# FinTech Borrowers: Lax-Screening or Cream-Skimming?[1]

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**Abstract**

Did FinTech lenders ease credit access for borrowers underserved by the traditional banking industry or are they attracting the most credit-worthy borrowers? Are borrowers able to lower their financing costs and improve their credit outcomes through a personal loan by a FinTech lender? We address these questions using a unique individual-level data providing detailed information about borrowers' credit histories and lenders' identities. We find limited evidence supporting the view that FinTech lenders target borrowers that have been credit-rationed by traditional banks. In contrast, these borrowers earn more, live in higher income neighborhoods, are on average younger, and more likely to be professionals. We show that in the first six months after origination, FinTech borrowers' credit outcomes improve; however, in the following several months, they are significantly more likely to be delinquent and exhibit higher indebtedness. While we find limited evidence of adverse selection based on ex-ante observables, our findings suggest that FinTech borrowers are more likely to be present-biased. In fact, they tend to carry a significant credit card balance, which tends to skyrocket during holidays, and are more likely to consume the additional funds rather than using them to consolidate high-cost credit card debt. Overall, these findings suggest that FinTech lenders enable households with a particular desire for immediate consumption to finance their expenses and borrow beyond their means.

Keywords: FinTech, Credit history, Self-control, Present-bias

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## 1. Introduction

Financial markets have recently witnessed a disruptive force: the rise of online intermediaries and, more generally, *FinTech* companies, i.e. firms that apply technology to improve financial activities. FinTech companies attracted more than $18 billion of investments by venture capital firms in 2017 (KPMG, 2017), and the FinTech space is one of the fastest growing sectors, with a global growth rate of 38% during the last quarter of 2017. FinTech companies have targeted the consumer credit market, which is one of the largest credit markets, with outstanding credit of $3.8 trillion in 2018 (FED, 2018). Their share of the lending market has been predicted to increase to 20% by 2020 (Transunion, 2017). Therefore, it is important to understand how they might affect households' borrowing and consumption decisions. Given their increase popularity, there are natural questions to ask: who borrows from FinTech lenders? Do FinTech lenders serve individuals underserved by the traditional banking system or are they able to attract the most credit-worthy borrowers? Do these loans help borrowers build a better credit history?

Some observers argue that FinTech lenders might be able to operate where the banks do not find it profitable.[2] This might be because they face significantly lower fixed costs, e.g., they do not have branches, or because they are less strictly regulated, which might induce them to have laxer lending standards.[3] Thus, the entry by FinTech lenders might alleviate credit frictions, such as credit rationing due to information asymmetries (Stiglitz and Weiss, 1981) or imperfect competition (Parlour and Rajan, 2001). This might result in access to credit for financially

[2] For instance, Jamie Dimon told investors in 2014 that: "There are hundreds of startups with a lot of brains and money working on various alternatives to traditional banking. The ones you read about most are in the lending business, whereby the firms can lend to individuals and small businesses very quickly and -- these entities believe-- effectively by using Big Data to enhance credit underwriting. They are very good at reducing the pain points in that they can make loans in minutes, which might take banks weeks." (JP Morgan Chase annual report, 2014)

[3] FinTech lenders are generally regulated by the Consumer Financial Protection Bureau and state regulators, rather than by the Federal Reserve or the Office of Comptroller of Currency (OCC).

constrained households or lower financing costs for those who switch from traditional banks to new online lenders. On the contrary, the use of different data and tools might enable FinTech lenders to capture the most creditworthy borrowers, which might result in lowering the average quality of the pool of households borrowing from banks.

In addition to these possibilities, Laibson (1997) cautions that financial innovation might enable individuals to *over-borrow*. FinTech, in particular, might be an attractive option for borrowers with self-control issues, because of the fully online application process and the significantly higher speed to being approved and having access to the new funds.[4] The ease with which borrowers have access to additional credit might tempt them to borrow beyond their means, leading to higher default rates and worse financial outcomes for the individuals borrowing from FinTech lenders. Thus, what the overall effect is remains an empirical question.

Ideally, to investigate these issues one would need individual-level data on borrowers' characteristics, including information about their liabilities, recorded not only at the time of the loan application but over time; furthermore, it would be critical to have a benchmark to assess FinTech borrowers' performance. This paper investigates these issues using novel and unique panel data from one of the three main credit bureaus in the country, which allows us to overcome these challenges. The key novelties of the data are the ability to distinguish between traditional and FinTech lenders; information about the terms of the loans, and the richness of the data which include information about all borrowers' liabilities, as well as some demographic information about the borrowers for the 2011-2017 period. In contrast to existing studies on FinTech lenders, we are able to include in our analysis multiple lenders, rather than focusing, for instance, on Lending Club, and our data are a monthly borrower-level panel rather than a cross section of loan

[4] Most FinTech lenders advertise their ability to deposit the funds within 48 hours.

applications. Furthermore, in contrast to previous studies, we observe a natural benchmark: individuals borrowing from traditional banks.

While this data covers multiple types of loans, we focus on personal loans for two key reasons. First, personal credit is one of the fastest-growing segments of the consumer credit market, and it has been the subject of particular interest to FinTech lenders.[5] Second, personal loans are unsecured loans, which make them more easily comparable across lenders, because the contract is standard and the only terms are the maturity and the interest rate (which we observe).

The paper has three main sets of findings. The first set of results investigates the *ex-ante* characteristics of the borrowers, by examining whether FinTech lenders substituted banks in underserved areas and whether the households borrowing from FinTech were previously rationed by traditional banks. We show that FinTech borrowers tend to be younger, have higher income, exhibit a better credit history due to lower delinquency rates, live in richer neighborhoods with higher house price appreciation, and are more likely to be professionals. Most of the FinTech borrowers have credit scores in the mid-range between 620 and 720. They are less likely to have a mortgage or an auto loan, but more likely to still have to pay student loans. They do tend to have a higher number of accounts and exhibit a higher credit utilization ratio, which suggests that one of the potential reasons to apply for a FinTech loan is to consolidate higher-rate credit card debts. In all specifications, to absorb any time-varying credit demand shock at the local level, such as changes in house prices or in employment opportunities, or heterogeneous diffusion of these new lenders, we control for region-times-month fixed effects.

[5] One of the three main credit bureaus, TranUnion, established that FinTechs have grown from a mere 1% of personal loan originations in 2010 to one-third of the entire market in 2017 (Transunion, 2017).

Additionally, borrowers that obtain a loan from a FinTech lender had a significantly higher financing cost in the past, as captured by the difference between the weighted average rate paid on their installment loans and the one paid by a representative borrower in their state with a similar risk profile. This finding suggests that borrowers that are discontent with the traditional banks are more likely to become new customers for the FinTech lenders. Overall, the evidence strongly suggests that FinTech lenders are not after the marginal borrowers who are left underserved by the traditional banking system, nor do they seem to concentrate in areas where banks are less likely to operate, such as the ones most affected by the crisis.

The second set of results exploits the panel nature of our data to follow borrowers over time and analyze their *ex-post* performance. We first show in the cross section that FinTech borrowers are 14% more likely to be in default after the loan origination. We then compare similar households borrowing from banks and FinTech, and show that households borrowing from FinTech lenders experience a short-lasting positive effect in the first few months after the loan origination: their credit score increases, their revolving balance decreases and they have a lower likelihood of defaulting. However, the outcomes are exactly the opposite in the 6-12 months after the loan origination. Specifically, their leverage tends to increase, their creditworthiness declines, and their likelihood of defaulting increases as well.

There are alternative hypotheses that might reconcile the ex-ante higher creditworthiness with ex-post worse performance. For instance, borrowers might be more likely to default on the FinTech lenders because these are marginal lenders, while access to the traditional banks is more important. We find limited evidence that this is the main channel driving our results. We provide evidence that one dimension in which FinTech borrowers are adversely selected is their impatience. Intuitively, households might be impatient in the short run relative to their long run preferences, which lead them to borrow excessively and default on their debts later, despite their earlier intention to repay. The third set of results provides several tests to further examine this underlying mechanism. First, we show that not all additional credit is used to consolidate their debt obligations; rather households borrow from FinTech lenders to support higher consumption levels. This makes them overextended and more likely to default. These results are even more pronounced for low credit score borrowers.

Second, we take advantage of the fact that borrowers are classified by credit reporting agencies into two brackets: “transactors” and “revolvers”. Transactors are borrowers that tend to fully repay their credit card debt at the end of each month, while revolvers are those who tend to submit the minimum payment and carry balance over time. This is a helpful categorization, because a growing empirical literature has shown that, controlling for disposable income, demographics, and credit constraints, present-biased individuals are more likely to have credit card debt and significantly higher amounts of credit card debt (see Meier and Sprenger, 2010 and Kuchler, 2013). Then, we can test the hypothesis proposed by Laibson (1997): FinTech borrowers should be more likely to be revolvers and the increased fragility due to higher leverage should be concentrated among this type of borrowers as these are more likely to exhibit self-control issues. This is indeed what we find in the data. The decline in credit score, increase in utilization and defaults are all more evident among the revolvers borrowers.

As additional evidence that FinTech borrowers are indeed more likely to be present-biased, we also collect information on sudden increase in store credit card spending during sale events and holidays, i.e. Black Friday and Christmas holidays, which are not repaid. We find that the borrowers that tend to spend above their means are indeed more likely to apply for a FinTech loan. Finally, to further show that FinTech borrowers are more likely to be impulse borrowers, we exploit the advertising by one of these FinTech lenders, SoFi, during the 2016 and 2017 Super Bowl games. We show a significant increase in loans granted in the immediate aftermath of such advertising, while we do not find a similar response when banks are the ones advertising. This further suggests that FinTech borrowers might be attracted by the possibility to have access to additional funds in a short amount of time and with an easy-to-access online application.

Taking stock of our results, we do not find evidence supporting the view that FinTech lenders allow access to credit to borrowers that have been denied by traditional financial institutions[6]. Furthermore, for those individuals borrowing from FinTech lenders, their credit profile only slightly improves right after the origination, but these effects are short-lived as their credit history worsen in the following quarters. The evidence points out that the increased ease and speed with which borrowers can have access to credit is particularly appealing to households with a desire for immediate consumption. These results contribute to the debate about the need to regulate FinTech companies. In the same way in which the Dodd-Frank Act induced banks to be more concerned about the borrowers' ability to repay, a similar intervention in this unsecured lending market might reduce the negative consequences of granting loans to borrowers who then default on them.

