.73
Total	-628.85	-757.60	0.83

Notes. The table shows the estimates of the change in aggregate borrowing in response to a 2.1 b.p. increase in the risk free rate, and the corresponding dampening factors. The estimates are computed using equations (9) - (11). Panel A presents $\frac{L_g}{N_g}$ and w_g used to compute these estimates (MPL_g, MPB_g, and EMA_g are those shown in Table 5).

by the same factor for all grades.[34]

7.2. Macroeconomic Implications

Table 6 presents the response of aggregate borrowing (ΔL^{agg}) implied by equation (9) and given my estimates for the MPL_g, MPB_g, and EMA_g. Note that the average loan amount (L_g/N_g) and weight (w_g) are also relevant for the computation of ΔL^{agg}, which is why Panel A includes this information.[35]

Panel B shows that a 2.1 b.p. increase in the FFR decreases aggregate

[34] Let $p_{\Delta r \neq 0}$ denote the probability that Lending's Club interest rate changes for at least one sub-grade. Then $\mathbb{E}\left[\frac{\Delta x_g}{\Delta i}\right] = p_{\Delta r \neq 0} \cdot \mathbb{E}\left[\frac{\Delta x_g}{\Delta i} \middle| \Delta r \neq 0\right] + (1 - p_{\Delta r \neq 0}) \cdot \mathbb{E}\left[\frac{\Delta x_g}{\Delta i} \middle| \Delta r = 0\right]$ for $x \in \left\{r, N^A\right\}$, and note that $\mathbb{E}\left[\frac{\Delta r_g}{\Delta i} \middle| \Delta r = 0\right] = 0 \; \forall g$.

[35] The average per loan amounts and weights are computed using the subsample of contractionary discontinuity dates. However, they are almost identical when based on the full data set.

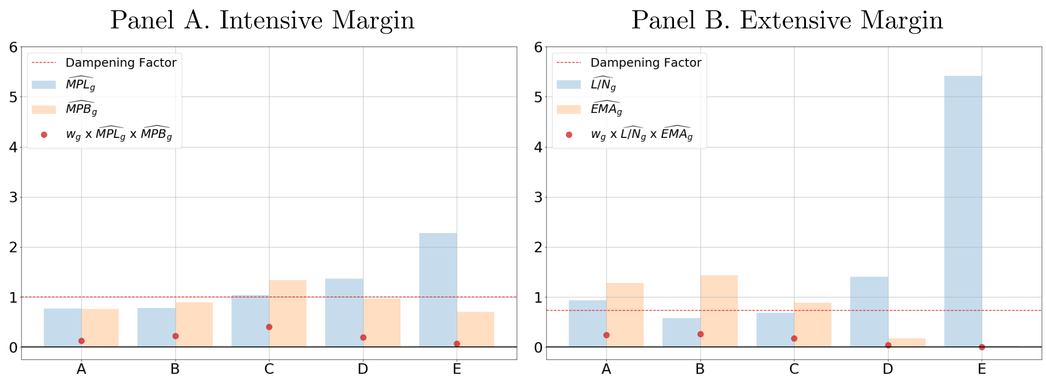

Fig. 7. Intensive and Extensive Margin Dampening Factors. The figure illustrates the relationship between the marginal propensities to borrow and lend (intensive margin), and between the number of approved loans and the average per loan amount (extensive margin), which are the key drivers behind the dampening factors – see equations (10) and (11).

borrowing by \$629. The change in the extensive margin accounts for about 55% of this decrease, while the remaining 45% is associated with adjustments in the intensive margin. To help contextualize the magnitude of this decrease, consider the marginal propensities to consume estimated by Parker et al. (2013).[36] Using these marginal propensities, and assuming that all of the borrowing is used to finance spending, my estimated decrease of \$629 in borrowing would be equivalent to a decrease in income between \$699 to $\$1,250$.

Panel B also shows that the predicted response of aggregate borrowing is about 1.2 times larger for the counterfactual that ignores heterogeneity.