Our paper contributes to a growing literature examining marketplace lending.[7] Vallee and Zeng (2018), for instance, examines how information provision by a marketplace lender to investors affects their performance, using a sudden reduction in the information about borrowers' characteristics provided by Lending Club after 2014. Hertzberg, Liberman and Paravisini (2018),

[6] It's possible that credit rationing may exist among borrowers who do not have valid credit reports, which are excluded from this and other analysis in the literature. There are many news reports that 30-45 million US adults are living without a credit score (e.g., CNBC, "45 million Americans are living without a credit score," May 5 2015).
[7] See Morse (2015) for an early review of this strand of the literature.

instead, shows how maturity choice can be used to screen borrowers by exploiting a natural experiment due to changes in the menu of loans offered by Lending Club. Whereas Buchak, Matvos, Piskorski and Seru (2018) and Fuster et al. (2018) study whether there is substitution or complementarity between FinTech lenders and traditional banks in the mortgage market.

There are also few recent studies that focus specifically on the consumer credit segment of the market, i.e. unsecured personal loans. For instance, Tang (2018) takes advantage of a regulatory change resulting in a contraction in the credit supplied by traditional banks to show that peer-to-peer lenders substituted banks for infra-marginal borrowers. Similarly, De Roure, Pelizzon and Thakor (2018) compare banks loans with the ones granted by a German peer-to-peer lender and show that the latter are riskier but exhibit lower risk-adjusted rates. Liao et al. (2017) focus on the largest platform in China and show that it is mainly attracting underserved borrowers. We contribute to this growing literature by taking advantage of the unique features of our data. Specifically, these previous studies have relied upon information provided by a single marketplace lender. Furthermore, the data is usually aggregated at the regional level and is only provided at origination. Our study, instead, uses a comprehensive panel data on FinTech borrowers that allows us to estimate the impact of obtaining a FinTech loan on the borrower's performance, controlling for a wide set of characteristics. In addition, we are able to compare FinTech loans to bank loans directly. Finally, our data include all the major FinTech lenders except Prosper.[8]

Finally, our results also belong to the literature showing how present bias or short-term impatience might explain households' borrowing behavior (e.g. Ausubel, 1991; Laibson, 1997; Heidhues and Koszegi, 2010). The empirical evidence has already uncovered how these behavioral

[8] Other related papers in this literature include: Wolfe and Yoo (2017), Mariotto (2016), Balyuk (2017), Balyuk and Davydenko (2016), and Iyer et al. (2015).

traits might play a role in numerous contexts (e.g. DellaVigna and Malmendier, 2006, Kaur, Kremer and Mullainathan, 2015). However, most related to our findings are the papers by Meier and Sprenger (2010) and Kuchler (2013) directly linking self-control to credit card spending and Laibson, Repetto and Tobacman (2007) and Nakajima (2015) who study the effects of present bias on credit card debt in a life-cycle model. We take advantage of the insights emerged in this literature to uncover evidence corroborating the view that easier access to credit might be misused by present-biased individuals.

The rest of the paper is organized as follows. Section 2 describes the data employed and the construction of the sample. Section 3 explores which characteristics of the borrowers are associated with obtaining a FinTech loan. Section 4 presents our identification strategy and the main results of the paper. Section 5 explores the potential channels explaining the borrowers' performance, while Section 6 concludes.

## 2. Data

### 2.1 Data Sources

Our analysis relies mainly on data available at one of the nation's largest credit bureaus. The credit bureau provides information on households' balance sheets, specifically, monthly payment history of all the borrower's loans, including auto loans, mortgages, home equity lines of credit, student loans and credit cards (revolving). It also contains information about the main features of these individual loans, such as date opened, account type, credit limits, monthly scheduled payment (for installments only), balance, lender and performance history.[9] It contains more than 200 million

9 Typical account types include unsecured personal loans, credit cards (bank card, department store card, retail card), auto loan, student loan, mortgage, junior lien, home equity line of credit, line of credit, etc.

consumer credit files and over a billion credit trades, i.e. information about single loans, and is updated monthly. Limited versions of this data have been employed in other papers studying households' financial decisions. However, our proprietary version is unique in a few respects.

First and foremost, to carry out our analysis we need to distinguish between traditional and FinTech lenders, which we can do since we observe the identity of the lenders through credit tradeline tables. Second, our data are not confined to households' balance sheet information but include several other information about the borrowers. For instance, for a significant sample of borrowers, we observe their masked employer identity, as well as the industry they work in and their main occupation, through proprietary employment data used in employment and income verification. We also observe demographic information, such as the gender, whether the borrower is married and a college graduate, which is collected by creditors. We complement this information with data about the median income, age and the fraction of whites and professionals in the borrower's census block. Overall, we believe our data give us a unique opportunity to study the characteristics of the individuals borrowing from FinTech lenders and the subsequent borrowers' performance and credit outcomes.

### 2.2 Sample Design

To create a representative and matched sample, we first identify all the individual accounts associated with the top FinTech companies in the credit tradeline data. We define FinTech lenders those who operate exclusively online and do not have a brick and mortar presence, do not accept deposits, and are not regulated by the Fed or the Office of the Comptroller of the Currency (OCC).

We also require them to be recently founded.[10] We restrict our sample to only the trades with a minimum of $500 credit limit, accounts opened since January 1, 2012 when there are at least 100 of these loans originated by these companies in a given month, and borrowers living in Continental USA. After excluding a few credit files with missing information, there are about 2.6 million FinTech loans. We then identify 18 million personal loans originated by banks. We randomly draw 50% of all personal loans originated by FinTech lenders and 10% of personal loans originated by non-FinTech lenders, excluding loans with missing origination date, missing credit score, missing total balance, missing number of accounts, and invalid loan balance (negative or zero). For the borrower by year-month panel data, we randomly draw 50% of the borrowers in our loan-level sample and match with monthly credit report data.

### 2.3 Summary Statistics

Our final sample contains 7,961,345 loans originated during the sample period, 2012-2016. Among them, 7,460,395 loans are for 2,558,177 borrowers who have either Fintech or bank loans, not both, which is our main sample. We present key summary statistics in Table 1 about the loan-level data (Panel A) as well as borrower x year-month data (Panel B). Our main analysis is at the borrower by year-month level. We start to track the credit outcomes of FinTech borrowers three months prior to when they open up a FinTech account through 15 months after that. For non-FinTech borrowers, we track them around a similar period measured in calendar time. Our panel data sample contains over 23 million records. On credit outcomes, we report typical information: the number of accounts, and the balance on all the main accounts, i.e. auto, student and mortgage,

[10] Few lenders have rebranded themselves as FinTech companies after the mortgage crisis. We only consider lenders founded after 2005.

borrower’s credit score which predicts borrower’s creditworthiness in the near future, the age of the credit history, delinquent (DLQ) balance and also DLQ rate at the time of origination. Panel A also reports information about borrower’s credit, demographic and employment characteristics at origination, as well as some regional characteristics such as house prices, unemployment, and median income at origination.

On average, US consumers in our sample have more than 20 financial accounts opened during the sample period and have an average credit score of 631. Revolving accounts (credit cards) balance is on average $8000, while the three installment accounts are somewhat higher: auto loans ($11000), student loans ($8200) and mortgages ($57000). Revolving utilization is on average 45%, although the standard deviation is significant (36%). On average the borrowers in our sample are 49 years old, 11% of the households have jobs in professional, technical and management occupations, and almost 20% are high income, i.e. defined as income above $100,000.

We are able to match credit limit and loan term for almost all the loans in our sample. On average, borrowers take out $7,144 per loan with average term of 31 months. With scheduled payment, term and limit, we calculate the original note rate to be about 12% on average for the vast majority of our loans. We also summarize the ex-post borrower and loan performance at the loan level based on the maximal delinquent balance during our observation window on any account and the personal loan, respectively. As of December 2017, 16% of the borrowers and 2% of the loans in our sample have experienced at least one delinquency.

Panel B also reports information about borrower’s credit dynamics for our panel data sample. On a monthly basis, 0.55% of the loans are in delinquency on average. We also report the information about Fintech and bank loan origination indicators defined as 1 if the loan is originated in a particular month and 0 otherwise used in our event analysis of Superbowl advertising and spending spikes. We will discuss these events in detail later.

Figure 1 plots total origination amount (in billions of dollars) of all personal loans originated by FinTech lenders and non-FinTech lenders. FinTech lenders include Lending Club Corporation, SoFi Lending Corp, Avant Credit Corporation, LoanDepot.com, Freedom Financial Asset Management, Upstart Network Inc, and Cashcall.[11] Non-FinTech lenders include all the other lenders, generally major banking institutions. The series are based on all personal loans reported to one of the credit bureaus. FinTech lenders were originating only a very small fraction of the personal loan market in 2011 and 2012, but starting in late 2013 they experienced a significant growth. The figure also suggests a non-complete substitution with the traditional banking sector, as this also experienced a significant growth in recent years.

To describe how this growth has been heterogeneous across states, Figure 2 plots the state fixed effects in a regression where the dependent variable is an indicator for FinTech loans. States on the west coast such as California and Arizona, as well as Florida in the south, and the east coast are the states with the highest number of FinTech loans. To control for the potential differences in demand factors that might have driven the heterogeneity in the rise of FinTech lenders between states, in our analysis we always control for region by time fixed effects.

## 3. Who Borrows from FinTech Lenders?

Since very little is known about this market and the borrowers that turn to FinTech borrowers, this section explores which borrowers' characteristics are related to entering in a lending relationship

[11] We excluded Payoff Inc and Rockloans MarketPlace from our final sample because of their low volume. There are no loans originated by Prosper in our data source.

with FinTech lenders. That is, before investigating how obtaining a FinTech loan affects borrowers' behavior and credit outcomes, we first explore the ex-ante heterogeneity among individuals borrowing from different types of lenders. In other words, we ask: who borrows from FinTech lenders? Different hypothesis have been proposed. On the one hand, FinTech lenders might be able to serve individuals that have been previously rationed, by being more competitive than traditional banks due to their lower fixed costs and laxer regulatory constraints. On the other hand, FinTech lenders might employ financial innovations, such as machine learning techniques applied to consumer data, to target the most profitable borrowers.

We test these hypotheses by estimating the following baseline specification:

$$Fintech\ Loan_{i,c,t} = \Omega X_{i,t} + \mu_c + \xi_t + \varepsilon_{i,c,t}, \qquad (1)$$

where the main dependent variable is a dummy variable equal to one if the borrower $i$, living in county $c$, has a FinTech loan in month $t$ and 0 otherwise. The main independent variables are the borrower's characteristics $X$. The sample includes all individuals borrowing from FinTech lenders and a random sample of borrowers that have borrowed from banks.

### 3.1 Regional Heterogeneity

Figure 2 has shown the distribution of these loans across states. However, we can exploit the information we have about where borrowers live to ask whether FinTech borrowers live in areas with different socio-economic characteristics. One possibility is that FinTech lenders are able to target borrowers living in neighborhoods where the traditional institutions are less likely to have a strong presence because of less appealing economic conditions.

Then, to test this hypothesis, Table 2 relates the FinTech loans to county characteristics. To capture time-varying demand, we control for state by year fixed effects, so that our main source of variation is the heterogeneity among counties within a state during the same year. We double cluster the standard errors at the county and year-month level to allow for arbitrary correlation along these two dimensions.

Columns (1) and (2) show that FinTech borrowers live in areas with a higher house price growth and a higher house price level. This confirms the stronger presence of FinTech lenders along the coasts, as shown in Figure 1. Column (3) also explores the relation between a FinTech loan origination and the 2008-2009 housing bust. It shows that FinTech borrowers are less likely to live in areas most hit by the crisis. In the other specifications, we show that FinTech borrowers are more likely to live in areas with lower unemployment rate (Column 4), higher income (Column 5) and a higher fraction of college graduates (Column 6).

Finally, Columns (7) – (9) explore other potentially relevant regional characteristics. We confirm that FinTech borrowers are significantly more likely to be located in areas with an already higher fraction of FinTech loans (Column 7). Given the market positioning of most of the FinTech lenders as providing a better rate and customer service to their clients than the one offered by traditional lenders, one could ask whether borrowers are more likely to switch from a traditional to a FinTech lender when they are overcharged by the traditional lenders. The challenge in addressing this question is finding a credible benchmark for the borrower's financing cost. One natural way is to look at the average rate paid by borrowers with similar risk profiles in the same regions. Then, we collect information on the average interest rate paid by borrowers in the same state within a 20-point credit score range. We show that FinTech might in fact compete on rates with traditional banks, because a higher bank loan rate is related to a higher likelihood of FinTech loans (Column 8). Lastly, areas with a high-speed internet coverage are also more likely to see more FinTech loans, which is consistent with the intuition that FinTech lenders are mainly based online and borrowers with better access to internet might be more likely to apply (Column 9).

Overall, this evidence seems to suggest that FinTech lenders are not substituting for the lack of traditional banks, but rather they are more commonly used by the borrowers living in more prosperous neighborhoods.

### 3.2 Socio-demographic characteristics

We exploit the granularity of our data to investigate whether FinTech borrowers are also different on other demographic information. Panel A of Table 3 shows that borrowers with FinTech loans are more likely to be male (Column 1), more likely to be married (Column 2) and more likely to have a college degree (Column 3). Column (4) shows that high-income borrowers (i.e. those earning more than $100,000) are 6% more likely to borrow from FinTech companies.. We complement the previous analysis with information about the borrowers' occupations: technician, management, cleric worker, laborer, student, homemaker, retired, or business owner. We find that professionals are significantly more likely to have a FinTech loan. These findings further suggest that the more educated borrowers and those with higher-paying jobs are more likely to turn to FinTech lenders for their financial needs.

### 3.3 Credit Characteristics

A natural question is whether the FinTech borrowers exhibit different risk profiles. Panel B of Table 3 focuses on several credit attributes. We standardize all the continuous independent variables so that the magnitude of these coefficients is associated with a one standard deviation (S.D.) increase in these variables. Furthermore, since both our dependent and independent variables are at the borrower level, Column (1) shows that each S.D. increase of credit score, about 84 points, is associated with 2.2% higher likelihood of borrower obtaining a FinTech loan on average. The specification is useful to compare the linear effects of credit score, but it is also important to understand whether the FinTech lenders focus on one particular segment of the market. For instance, are they targeting the subprime borrowers or are they trying to attract the best-performing customers? An intuitive way of addressing these questions is to run a similar specification to (1) but with different dummies for different credit score bins, and then plot the coefficients. We do so in the top panel of Figure 3 using 20-point bins. We find that borrowers with credit scores between 620 and 740 are the most likely to have a FinTech loan. In other words, the bulk of customers for FinTech lenders is neither in the bottom nor in the very top of the credit score distribution.

Are FinTech lenders strategically focusing on customers with a longer credit history potentially to exploit the higher degree of information available about their profiles? Column (2) provide evidence supporting this hypothesis, because it shows that FinTech borrowers have on average a longer credit history. The bottom panel of Figure 3 further examines this question by plotting the fixed effects for different individual ages. It shows that FinTech borrowers are more likely to be in their mid-thirties to mid-forties. This is consistent with the hypothesis that FinTech borrowers are in general younger than those borrowing from traditional lenders. Column (3) suggests that FinTech borrowers have also on average a higher number of credit accounts.

Consistent with the intuition that one of the main purposes of obtaining a personal loan is to consolidate existing debts with higher interest rates, Column (4) shows that FinTech borrowers are more likely to have a higher revolving utilization ratio. Each S.D. increase of credit card utilization, 36%, is associated with 1.8% higher likelihood of borrower obtaining a FinTech loan. However, Column (5) shows that these borrowers are significantly less likely to be delinquent at the time of origination, suggesting that although they might be younger and not super prime borrowers, they are less likely to have defaulted on their debts before.

Another complementary way to assess the borrowers' profiles is to investigate how they manage their current accounts. The credit bureaus classify borrowers in *revolvers* and *transactors*, depending on their use of credit cards. Revolvers are borrowers that carry balance over multiple months, while transactors tend to pay off their credit cards at the end of each month. We find that FinTech borrowers are significantly less likely to be transactors. This evidence is noteworthy as it is one of the findings supporting the view that FinTech borrowers might be present-biased. Columns (7) and (8) show that these borrowers are also more likely to have a student loan or a mortgage.

Finally, one possibility is that FinTech lenders attract borrowers with just higher credit score; another possibility is that, even within credit score bins, they are able to cater to more creditworthy borrowers. Panel C of Table 3 explores these hypotheses by separately examining borrowers with credit scores below 700 and above 740. We find that among lower credit scores borrowers, those with a longer age of credit history, lower number of accounts, and lower utilization are more likely to borrow from FinTech firms. Whereas among high credit scores borrowers, those exhibiting a shorter credit history and a higher utilization are more likely to borrow from FinTech firms. These findings suggest that the credit score is not the only dimension the FinTech lenders pay attention to.

### 3.4 Loan Terms

Having established that FinTech borrowers tend to be more creditworthy, we now explore the main loan features. Table 4 regresses the credit limit, the loan term and the interest rate on a FinTech loan indicator, which compares them to personal loans granted by banks. Columns (1)-(3) control for the borrower's credit attributes described in Panel B of Table 3 as well as ZIP Code by year-month fixed effect, while Columns (4)-(6) include also borrower fixed effects. When we analyze the interest rate, we control for the credit limit and the term of the loan. Effectively, the first three columns compare borrowers that have FinTech loans with those having bank loans, while the last three columns take advantage of the panel nature of the loan-level data to capture the fact that some borrowers can be different on unobservable time-invariant characteristics, e.g. they might systematically ask for larger loans or be considered riskier by financial institutions.

We find that FinTech are more generous about granting larger loans: on average, a FinTech loan has a $3600 higher balance. We also find that usually the maturity of the loan is about two months shorter. A larger loan and a shorter maturity come at the expense of a 12 bps higher interest rate on average.

Interestingly, once we control for borrower fixed effects and restrict attention to borrowers having both a FinTech and a bank personal loan, the results for credit balance and loan maturity are similar, although the magnitude decreases to $2800 and less than a month respectively, but the interest rate is not significantly different between FinTech and bank loans. This is probably because the borrower fixed effect is capturing most of the variation in the borrower's riskiness profile, and that is the main dimension that drives variation in the interest rate.

## 4. Loan and Borrower Ex-Post Performance

Having described the differences in the characteristics of the FinTech borrowers with respect to the bank borrowers, we can then investigate how the borrowers perform after obtaining these loans. On the one hand, borrowers often state that they use these personal loans to consolidate their existing debts, which suggests that they might be less prone to default as their interest expenses should significantly drop. On the other hand, borrowers might misuse the additional credit by increasing their consumption expenditures, leaving them with too much leverage and unaffordable monthly payments.

To investigate these hypotheses, we first compare borrowers with and without FinTech loans by looking at the likelihood for the borrower to have any delinquent balance since the origination of the FinTech loan. We report the results in Panel A of Table 5. Column (1) shows that FinTech borrowers are 16%p more likely to be in default. This result might potentially be affected by numerous factors such as differences in the location of the borrowers or on borrowers' characteristics. Then, in Column (2) we control for ZIP Code by year month fixed effects, which allows us to compare borrowers living in the same ZIP Code and in the same month. This specification should capture shocks at the regional level that might affect the borrowers' ability to repay, e.g. unemployment increases, house prices declines, contraction in firms' investment. We find that the coefficient is still statistically and economically significant as FinTech borrowers are about 13%p more likely to default.

Finally, Column (3) aims to capture heterogeneity in the creditworthiness of borrowers with and without FinTech loans by including a comprehensive set of credit attributes, such as those examined in Table 3, demographic information and loan attributes. That is, we are comparing borrowers with the same observable characteristics, whose main difference is the presence of a

FinTech loan on their credit report. Even in this more restrictive specification we find that those with a FinTech loan are 14% more likely to have a delinquent balance.

The previous result shows that FinTech borrowers are disproportionately more likely to be in default on one of their accounts; we examine next whether they are more likely to default on the FinTech loan. To do so, in Panel B we exploit the loan-level data which also allows us to take advantage of within-borrower variation as we observe multiple loans for the same borrower. Column (1) reports the results with the same set of controls as Column (3) in Panel A and county and time fixed effects. We find that FinTech loans are about 2% more likely to be delinquent. Column (2) shows similar results once we control for ZIP Code by month fixed effects.