[36]These authors estimate marginal propensities to consume that range between $0.5-0.9$. Their estimates are based on the rebate payments from the 2008 Economic Stimulus Act, which were \$300-\$600 for individuals and \$600-\$1,200 for families.

Importantly, the dampening factors suggest that all of the effect of heterogeneity operates via the extensive margin: $f_{ext}^{\text{damp}} = 0.73$ compared to $f_{int}^{\text{damp}} \simeq 1$. Figure 7 presents the key drivers behind these dampening factors to illustrate why their magnitudes differ. Panel A shows the relationship between the marginal propensities to borrow and lend (intensive margin), and Panel B the relationship between the number of approved loans and the average per loan amount (extensive margin). The non-monotonicity of the marginal propensity to borrow implies that the MPL and MPB are positively correlated for low to mid-risk borrowers (grades A to C), and negatively correlated for mid to high-risk borrowers (grades C to E). The former amplifies the response of aggregate borrowing, while the later dampens it. Overall, these two opposing effects cancel each other out and the heterogeneity in the intensive margin does not affect the response of aggregate borrowing. Meanwhile, the EMA and the average loan amount are negatively correlated across all grades, which unambiguously dampens the response of aggregate borrowing.

I am not the first to document the dampening effect of heterogeneity. Agarwal et al. (2018) also show that heterogeneity dampens the response of aggregate borrowing. However, they focus only on the intensive margin and document a much larger effect – their dampening factor is about 0.50, while mine is 0.83. The difference in the magnitude of our estimates is likely due to two factors. First, they find a monotonic MPB. This implies that for them the MPL and MPB are negatively correlated across the entire risk distribution. Keep in mind that our definitions of the MPB are not exactly the same – theirs captures the response of borrowers to changes in credit card limits, mine captures the response to changes in interest rates. Second, the Lending Club data is missing borrowers at both tails of the risk distribution.[37] Recall that the dampening effect is driven by the negative correlation between the EMA and the average loan amount across the borrowers' risk distribution. Therefore, missing both tails implies a smaller effect (assuming that the negative correlation extends to the tails of the distribution).

8. Conclusion

I investigate the effect of a change in the Federal Funds Rate (FFR) on loan interest rates, the number of approved loans, and the requested loan amounts. I document substantial heterogeneity across borrowers in these responses. For a 2.1 b.p. increase in the FFR (the average over the sample period I study), the least risky borrowers experience a 21 b.p. increase in the interest rate, a \$165 decrease in the requested loan amount, and a decrease of 7 approved loans per day. Medium-risk borrowers experience a 29 b.p. increase in the interest rate, a \$338 decrease in the requested loan amount, and a decrease of 5 approved loans per day. The riskiest borrowers experience a 63 b.p. increase in the interest rate, a \$449 decrease in the requested loan amount, and no change in the number of approved loans.

These results support two key predictions from standard models of consumer debt and default. First, interest rates increase more for the riskiest borrowers as predicted by models à la Chatterjee et al. (2007) and Livshits et al. (2007). Second, the total number of approved loans decreases follow-

[37] Section 4.3.

ing the increase in the FFR. This consistent with models that incorporate the extensive margin à la Livshits et al. (2016). Although these models abstract from the heterogeneity across borrowers, my estimates suggest that the number of approved loans changes the most for the least risky borrowers.

My results also have important implications for the response of aggregate borrowing. I find that the change in the number of approved loans and the average loan amounts are negative correlated. In simple terms, the number of approved loans changes the most for the the borrowers that request the lowest loan amounts. This negative correlation dampens the response of aggregate borrowing by a factor of about 0.83. The intensive margin plays a less significant role. The non-monotonicity of the response in the requested loan amount implies that the marginal propensities to lend (the change in loan interest rates given the change in the FFR) and borrow (the change in the requested loan amount given a change in the loan interest rate) are positively correlated for low to mid-risk borrowers, and negatively correlated for mid to high-risk borrowers. The former amplifies the response of aggregate borrowing, and the later dampens it. Overall, these two opposing effects cancel each other out.