However, this result could be driven by unobservable borrower characteristics between those that have a FinTech loan and those who do not. Then, Column (3) includes borrower fixed effects, which allows us to compare whether a borrower with a FinTech loan is more or less likely to default on its FinTech loan rather than on the other loans. We find that the FinTech loan is about 3% more likely to be in default. In other words, conditional on having a FinTech loan, a borrower is significantly more likely to default on the FinTech loan. This is noteworthy because controlling for borrower fixed effects make sure that the higher delinquency is not driven by potential adverse selection that might drive borrowers away from traditional banks and towards new lenders.

Finally, Column (4) tests whether the loan performance of FinTech lenders further diminishes as their market share increases. Intuitively, if the presence of FinTech lenders does not affect the distribution of risky borrowers, then they would tend to grant loans to the more risky borrowers as their market share increases, which should predict a higher likelihood to default. We interact the FinTech loan indicator with the previous quarter FinTech market share in the county. In accordance with this hypothesis, we find that the interaction coefficient is statistically positive showing a higher likelihood to default as the FinTech market share increases. In sum, the findings suggest that FinTech lenders are associated with higher levels of defaults both at the borrower's level as well as at the loan level and they become even more pronounced in areas where they have a stronger market position.

These results are noteworthy given the initial findings on the better ex-ante characteristics of the FinTech borrowers. To further examine the performance of these loans, we can analyze how the borrowers' performance changes over time since the loan origination. Specifically, in Table 6 we estimate the following specification:

$$Outcome_{i,f.c,t} = \sum_{\tau=-3}^{\tau=15} 1_{\tau} \times Fintech\ Borrower_f + \sum_{\tau=-3}^{\tau=15} 1_{\tau} + \Omega X_{i,t} + \delta_i + \xi_{c,t} + \varepsilon_{i,t},$$

in which, on the left hand side, we explore different credit outcomes, such as the credit score, the delinquency, the revolving utilization and the total debt. The main independent variables are the interaction between time dummies identifying the periods before and after the FinTech loan origination times the FinTech borrower indicator with exact month when the Fintech loan is originated omitted as the reference bucket. This dynamic specification allows us to include borrower fixed effects $\delta_i$ as well as county-by-month fixed effects $\xi_{c,t}$. In other words, we are comparing the main outcomes before and after obtaining a FinTech loan for the same borrower relative to the month when the borrower obtained the Fintech loan controlling for changes in local economic conditions.

Table 6 investigates borrowers' ex-post performance by investigating whether they are more likely to have delinquent balance on any account, and whether they tend to default on the personal loan. In Columns (1)-(3) the dependent variable is delinquency on any account, while in

Columns (4)-(6) the dependent variable is loan delinquency, which would then capture whether borrowers are more or less likely to default on FinTech loans.

Column (1) shows that, until three months after origination, the likelihood of having an account in default is slightly lower for the borrowers with Fintech loans compared to those with bank loans, controlling for borrower fixed effects. Although the coefficients are statistically significant, the effects are small, as they are between 1 and 3 basis points. However, starting in month 3 the likelihood that FinTech borrowers default is increasing over time and reaches 2.5% one year after origination. This corresponds to about a 15% increase in the likelihood to default. Columns (2) and (3) report the same specification but looking at two subsamples: the borrowers with credit score below 700 and above 740, which are the two thresholds commonly used in credit industry to delineate borrower quality. The evidence clearly shows that, although the effects are statistically significant for both subsamples, the magnitude of the effects is greater for the low credit score borrowers. In fact, one year after origination, low-credit-score Fintech borrowers are about 3% more likely to default than bank borrowers.

We complement the previous analysis by showing that FinTech loans are also more likely to be delinquent by 2.1% after one year from origination. Columns (2) and (3) further confirm that low credit score borrowers are the ones performing the worst in the aftermath of the FinTech loan origination.

What might be the reason for this increase in delinquency? One possibility is that the FinTech borrowers are using the additional funds not to consolidate their debts, but rather to support additional expenditures. Table 7 shows evidence supporting this view. Specifically, Columns (1) and (2) show that total debt starts significantly increase more for FinTech borrowers since the third month after the origination. The effects are quite large, as the FinTech borrowers' indebtedness increases by almost five thousand dollars one year after origination. Intuitively, borrowers might use the additional funds to repay their credit cards, but then might start financing their expenditures with these credit cards again, which results in a greater total indebtedness and higher financial fragility.

Our data does not contain explicit measures of consumption, but we can follow Di Maggio et al. (2018) and compute the probability to purchase a car using changes in the auto loan balance, which can be a valuable measure of durable consumption. Columns (3) and (4) show that FinTech borrowers are more likely to purchase a car in the months following the loan origination, with the highest spike in the first two months by as high as 0.51%. This evidence corroborates the view that part of the reason for the increase in defaults is the propensity of the FinTech borrowers to spend the additional funds rather than using them to achieve financial responsibility.

Figure 4 complements the previous findings by plotting the coefficients on the interaction term of FinTech loan indicator and relative monthly dummies from regressions of consumer credit outcomes split by borrowers' original credit scores. Panels A, C and E are based on borrowers who have original credit score above 740 when the FinTech loan is originated. Panels B, D and G are based on borrowers who have original credit score below 700 when the FinTech loan is originated. Relative monthly dummies are defined as the interval, in months, from origination date of the FinTech loan. Dependent variables are credit score (Panels A and B), indicator of any credit delinquency (Panels C and D), and revolving balance (Panels E and F). These results further show that low-credit score borrowers tend to be the ones experiencing worse ex-post performance, i.e. increase in revolving utilization, higher likelihood to default and decrease in credit score.

## 5. Discussion

What can explain the lower performance of the FinTech borrowers? One possibility is that our default results are driven by borrowers who default because they do not have a relationship with the FinTech lender, and consider the traditional bank their main lender. To analyze whether this is the main force driving our results, we can report our loan delinquency results by differentiating between the cases in which the FinTech and the bank that are providing the personal loan are the main lenders and those in which they are not. We define as main lenders the institution providing the largest loan to the borrower. We report the results in Table 8 for these two subsamples.

Odd columns report the results for the non-main lenders, while even columns analyze whether the effects are different for the main lenders. We find that for both subsamples the FinTech borrowers are more likely to default, irrespective of whether the FinTech institution is the main lender or not. However, we do find that the magnitude of the effects is significantly higher for the case in which the FinTech is not the main lender, with coefficients being about 60% lower for the case in which FinTech are only marginal for the borrowers. This evidence shows that borrowers are strategic about their repayment behavior, but that, even taking that into account, FinTech loans are still more likely to default.

We can now ask whether our results can be fully explained by the FinTech borrowers being adversely selected, i.e. most of the borrowers that default have been previously rejected by traditional banks. We can do this in two ways. First, we can estimate the delinquency results for two samples, those who have, at most, one inquiry in the quarter before the personal loan origination and those who have multiples. Intuitively, if borrowers got rejected by a traditional bank before turning to a FinTech company, they need to have at least two recent inquiries, for the FinTech and for the bank. Notice that the number of inquiries is already taken into account in the credit score, which we control for, so our estimates are going to capture the additional riskiness due to being rejected by a bank. Columns (1) and (2) of Table 9 investigate total delinquency, while Columns (3) and (4) focus on the personal loan delinquency. For both dependent variables, we find that a higher number of inquiries is related to a higher likelihood to default on average. However, while for the general delinquency measure there is no difference between borrowers depending on the number of inquiries and whether they have a FinTech loan or not, we do find a significant difference for the loan delinquency measure. Specifically, we find that FinTech borrowers are more likely to default than bank borrowers starting in the third month after origination, when they have a higher number of inquiries. The difference in the results for the two delinquency measures corroborates the view that a higher number of inquiries is a proxy for being rejected by the banks, since the additional risk is concentrated in the personal loan.

Although the effects are statistically significant for both subsamples, which suggests that our results cannot be entirely driven by FinTech borrowers being all rejected by banks, a comparison of the coefficients is informative on the relative importance of this channel. At 8-12 months and 13-15 months the coefficients on the loan delinquency for the low inquiries subsample are 62% and 72% of those for the high number of inquiries subsample. This suggests that the adverse selection is an important channel but not the only one.

Another possibility that could explain both our results on delinquency and the results on increasing indebtedness and consumption after the loan origination is that FinTech borrowers are more likely to be present-biased. To investigate whether this hypothesis is supported by the data, we take inspiration from the existing works showing that, even controlling for credit and demographic characteristics, present-biased individuals are more likely to have credit card debt and to have significantly higher amounts of credit card debt (see Meier and Sprenger, 2010 and

Kuchler, 2013). This suggests that FinTech borrowers should be more likely to be revolvers and the increased fragility due to higher leverage should be concentrated among this type of borrowers, as these are more likely to exhibit self-control issues.

Table 10 shows that this is indeed what we find in the data. Columns (1) and (2) investigate any delinquency, while Columns (3) and (4) analyze loan delinquency. The effects are more than twice as large for the revolvers as for transactors. For instance, after 8 months, FinTech borrowers that are revolvers are 2% more likely to default than bank borrowers, while for Fintech borrowers that are transactors the difference is 0.5%. For loan delinquency, one year after origination, the revolvers are 1.8% while the transactors are 0.97% more likely to be delinquent on the personal loan than bank borrowers.

To provide additional evidence that FinTech borrowers are indeed more likely to be present-biased, we also collect information on sudden increase in store credit card spending, such as Best Buy and Macy's, during sale events and holidays, i.e. Black Friday and Christmas holidays, which are not repaid in the following months. Intuitively, borrowers that use credit cards over the holidays and do not repay their cards are more likely to be present-biased because they trade-off the immediate consumption for lower expected consumption in the future due to higher likelihood to default and credit constrained.

Table 11 reports the results. Column (1) shows that the borrowers that tend to spend above their means are indeed more likely to apply for a FinTech loan rather than a bank one in the three months after the increase in balance. In Column (2) we interact the dummy for the balance spike with dummies for young borrowers and those with a high revolving utilization. Column (3) interacts it with a dummy for being revolver. Intuitively, these are more likely to be unable to afford the sudden increase in balance and then more likely to face self-control issues. These interactions are positive and significant, showing that these borrowers are even more likely to get a FinTech loan rather a bank one. In all specifications, we control for borrower fixed effects.

Finally, to further show that FinTech borrowers are more likely to be impulse borrowers, we exploit the advertising by one of these FinTech lenders, SoFi, during the overtime in the 2016 and 2017 Super Bowl games. Column (4) of Table 11 shows a significant increase in loans granted in the immediate aftermath of such advertising, while we do not find a similar response when banks are the ones advertising (Column 5)[12]. This further suggests that FinTech borrowers might be attracted by the possibility of having access to additional funds in a short amount of time and with an easy-to-access online application.

Overall, our findings point out that FinTech might suffer from adverse selection on one key behavioral dimension: the borrowers' intertemporal preferences, which affect their financial responsibility.

## 6. Conclusion

The growing importance of FinTech lenders in the consumer lending market poses the question of whether they provide credit access to borrowers who were underserved by traditional banks or whether these financial innovations are just a vehicle for borrowers to finance higher consumption expenditures. We find evidence supporting the latter hypothesis. In fact, borrowers exhibit good credit scores at origination, are less likely to have been delinquent on an account in the past, have numerous credit accounts with traditional institutions, and are more likely to live in prosperous

[12] These ads include Bank of America and American Express ads in 2014, Suntrust ads in 2016, and US BankCorp ads in 2018.

neighborhoods. However, their credit outcomes significantly worsen in the months following the loan origination.

The underlying mechanism seems to be the borrowers' tendency to use the additional credit to finance consumption rather than improve their financial situation. We present several tests showing that these results seem to be driven by consumers with present bias and short-term impatience exploiting the credit access ease of the FinTech lenders to borrow excessively to support their consumption. In contrast, we do not find significant evidence of adverse selection as we are able to focus on within-borrower variation.

These findings have also policy implications that are relevant to the current debate about the optimal way to regulate these new financial institutions. Specifically, our results suggest that consumers are prone to use the relaxation of their credit constraints due to the entry of these new lenders to borrow above their means. Then, in the same spirit as regulators introduced the "ability to repay" rules for mortgage products in the aftermath of the subprime crisis, one dimension of interest for regulators might be the need for FinTech lenders to more closely monitor the borrowers' ability to service their unsecured debt.

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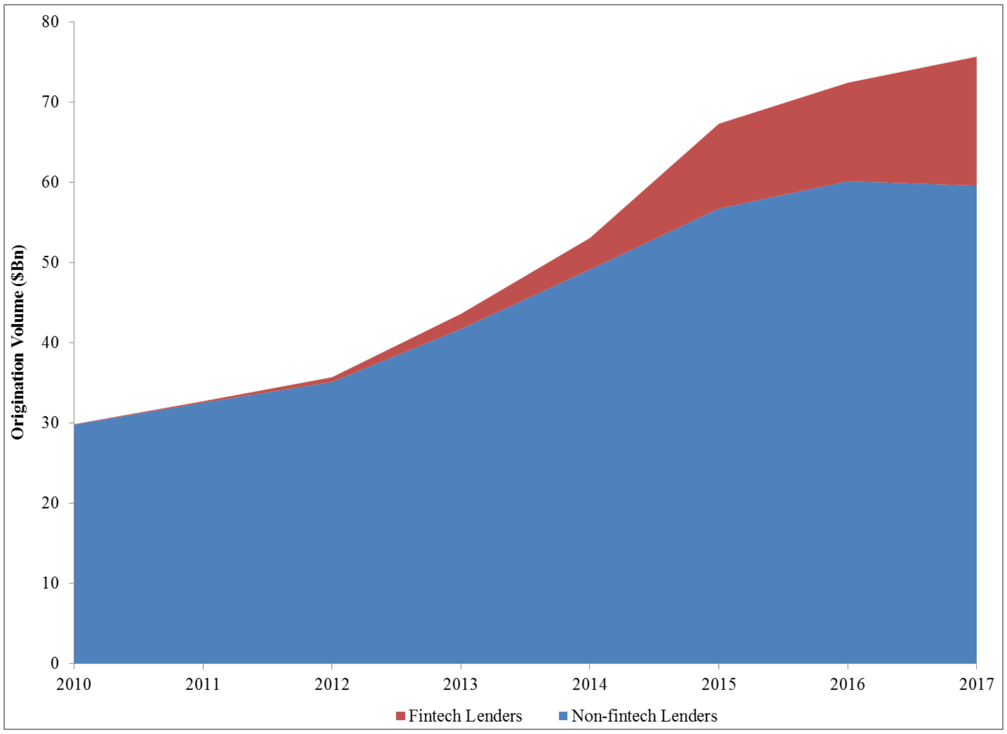



**Figure 1**

This figure plots total origination amount (in billions of dollars) of all personal loans originated by FinTech lenders and non-FinTech lenders. FinTech lenders include LendingClub Corporation, SOFI Lending Corp, Avant Credit Corporation, LoanDepot.com, Freedom Financial Asset Management, Upstart Network Inc, Cashcall, Payoff Inc, and Rockloans Marketplace. Non-FinTech lenders include all the other lenders. The series are based on all personal loans reported to one of the main credit bureaus.

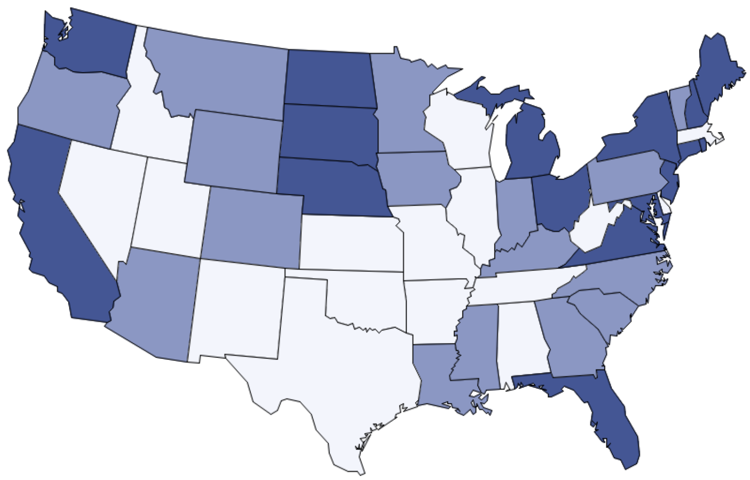
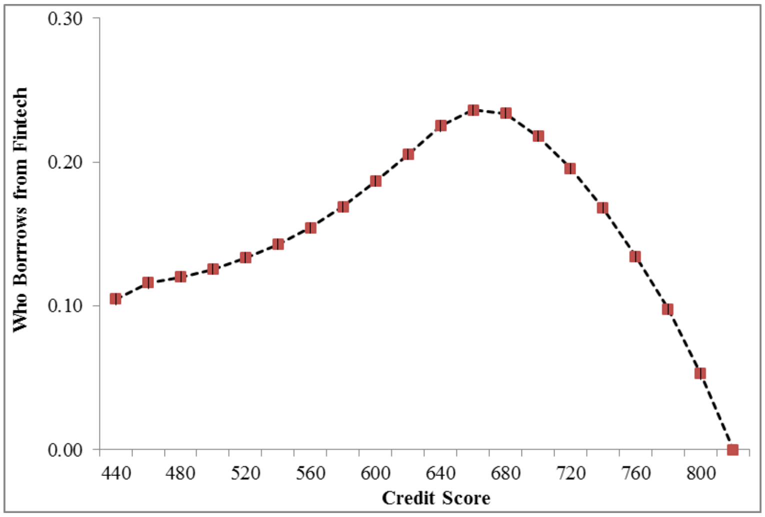


**Figure 2**

The figure plots the coefficients on state dummies from a regression of who borrows from FinTech lenders. The shades in different colors are defined based on terciles of coefficients: darker areas capture the largest positive coefficients, light blue represents states in the middle tercile, while white states capture those in the lowest terciles. The dependent variable is FinTech loan indicator. We also control for origination year and month fixed effects. Standard errors are clustered at county and origination year and month. The regression is based on loan-level data for our random sample of personal loans.