Appendix A. Dates with Interest Rates Changes

Table A.1. Discontinuity Dates

Date	Fed Funds Rate Change (%)	FOMC Meetings Start Date	FOMC Meetings End Date	Surprise in the FF_3 Change (%)
2013-06-19	-0.03	2013-06-18	2013-06-19	0.005
2013-09-10	0.02	2013-09-17	2013-09-18	0
2013-10-23	-0.02	2013-10-16	2013-10-16	0
2014-02-13	-0.01	NA	NA	0
2014-05-01	-0.02	2014-04-29	2014-04-30	0
2015-02-04	-0.01	2015-01-27	2015-01-28	0
2015-10-28	-0.01	2015-10-27	2015-10-28	-0.010
2015-12-22	0.03	2015-12-15	2015-12-16	0.010
2016-01-28	0.02	2016-01-26	2016-01-27	0.005
2016-06-07	0.04	2016-06-14	2016-06-15	-0.010
2016-10-14	0.01	NA	NA	-0.005
2018-05-08	0.02	2018-05-01	2018-05-02	NA
2018-06-29	0.02	NA	NA	NA
2018-11-06	0.01	2018-11-07	2018-11-08	NA

Notes. Table shows the 14 discontinuity dates on which there are changes in the loan interest rates and in the FFR. NA stands for not applicable or not available.

Table A.1 presents the 14 discontinuity dates on which there are changes in the loan interest rates and in the FFR. The second column lists the change in the FFR (in percentage points). There are eight dates on which the FFR increases (contractionary dates), and six on which it decreases (expansionary dates). The table includes information on the start and end dates of an FOMC meeting if it took place within a 7-day window around the discontinuity date. The last column presents the surprise in the three months ahead fed funds futures (FF_3). I compute this surprise using the monthly time series constructed by Jarociński and Karaki (2020), which covers the period Jan. 1990 to Dec. 2016. The surprise reported on the table is the average between the two months leading up to the discontinuity date.