*Panel A*




*Panel B*

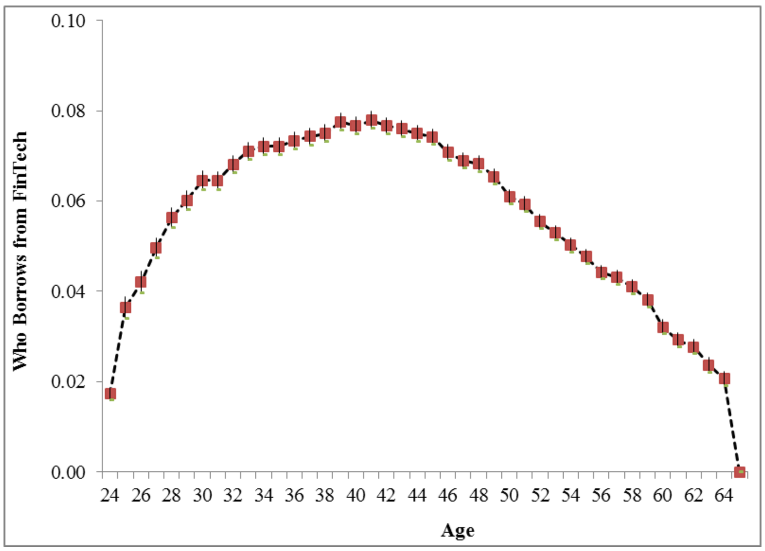
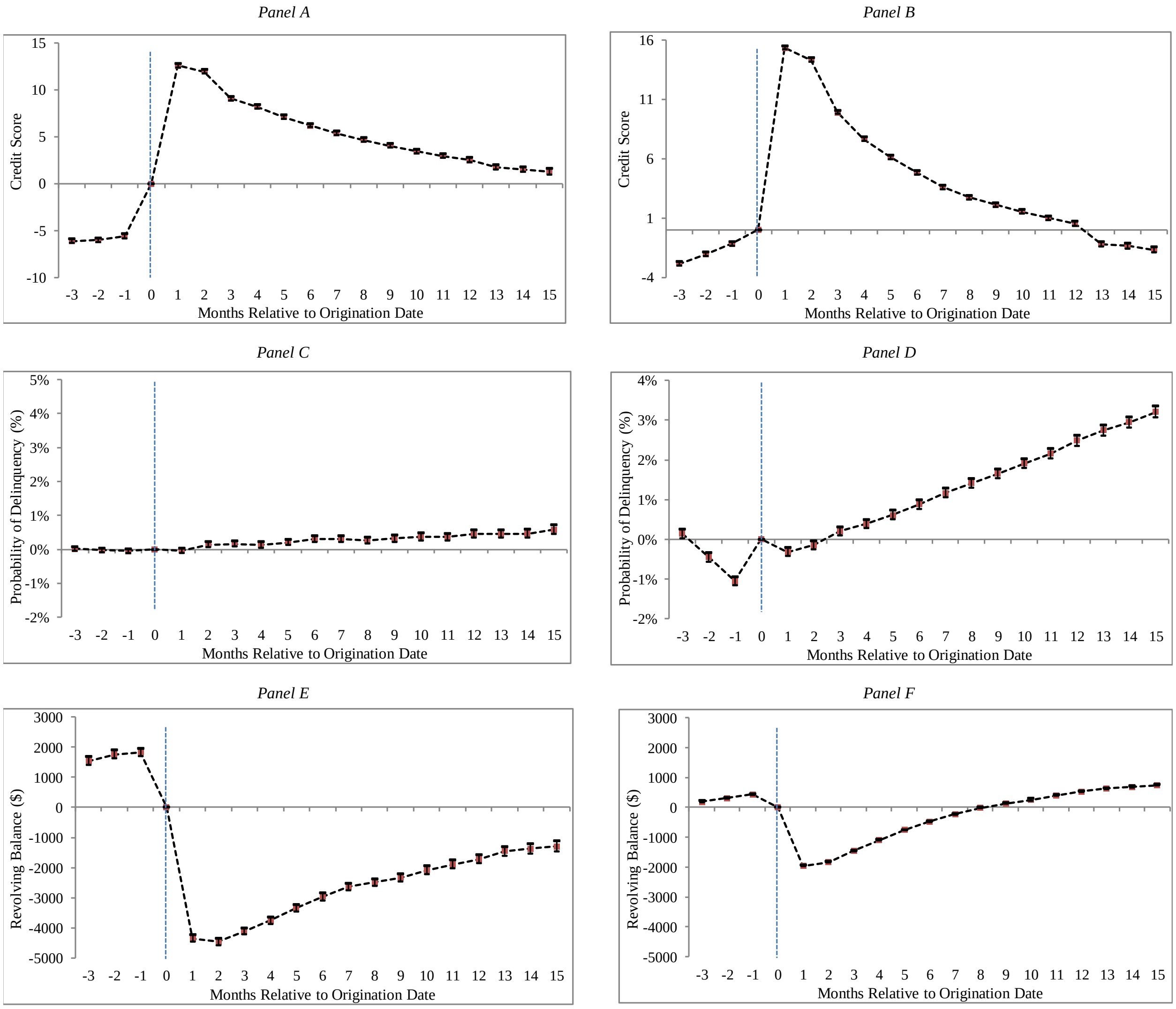



**Figure 3**

These figures plot the coefficients on credit score (Panel A) and borrower age dummies (Panel B) from regressions where the dependent variable is FinTech loan indicator. Panel A plots the fixed effects identifying 20-point bins for the credit score. The credit score is the Vantage score which is distributed from 350 to 850. We also control for origination year-month fixed effects. Standard errors are double clustered at the county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans.




# Figure 4

These figure plots the coefficients on the interaction term of FinTech loan indicator and relative monthly dummies from regressions of consumer credit outcomes split by borrowers' original credit scores. Relative monthly dummies are defined as the interval, in months, from origination date of the FinTech loan. Dependent variables are credit score (Panels A and B), indicator of any credit delinquency (Panels C and D), and revolving balance (Panels E and F). Credit score is the Vantage score that has a distribution from 350 to 850. Delinquency indicator is defined if the borrower has a positive delinquent balance in that month. Revolving balance is the total outstanding balance of all revolving accounts. Panels A, C and E are based on borrowers who have original credit score above 740 when the FinTech loan is originated. Panels B, D and G are based on borrowers who have original credit score below 700 when the FinTech loan is originated. On the right hand side, we also control for borrower fixed effects, FinTech loan indicator, relative monthly dummies and origination year-month fixed effects. Standard errors are double clustered at county and origination year-month cohort level. The regression is based on panel data for our random sample of personal loans.

## Table 1

## Summary Statistics

This table reports summary statistics of loan-level data (Panel A) based on our random sample of personal loans as well as loan x month panel data (Panel B). We randomly draw 50% of all personal loans originated by FinTech lenders and 10% of personal loans originated by non-FinTech lenders, excluding loans with missing origination date, missing credit score, missing total balance, missing number of accounts, and invalid loan balance (negative or zero). In Panel A, we report statistics on consumer credit variables at the time of origination of personal loans. All the variables are from credit report data from one of the credit bureaus. Borrower DLQ indicator is defined as an indicator for the borrowers who have positive delinquent balance. We also report statistics on the loan-level and borrower-level demographic characteristics for the sample we analyze in the paper. All the variables are from credit trade data as well as demographic data from the credit bureau. High income indicator is defined as an indicator for the households whose income is more than $100,000. Professional indicator is defined as an indicator for the households whose heads work in the professional, technical and management occupations. FinTech and bank borrower indicator is defined as an indicator for borrowers who have borrowed from both FinTech and non-FinTech lenders during our sample period. We also report few county-level statistics from various sources. Home price and home price changes are from Zillow. Unemployment rate, fraction of college degree and median household income are from Census Bureau. Fraction of FinTech loans and average bank loan rate are computed based on all loans in our sample originated in the prior three months in a given county. High-speed internet coverage is from Census Bureau's American Community Survey (available from 2013 by county). In Panel B, we report statistics on dynamic consumer credit variables between four months before and fifteen months after the time of origination of personal loans. To keep the sample size manageable, we randomly draw 50% of the borrowers reported in Panel A and match with monthly credit report data. We also report statistics on the main variables used in our analysis of payment spikes and advertising. Origination indicator is defined to be 1 if a loan (Fintech or bank) is originated in that month and 0 otherwise.

Panel A

| Variable | N | Mean | Median | Std Dev | 25th Pctl | 75th Pctl |
|---|---|---|---|---|---|---|
| *Credit Variables at Origination* | | | | | | |
| Credit Score | 7,460,395 | 630.80 | 631 | 84.32 | 577.00 | 688.00 |
| Age of Credit History | 7,460,395 | 175.87 | 159 | 92.56 | 116.00 | 223.00 |
| No of Accounts | 7,460,395 | 27.56 | 25 | 15.84 | 16.00 | 36.00 |
| Rev. Utilization | 7,460,395 | 45.00 | 45.74 | 36.02 | 2.21 | 78.40 |
| Rev. Balance | 7,460,395 | 8,149 | 2,595 | 20,250 | 110 | 9,193 |
| Student Loan Balance | 7,460,395 | 8,275 | 0 | 26,457 | 0 | 0 |
| Mortgage Balance | 7,460,395 | 57,276 | 0 | 114,517 | 0 | 80,163 |
| Borrower DLQ Indicator | 7,460,395 | 0.22 | 0.00 | 0.42 | 0.00 | 0.00 |
| Transactor Indicator | 7,460,395 | 0.07 | 0.00 | 0.26 | 0.00 | 0.00 |
| Student Loan Indicator | 7,460,395 | 0.28 | 0.00 | 0.45 | 0.00 | 1.00 |
| Mortgage Indicator | 7,460,395 | 0.48 | 0.00 | 0.50 | 0.00 | 1.00 |
| No of Inquiries | 7,460,395 | 1.36 | 1.00 | 1.70 | 0.00 | 2.00 |
| *Borrower Demographic Variables* | | | | | | |
| Borrower Age | 7,460,395 | 48.91 | 49.00 | 13.90 | 38.00 | 59.00 |
| Male Indicator | 7,460,395 | 0.50 | 0.00 | 0.50 | 0.00 | 1.00 |
| Married Indicator | 7,460,395 | 0.56 | 1.00 | 0.50 | 0.00 | 1.00 |
| College Indicator | 7,460,395 | 0.20 | 0.00 | 0.40 | 0.00 | 0.00 |
| High Income Indicator | 7,460,395 | 0.18 | 0.00 | 0.38 | 0.00 | 0.00 |
| Professional Indicator | 7,460,395 | 0.11 | 0.00 | 0.31 | 0.00 | 0.00 |
| *Personal Loan Term Variables* | | | | | | |
| Original Note Rate | 3,995,076 | 12.11 | 11.02 | 10.71 | 0.00 | 19.28 |
| Credit Limit | 7,178,701 | 7,144 | 3,165 | 9,486 | 1,120 | 10,000 |
| Loan Term | 6,887,908 | 31.40 | 36.00 | 24.06 | 8.00 | 48.00 |
| *Ex Post Performance* | | | | | | |
| Borrower DLQ Indicator | 7,460,395 | 0.16 | 0.00 | 0.37 | 0.00 | 0.00 |
| Loan DLQ Indicator | 6,887,908 | 0.02 | 0.00 | 0.13 | 0.00 | 0.00 |
| *County-Level Macro Variables* | | | | | | |
| QoQ HP Change | 5,758,523 | 0.01 | 0.01 | 0.02 | 0.00 | 0.02 |
| HP Level | 5,758,523 | 198,526 | 150,100 | 145,678 | 112,400 | 226,200 |
| Unemployment Rate | 5,050,526 | 6.48 | 6.10 | 2.13 | 5.00 | 7.60 |
| Fraction of College Degree | 5,050,526 | 24.54 | 22.91 | 9.93 | 16.42 | 30.18 |
| Median HH Income | 6,437,421 | 52,181 | 49,782 | 14,527 | 41,957 | 58,764 |
| Cum. HP Decline 2007-10 | 5,758,523 | -0.17 | -0.16 | 0.19 | -0.30 | -0.04 |
| Fraction of Fintech Loans | 7,367,134 | 0.22 | 0.10 | 0.20 | 0.03 | 0.38 |
| Average Bank Loan Rate | 7,364,716 | 11.71 | 12.41 | 204.51 | 4.69 | 16.42 |
| High-Speed Internet Coverage | 5,879,624 | 0.73 | 0.74 | 0.08 | 0.69 | 0.78 |

Panel B

| Variable | N | Mean | Median | Std Dev | 25th Pctl | 75th Pctl |
|---|---|---|---|---|---|---|
| *Credit Variables* | | | | | | |
| Credit Score | 23,466,488 | 654.31 | 658.00 | 88.13 | 600.00 | 716.00 |
| Borrower DLQ Indicator | 23,466,488 | 0.17 | 0.00 | 0.37 | 0.00 | 0.00 |
| Loan DLQ Indicator x 100 | 23,466,488 | 0.55 | 0.00 | 7.40 | 0.00 | 0.00 |
| Total Debt | 23,466,488 | 93,636 | 48,878 | 122,872 | 17,830 | 128,418 |
| Rev. Balance | 23,466,488 | 10,159 | 4,348 | 24,038 | 820 | 11,307 |
| Indicator of Buying a Car x 100 | 22,204,593 | 6.11 | 0.00 | 23.96 | 0.00 | 0.00 |
| *Superbowl Events* | | | | | | |
| Fintech Loan Origination Indicator | 868,915 | 0.02 | 0.00 | 0.13 | 0.00 | 0.00 |
| Bank Loan Origination Indicator | 673,189 | 0.003 | 0.00 | 0.05 | 0.00 | 0.00 |
| *Personal Loan Payment Spikes* | | | | | | |
| Fintech Loan Origination Indicator | 431,262 | 0.01 | 0.00 | 0.07 | 0.00 | 0.00 |
| Post Indicator | 431,262 | 0.38 | 0.00 | 0.49 | 0.00 | 1.00 |
| x Young Borrower | 431,262 | 0.18 | 0.00 | 0.38 | 0.00 | 0.00 |
| x High Rev. Utilization | 431,262 | 0.17 | 0.00 | 0.37 | 0.00 | 0.00 |
| x Revolver | 297,516 | 0.31 | 0.00 | 0.46 | 0.00 | 1.00 |

## Table 2

## Geographic Characteristics

The table reports the estimated coefficients on geographic characteristics at the county level from specifications where the dependent variable is a FinTech loan indicator (0/1). We also control for state by origination year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. The regressions are OLS regressions based on loan-level data for our random sample of personal loans. Home price and home price changes are from Zillow. Unemployment rate, fraction of college degree and median household income are from Census Bureau. Fraction of FinTech loans and average bank loan rate are computed based on all loans in our sample originated in the prior three months in a given county. High-speed internet coverage is from Census Bureau American Community Survey (available from 2013 by county). Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Fintech Loan Indicator | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| QoQ HP Change | 0.014*** | | | | | | | | |
| | (0.001) | | | | | | | | |
| HP Level | | 0.052*** | | | | | | | |
| | | (0.001) | | | | | | | |
| Cum. HP Decline 2007-10 | | | -0.041*** | | | | | | |
| | | | (0.001) | | | | | | |
| Unemployment Rate | | | | -0.021*** | | | | | |
| | | | | (0.001) | | | | | |
| Median HH Income | | | | | 0.047*** | | | | |
| | | | | | (0.001) | | | | |
| Fraction of College Degree | | | | | | 0.042*** | | | |
| | | | | | | (0.001) | | | |
| Fraction of Fintech Loans | | | | | | | 0.199*** | | |
| | | | | | | | (0.000) | | |
| Average Bank Loan Rate | | | | | | | | 0.001*** | |
| | | | | | | | | (0.0002) | |
| High-Speed Internet Coverage | | | | | | | | | 0.037*** |
| | | | | | | | | | (0.001) |
| STATE x Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SE Clustered | | | | | County; YM | | | | |
| Observations | 5758523 | 5763100 | 5233136 | 5050526 | 6437421 | 5050526 | 7367134 | 7364716 | 5455516 |
| R-Square | 0.008 | 0.015 | 0.011 | 0.008 | 0.019 | 0.021 | 0.071 | 0.007 | 0.014 |

## Table 3

## Borrowers' Characteristics

These tables report the regression results of specifications where the dependent variable is FinTech loan indicator (0/1). In Panel A, we report coefficients on borrower demographics as collected by the credit bureau. In Panel B, we report results on borrower credit attributes. High income indicator is defined as an indicator for the households whose income is more than $100,000. Professional indicator is defined as an indicator for the households whose heads work in the professional, technical and management occupations. In Panel C, we report results on borrowers' dynamic credit attributes based on regressions split by borrower's original credit score. High credit score cohort identifies borrowers who have original credit score above 740 when the FinTech loan is originated. Low credit score cohort identifies borrowers who have original credit score below 700. In addition to the variables reported in the table, we also control for ZIP Code by origination year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

| | Fintech Loan Indicator | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Male Indicator | 0.010*** | | | | | 0.007*** |
| | (0.0004) | | | | | (0.0004) |
| Married Indicator | | 0.001*** | | | | -0.009*** |
| | | (0.0003) | | | | (0.0003) |
| College Indicator | | | 0.041*** | | | 0.028*** |
| | | | (0.001) | | | (0.001) |
| High Income Indicator | | | | 0.062*** | | 0.058*** |
| | | | | (0.001) | | (0.001) |
| Professional Indicator | | | | | 0.040*** | 0.029*** |
| | | | | | (0.001) | (0.001) |
| ZIP x YM FE | Yes | Yes | Yes | Yes | Yes | Yes |
| SE Clustered | County; YM | | | | | |
| Observations | 7460395 | 7460395 | 7460395 | 7460395 | 7460395 | 7460395 |
| R-Square | 0.0002 | 0.0000 | 0.0016 | 0.0038 | 0.0013 | 0.0057 |

Panel B

| | Fintech Loan Indicator | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Credit Score | 0.022*** | | | | | | | | -0.005*** |
| | (0.000) | | | | | | | | (0.001) |
| Age of Credit History | | 0.009*** | | | | | | | 0.004*** |
| | | (0.000) | | | | | | | (0.0003) |
| No of Accounts | | | 0.0001*** | | | | | | -0.013*** |
| | | | (0.000) | | | | | | (0.0003) |
| Rev. Utilization | | | | 0.018*** | | | | | 0.002*** |
| | | | | (0.000) | | | | | (0.0002) |
| DLQ Indicator | | | | | -0.065*** | | | | -0.082*** |
| | | | | | (0.001) | | | | (0.001) |
| Transactor Indicator | | | | | | -0.039*** | | | -0.040*** |
| | | | | | | (0.001) | | | (0.001) |
| Student Loan Indicator | | | | | | | 0.069*** | | 0.085*** |
| | | | | | | | (0.000) | | (0.001) |
| Mortgage Indicator | | | | | | | | 0.035*** | 0.031*** |
| | | | | | | | | (0.000) | (0.0005) |
| ZIP x YM FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SE Clustered | | | | | County; YM | | | | |
| Observations | 7477419 | 7477414 | 7477419 | 7477419 | 7477419 | 4725395 | 7477419 | 7477419 | 4725395 |
| R-Square | 0.0033 | 0.0007 | 0.0000 | 0.0026 | 0.0064 | 0.0006 | 0.0080 | 0.0025 | 0.0177 |

Panel C

| | Fintech Loan Indicator | |
|---|---|---|
| | High Credit Score | Low Credit Score |
| | (1) | (2) |
| Credit Score | -0.054*** | 0.031** |
| | (0.001) | (0.001) |
| Age of Credit History | -0.006*** | 0.011** |
| | (0.0004) | (0.0003) |
| No of Accounts | -0.010*** | -0.013*** |
| | (0.001) | (0.000) |
| Rev. Utilization | 0.023** | -0.010*** |
| | (0.001) | (0.000) |
| DLQ Indicator | -0.344*** | -0.045*** |
| | (0.003) | (0.001) |
| Transactor Indicator | -0.043*** | -0.011*** |
| | (0.001) | (0.001) |
| Student Loan Indicator | 0.095** | 0.081** |
| | (0.001) | (0.001) |
| Mortgage Indicator | 0.046** | 0.025** |
| | (0.001) | (0.000) |
| ZIP x YM FE | Yes | Yes |
| SE Clustered | County; YM | |
| Observations | 1142143 | 3583252 |
| R-Square | 0.031 | 0.025 |

## Table 4

## Loan Terms

The table reports the regression results examining the difference in the loan terms between the FinTech and banks personal loans in our sample. The dependent variable is column title: credit limit, loan term and note rate. In addition to the FinTech loan indicator, we also control for borrowers' credit score and age of credit history. For the regression of note rate, we also control for credit balance and term. For regressions reported in Columns (1)-(3), we control for ZIP Code by origination year-month fixed effects, while for those in Columns (4)-(6), we include borrower and year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Credit Limit | Loan Term | Note Rate | Credit Limit | Loan Term | Note Rate |
|---|---|---|---|---|---|---|
| | Borrowers that have Fintech or Bank Loans | | | Borrowers that have Fintech and Bank Loans | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Fintech Loan Indicator | 3677.4*** | -1.892*** | 0.120*** | 2873.9*** | -0.529*** | -0.010 |
| | (19.836) | (0.047) | (0.019) | (22.596) | (0.052) | (0.021) |
| Credit Attributes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Terms | No | No | Yes | No | No | Yes |
| ZIP x YM FE | Yes | Yes | Yes | No | No | No |
| Borrower FE | No | No | No | Yes | Yes | Yes |
| YM FE | No | No | No | Yes | Yes | Yes |
| Observations | 7178701 | 6887908 | 3995076 | 468732 | 464956 | 288645 |
| R-Square | 0.052 | 0.016 | 0.057 | 0.060 | 0.008 | 0.032 |

## Table 5

## Borrower Delinquency

These tables report the regression results of borrower and loan performance based on loan-level data. The dependent variable is delinquent borrower indicator in Panel A, which identifies whether borrower has any delinquent account; and delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017 in Panel B. In Column (3) of Panel A and in Panel B, we control for borrowers' credit score, age of credit history, number of accounts, revolving utilization, whether borrower had prior delinquency, indicator for *transactor* borrowers, student loan indicator, mortgage indicator, male indicator, married indicator, college indicator, high-income indicator, professional indicator, personal loan balance, personal loan term and ZIP Code by cohort year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

| | Borrower DLQ Indicator | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Fintech Loan Indicator | 0.167*** | 0.132*** | 0.140*** |
| | (0.001) | (0.001) | (0.001) |
| Credit Attributes | No | No | Yes |
| Demographics | No | No | Yes |
| Loan Attributes | No | No | Yes |
| ZIP x YM FE | No | Yes | Yes |
| Observations | 7460395 | 7460395 | 4576162 |
| R-Square | 0.127 | 0.018 | 0.053 |