Appendix B. Evolution of Variables Around Expansionary Dates

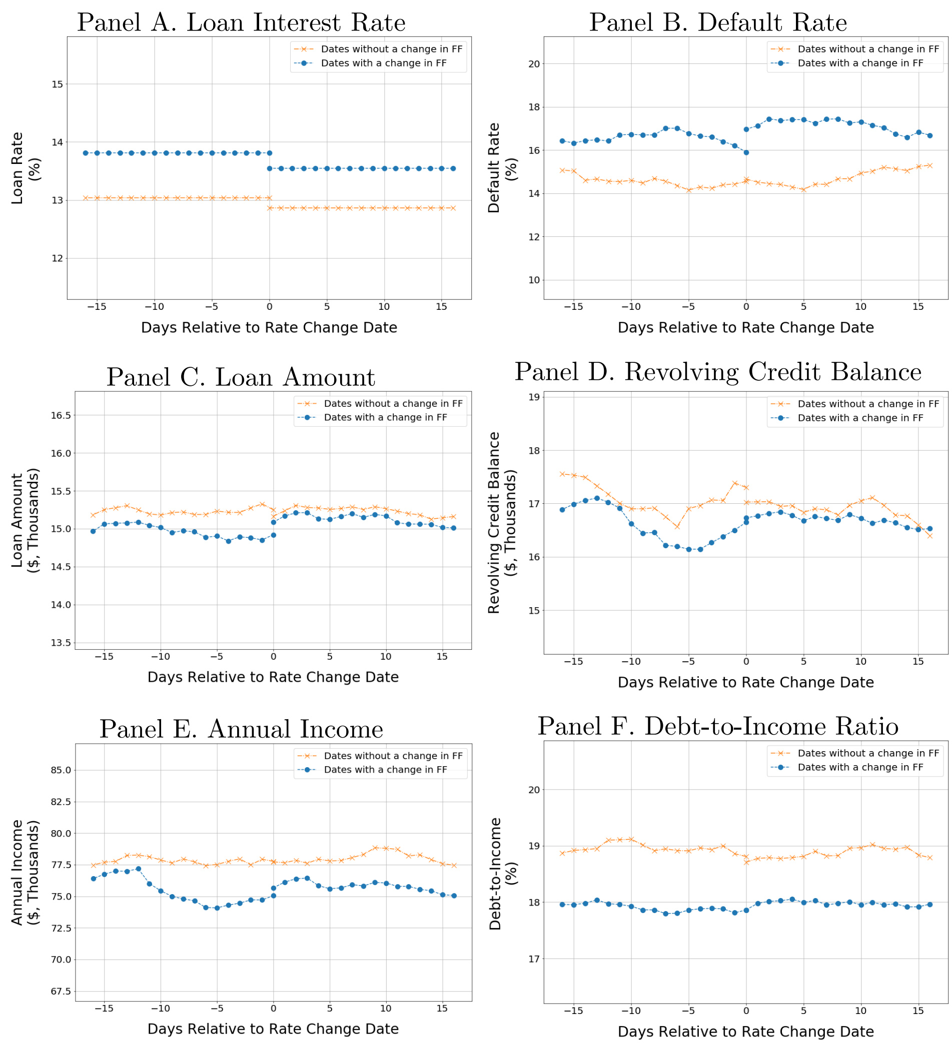

Fig. B.1. Loan Interest Rate, Default Rate, Loan Amount, Revolving Credit Balance, Annual Income, and Debt-to-Income Ratio Around Expansionary Discontinuity Dates. The figure shows predicted values from locally linear regressions estimated separately on either side of the discontinuity date. The horizontal axis measures the number of days relative to the discontinuity date.

Appendix C. Robustness

Appendix C.1. Expansionary Discontinuity Dates

Table C.2. Marginal Propensities and Extensive Margin Adjustments

	Regression Specification		
Coefficient	MPL ($x = r$)	EMA ($x = N^A$)	MPB ($x = L$)
β^x_A	9.36***	-273.49***	-413.32
	(2.54)	(60.10)	(581.85)
β^x_B	14.00***	-283.23***	-502.88
	(3.33)	(78.58)	(340.38)
β^x_C	16.18***	-172.61	-1071.92*
	(3.16)	(98.31)	(534.58)
β^x_D	18.50***	-48.95	-543.86
	(5.26)	(64.93)	(317.87)
β^x_E	26.08***	-21.65	-377.26
	(6.30)	(38.95)	(308.54)
Number of Observations	308	308	308
Adjusted R^2	0.55	0.21	0.42

Notes. Table shows the estimates of the coefficients $\left\{\beta^r_g, \beta^L, \beta^{N^A}_g\right\}_{g\in\mathbb{G}}$ for the baseline specification of regressions (7) and (8). The estimates are based on the full sample of discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_0$). Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Table C.2 shows that the MPL_g estimates remain qualitatively and quantitatively similar to the baseline results when including the expansionary discontinuity dates in the analysis. The estimates for the MPB_g and EMA_g are qualitatively similar, but their magnitude is smaller. To get a better sense of the difference in magnitude of the estimates, consider a 2.1 b.p. increase in the FFR like in the main text. The point estimates from Table C.2 imply that the least risky borrowers (grade A) would experience a 20 b.p. increase in the interest rate, a \$81 decrease in the requested loan amount, and a decrease of 6 approved loans per day. Medium-risk borrowers (grade C) would experience a 34 b.p. increase in interest rates, a \$170 decrease in the requested loan amount, and a decrease of 4 approved loans per day. The riskiest borrowers (grade E) would experience a 55 b.p. increase in interest rates, a \$207 decrease in the requested loan amount, and no change in the number of approved loans. These changes are smaller than those implied by the baseline estimates, particularly the decrease in the requested loan amount. However, the implications for the responses of aggregate borrowing are still the same as in the baseline scenario.

Appendix C.2. Bandwith Robustness

Table C.3 shows that the MPL_g, EMA_g, and MPB_g estimates are robust to the choice of bandwidth in the locally linear regressions (4) - (6). The MPL_g estimates are actually identical regardless of the choice of bandwidth, which is a consequence of the three features of the Lending Club data that allow me to precisely identify the discontinuity dates: (i) all borrowers within a sub-grade all get the same interest rate, (ii) changes in interest rates happen instantaneously, and (iii) changes in interest rates happen sporadically (the shortest time interval within rate changes is 30 days). The magnitude of the MPB_g estimates varies slightly with the choice of bandwidth, but the main qualitative features remain unchanged.

The EMA_g estimates are perhaps the ones that vary the most across different bandwidths. The magnitude of the EMA_g estimates decreases with the bandwidth for the least risky borrowers (grades A and B), while it increases for the riskiest borrowers (grades D and E). Recall that the dampening in the response of aggregate borrowing is driven by the heterogeneity in the

Table C.3. Estimates of the Marginal Propensities to Lend and Borrow

	Bandwidth $b = 5$			Bandwidth $b = 15$		
Coefficient	MPL ($x = r$)	EMA ($x = N^A$)	MPB ($x = L$)	MPL ($x = r$)	EMA ($x = N^A$)	MPB ($x = L$)
β_A^x	10.19**	-319.71***	-385.64	10.19**	-214.78*	-595.91
	(3.75)	(97.06)	(955.93)	(3.75)	(103.30)	(416.07)
β_B^x	10.32**	-374.72***	-763.20	10.32**	-225.26*	-792.49**
	(3.63)	(78.37)	(477.24)	(3.63)	(98.43)	(294.60)
β_C^x	13.63***	-225.83	-1095.30**	13.63***	-221.04*	-832.36**
	(3.39)	(120.96)	(374.32)	(3.39)	(91.38)	(286.24)
β_D^x	18.03***	-33.82	-292.70	18.03***	-150.37	-828.77**
	(4.90)	(151.75)	(626.63)	(4.90)	(94.38)	(268.56)
β_E^x	30.02***	-1.71	-781.32	30.02***	-98.46	-666.48
	(5.06)	(171.49)	(431.66)	(5.06)	(110.83)	(447.94)
Number of Observations	178	178	178	178	178	178
Adjusted R^2	0.34	0.11	0.40	0.34	0.10	0.61

Notes. Table shows the estimates of the coefficients $\left\{\beta_g^r, \beta_g^L, \beta_g^{N^A}\right\}_{g\in\mathbb{G}}$ for the baseline specification of regressions (7) and (8) when the changes around discontinuity dates are computed using locally linear regression with bandwidths $b = 5$ and $b = 15$. The estimates are based on the sample that includes only the contractionary discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_{0+}$). Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

EMA$_g$. Thus larger bandwidths imply a smaller dampening effect in the response of aggregate borrowing: the dampening factor is 1.2 for the baseline bandwidth of $b = 6$, while it is 1.07 for $b = 15$. Nonetheless, the main takeaway remains the same – the magnitude of the EMA$_g$ is decreasing in borrowers' risk, the average loan amount is increasing in borrowers' risk, and this negative correlation dampens the response of aggregate borrowing.

Table C.4. Marginal Propensities and Extensive Margin Adjustment

Coefficient	MPL ($x = r$)	EMA ($x = N^A$)	MPB ($x = L$)
	Regression Specification		
β_A^x	9.74**	-357.59**	-893.01
	(3.52)	(120.44)	(505.39)
β_B^x	8.97**	-335.12**	-1037.71**
	(3.40)	(124.55)	(370.03)
β_C^x	13.44***	-201.81	-1197.53***
	(3.51)	(158.41)	(333.41)
β_D^x	16.71**	-19.26	-858.82***
	(5.18)	(173.28)	(207.10)
β_E^x	30.95***	-1.25	-819.78**
	(5.21)	(187.10)	(288.31)
Number of Observations	178	178	178
Adjusted R^2	0.35	0.14	0.57

Notes. Table shows the estimates of the coefficients $\left\{\beta_g^r, \beta_g^L, \beta_g^{N^A}\right\}_{g\in\mathbb{G}}$ when including the full set of controls for borrower characteristics in regressions (7) and (8). The estimates are based on the sample that includes only the contractionary discontinuity dates ($t_0 \in \tilde{\mathbb{T}}_{0+}$). Standard errors in parentheses (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Appendix C.3. Full Set of Controls

Table C.4 shows that the estimates for the MPL_g, EMA_g, and MPB_g remain qualitatively and quantitatively similar when including the full set of controls for borrower characteristics in regressions (7) and (8). Note that the adjusted R^2 for the MPL_g and EMA_g regressions is virtually identical regardless of whether or not one includes the vector of controls Z_{s,t_0}. Meanwhile, the adjusted R^2 for the MPB_g regression increases from 0.39 to 0.57 when including the full set of controls X_{s,t_0}. This suggest that there is some additional variation in the loan amount due to changes in borrower characteristics, but it is mostly uncorrelated with the variation explained by the changes in interest rates.

Abrahams, M., Adrian, T., Crump, R. K., Moench, E., 2015. Decomposing real and nominal yield curves. Journal of Monetary Economics 84, 182–200.

Agarwal, S., Chomsisengphet, S., Stroebel, J., Mahoney, N., 2018. Do banks pass through credit expansions to consumers who want to borrow? The Quarterly Journal of Economics 133 (1), 129–190.

Argudo, E., 2021. Monetary policy transmission via loan contract terms in the united states. International Journal of Central Banking 17 (4), 85–115.

Argudo, E., 2023. Can repatriation tax holidays teach us something about monetary policy transmission? Journal of Money, Credit and Banking (forthcoming).

Aydin, D., 2021. Consumption response to credit expansions: Evidence from experimental assignment of 45,307 credit lines. Working Paper.

Bernanke, B. S., Gertler, M., 1995. Inside the black box: The credit channel of monetary policy transmission. Journal of Economic Perspectives 9 (4), 27–48.

Chatterjee, S., Corbae, D., Dempsey, K., Ríos-Rull, J.-V., forthcoming. A quantitative theory of the credit score. Econometrica.

Chatterjee, S., Corbae, D., Nakajima, M., Ríos-Rull, J.-V., 2007. A quantitative theory of unsecured consumer credit with risk of default. Econometrica 75 (6), 1525–1589.

Ciccarelli, M., Maddaloni, A., Peydró, J.-L., 2015. Trusting the bankers: A new look at the credit channel of monetary policy. Review of Economic Dynamics 18 (4), 979–1002.

Crump, R. K., Eusepi, S., Moench, E., 2018. The term structure of expectations and bond yields. Federal Reserve Bank of New York Staff Reports, no. 775.

Dell'Ariccia, G., Laeven, L., Suarez, G. A., 2017. Bank leverage and monetary policy's risk-taking channel: Evidence from the united states. The Journal of Finance 72 (2), 613–654.
URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12467

Dell'Ariccia, Giovanni, G., Marquez, R., 2006. Lending booms and lending standards. The Journal of Finance 61 (5), 2511–2546.
URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2006.01065.x

Dempsey, K., Ionescu, F., 2022. Borrowing premia in unsecured credit markets. Working Paper.

Gertler, M., Gilchrist, S., 05 1994. Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms*. The Quarterly Journal of Economics 109 (2), 309–340.
URL https://doi.org/10.2307/2118465

Gertler, M., Karadi, P., 2015. Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics 7 (1), 44–76.

Gilchrist, S., López-Salido, D., Zakrajšek, E., 2015. Monetary policy and real borrowing costs at the zero lower bound. American Economic Journal: Macroeconomics 7 (1), 77–109.

Gross, D. B., Souleles, N. S., 2002. Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data. Quarterly Journal of Economics 117 (1), 149–185.

Gross, T., Notowidigdo, M. J., Wang, J., 2020. The marginal propensity to consume over the business cycle. American Economic Journal: Macroeconomics 12 (2), 351–384.

Gürkaynak, R. S., Sack, B., Swanson, E. T., 2005. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. International Journal of Central Banking 1 (1), 55–93.

Hanson, S. G., Stein, J. C., 2015. Monetary policy and long-term real rates. Journal of Financial Economics 115, 429–448.

Hertzberg, A., Liberman, A., Paravisini, D., 2018. Screening on loan terms: Evidence from maturity choice in consumer credit. Review of Financial Studies 31, 3532–3567.

Ioannidou, V., Ongena, S., Peydró, J.-L., 09 2015. Monetary Policy, Risk-Taking, and Pricing: Evidence from a Quasi-Natural Experiment*. Review of Finance 19 (1), 95–144.
URL https://doi.org/10.1093/rof/rfu035

Jarociński, M., Karaki, P., 2020. Deconstructing monetary surprises - the role of information shocks. American Economic Journal: Macroeconomics.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J., 2012. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. American Economic Review 102 (5), 2301–2326.

Jiménez, G., Ongena, S., Peydró, J.-L., Saurina, J., 2014. Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credits risk-taking? Econometrica 82 (2), 463–505.

Kashyap, A., Stein, J. C., 1994. Monetary policy and bank lending. In: Mankiw, N. G. (Ed.), Monetary Policy. University of Chicago Press, pp. 221–256.

Kashyap, A. K., Stein, J. C., Wilcox, D. W., 1993. Monetary policy and credit conditions: Evidence from the composition of external finance. American Economic Review 83, 78–98.

Kishan, R. P., Opieda, T. P., 2000. Bank size, bank capital, and the bank lending channel. Journal of Money, Credit and Banking 32 (121-141).

Kuttner, K. N., 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures markets. Journal of Monetary Economics 47 (3), 523–544.

Livshits, I., Mac Gee, J. C., Tertilt, M., 03 2016. The Democratization of Credit and the Rise in Consumer Bankruptcies. The Review of Economic Studies 83 (4), 1673–1710.
URL https://doi.org/10.1093/restud/rdw011

Livshits, I., MacGee, J., Tertilt, M., 2007. Consumer bankruptcy: A fresh start. The American Economic Review 97 (1), 402–418.

Maddaloni, A., Peydró, J.-L., 2011. Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the euro area and the u.s. lending standards. Review of Financial Studies 24, 2121–2165.

Maddaloni, A., Peydró, J.-L., 2013. Monetary policy, macroprudential policy, and banking stability: evidence from the euro area. International Journal of Central Banking 9, 121–169.

Nakamura, E., Steinsson, J., 2018. High-frequency identification of monetary non-neutrality: The information effect. The Quarterly Journal of Economics 133 (3), 1238–1330.

Paligorova, T., Santos, J. A., 2017. Monetary policy and bank risk-taking: Evidence from the corporate loan market. Journal of Financial Intermediation 30, 35–49.
URL https://www.sciencedirect.com/science/article/pii/S1042957316300626

Paravisini, D., Rappoport, V., Ravina, E., 2016. Risk aversion and wealth: Evidence from person-to-person lending portfolios. Management Science 63 (2), 279–297.

Parker, J. A., Souleles, N. S., Johnson, D. S., McClelland, R., 2013. Consumer spending and the economic stimulus payments of 2008. American Economic Review 103 (6), 2530–2553.

Ravina, E., 2019. Love & loans. the effect of beauty and personal characteristics in credit markets. Working Paper.

Tang, H., 2019. Peer-to-peer lenders versus banks: Substitutes or complements? Review of Financial Studies 32 (5), 1900–1938.

Tertilt, M., Exler, F., 10 2020. Consumer debt and default: A macro perspective. Oxford Research Encyclopedia of Economics and Finance.