Panel B

| | Loan DLQ Indicator | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fintech Loan Indicator | 0.019*** | 0.033*** | 0.028*** | 0.019*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| x Fraction of Fintech Loans | | | | 0.033*** |
| | | | | (0.001) |
| Fraction of Fintech Loans | | | | 0.003*** |
| | | | | (0.000) |
| Credit Attributes | Yes | Yes | Yes | Yes |
| Loan Attributes | Yes | Yes | Yes | Yes |
| County FE | Yes | No | No | Yes |
| YM FE | Yes | No | No | Yes |
| ZIP x YM FE | No | Yes | No | No |
| Borrower FE | No | No | Yes | No |
| Observations | 6887908 | 6887908 | 5953821 | 6786486 |
| R-Square | 0.006 | 0.013 | 0.007 | 0.016 |

## Table 6

## Borrower Delinquency: Dynamics

This table reports the regression results of borrower and loan performance based on loan-level data. The dependent variable is delinquent borrower indicator in Columns (1)-(3), which identifies whether borrower has any delinquent account; and delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017 in Columns (4)-(6). Columns (2) and (4) restrict attention to borrowers with credit score above 740 at origination, while Columns (3) and (6) restrict attention to borrowers with credit score below 700. Credit score is the Vantage score that has a distribution from 350 to 850. All specifications include borrower fixed effects, FinTech loan indicator, relative monthly dummies, interaction of the two, and origination year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Borrower DLQ Indicator | | | Loan DLQ Indicator x 100 | | |
|---|---|---|---|---|---|---|
| | All | High Credit Score | Low Credit Score | All | High Credit Score | Low Credit Score |
| Fintech Borrower Indicator | | | | | | |
| x 1-3 Months Before | -0.004*** | -0.0003 | -0.005*** | 0.006 | 0.002 | 0.009 |
| | (0.000) | (0.0003) | (0.001) | (0.009) | (0.008) | (0.012) |
| x 1 Month After | -0.003*** | -0.0004 | -0.004*** | -0.046*** | -0.003 | -0.081*** |
| | (0.001) | (0.0004) | (0.001) | (0.013) | (0.010) | (0.017) |
| x 2 Months After | -0.001*** | 0.001*** | -0.002*** | -0.051*** | -0.004 | -0.095*** |
| | (0.001) | (0.001) | (0.001) | (0.013) | (0.010) | (0.018) |
| x 3-7 Months After | 0.006*** | 0.002*** | 0.006*** | 0.172*** | -0.015*** | 0.175*** |
| | (0.000) | (0.000) | (0.001) | (0.013) | (0.008) | (0.018) |
| x 8-12 Months After | 0.016*** | 0.003*** | 0.019*** | 1.170*** | 0.024*** | 1.471*** |
| | (0.000) | (0.000) | (0.001) | (0.019) | (0.009) | (0.025) |
| x 13-15 Months After | 0.025*** | 0.005*** | 0.029*** | 2.161*** | 0.073*** | 2.759*** |
| | (0.001) | (0.001) | (0.001) | (0.024) | (0.016) | (0.031) |
| 1-3 Months Before | -0.003*** | 0.001*** | -0.004*** | 0.004 | 0.001 | 0.004 |
| | (0.000) | (0.000) | (0.000) | (0.004) | (0.003) | (0.006) |
| 1 Month After | -0.006*** | 0.003*** | -0.010*** | 0.002 | -0.004 | 0.022*** |
| | (0.000) | (0.000) | (0.001) | (0.005) | (0.004) | (0.007) |
| 2 Months After | -0.002*** | 0.005*** | -0.006*** | 0.021*** | -0.004 | 0.054*** |
| | (0.000) | (0.000) | (0.001) | (0.005) | (0.004) | (0.008) |
| 3-7 Months After | 0.013*** | 0.008*** | 0.014*** | 0.346*** | 0.050*** | 0.506*** |
| | (0.000) | (0.000) | (0.000) | (0.005) | (0.004) | (0.007) |
| 8-12 Months After | 0.029*** | 0.012*** | 0.034*** | 0.616*** | 0.096*** | 0.865*** |
| | (0.000) | (0.000) | (0.000) | (0.006) | (0.004) | (0.008) |
| 13-15 Months After | 0.040*** | 0.016*** | 0.047*** | 0.773*** | 0.151*** | 1.053*** |
| | (0.000) | (0.000) | (0.000) | (0.007) | (0.006) | (0.010) |
| Borrower FE | Yes | Yes | Yes | Yes | Yes | Yes |
| R-Square | 0.008 | 0.005 | 0.009 | 0.012 | 0.001 | 0.016 |
| Observations | 23466488 | 3738452 | 16402608 | 23466488 | 3738452 | 16402608 |

## Table 7

## Evidence on the Mechanism: Indebtedness and Spending

The table reports results from regressions of consumer credit outcomes based on loan-month panel data. Dependent variables are total amount of debt in Columns (1) and (2), and indicator for car purchases in Columns (3) and (4). The indicator for car purchases is equal to one whenever a borrower opened a new auto tradeline, or their existing auto balance changes by more than $5,000. On the right hand side, we include FinTech loan indicator, relative monthly dummies, interaction of the two, and origination year-month fixed effects. Columns (2) and (4) also include borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Total Debt | | Prob of Buying a Car x 100 | |
|---|---|---|---|---|
| | All | | All | |
| Fintech Borrower Indicator | | | | |
| x 1-3 Months Before | -110.354 | 75.467 | 0.150*** | 0.174*** |
| | (232.4915) | (73.4492) | (0.041) | (0.039) |
| x 1 Month After | 2404.208*** | -2,065.050*** | 0.406*** | 0.236*** |
| | (314.231) | (86.845) | (0.055) | (0.051) |
| x 2 Months After | 3538.183*** | -1,279.160*** | 0.724*** | 0.512*** |
| | (318.776) | (85.891) | (0.055) | (0.051) |
| x 3-7 Months After | 8361.885*** | 2183.764*** | 0.760*** | 0.453*** |
| | (240.973) | (71.107) | (0.040) | (0.037) |
| x 8-12 Months After | 11567.740*** | 3721.540*** | 0.748*** | 0.319*** |
| | (256.880) | (78.377) | (0.040) | (0.038) |
| x 13-15 Months After | 13582.630*** | 5056.460*** | 0.639*** | 0.128*** |
| | (298.954) | (93.761) | (0.056) | (0.052) |
| 1-3 Months Before | 181.130 | -35.891 | -0.705 | -0.723 |
| | (135.527) | (43.928) | (0.026) | (0.024) |
| 1 Month After | -2,268.100*** | 4149.267*** | -0.469*** | -0.369*** |
| | (175.473) | (49.711) | (0.034) | (0.031) |
| 2 Months After | -2,358.370*** | 5006.472*** | -0.640*** | -0.536*** |
| | (180.455) | (49.365) | (0.033) | (0.031) |
| 3-7 Months After | -3,855.910*** | 6277.907*** | -0.104*** | -0.007*** |
| | (139.932) | (42.916) | (0.025) | (0.023) |
| 8-12 Months After | -7,001.230*** | 7788.187*** | -0.560*** | -0.463*** |
| | (147.568) | (46.212) | (0.025) | (0.024) |
| 13-15 Months After | -9,245.690*** | 9054.380*** | 2.803*** | 2.522*** |
| | (169.610) | (52.648) | (0.034) | (0.031) |
| Borrower FE | No | Yes | No | Yes |
| R-Square | 0.024 | 0.013 | 0.003 | 0.002 |
| Observations | 23466488 | 23466488 | 22204593 | 22204593 |

## Table 8

## Evidence on the Mechanism: Main vs Marginal Lenders

This table reports the regression results of loan performance based on loan-level data. The dependent variable is delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017. Odd Columns restrict attention to the subsample of borrowers whose personal loan is from a lender that is not the borrower's largest personal loan creditor. Even Columns restrict attention to borrowers whose personal loan is from a lender that is the borrower's largest personal loan creditor. On the right hand side, we include FinTech loan indicator, relative monthly dummies, interaction of the two, origination year-month fixed effects, and in Columns (3) and (4) we also include borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Loan DLQ x 100 | | | |
|---|---|---|---|---|
| | Non-Main | Main Lender | Non-Main | Main Lender |
| Fintech Borrower Indicator | | | | |
| x 1-3 Months Before | 0.018 | 0.003 | -0.004 | 0.006 |
| | (0.042) | (0.0009) | (0.283) | (0.0088) |
| x 1 Month After | 0.084 | 0.0003 | 0.450 | -0.048*** |
| | (0.061) | (0.002) | (0.358) | (0.012) |
| x 2 Months After | -0.079 | 0.0017 | -0.149 | -0.051*** |
| | (0.099) | (0.004) | (0.373) | (0.013) |
| x 3-7 Months After | 0.776*** | 0.232*** | 0.799*** | 0.169*** |
| | (0.216) | (0.013) | (0.303) | (0.013) |
| x 8-12 Months After | 3.319** | 1.233** | 3.352** | 1.162** |
| | (0.392) | (0.022) | (0.369) | (0.019) |
| x 13-15 Months After | 5.362*** | 2.241*** | 5.511*** | 2.149*** |
| | (0.683) | (0.030) | (0.572) | (0.024) |
| 1-3 Months Before | -0.001 | 0.003 | 0.036 | 0.004 |
| | (0.021) | (0.001) | (0.112) | (0.004) |
| 1 Month After | -0.055* | -0.016*** | -0.063 | 0.003 |
| | (0.029) | (0.001) | (0.152) | (0.005) |
| 2 Months After | 0.048** | 0.0004 | 0.202 | 0.020** |
| | (0.081) | (0.002) | (0.141) | (0.005) |
| 3-7 Months After | 0.636*** | 0.311*** | 0.792*** | 0.344*** |
| | (0.093) | (0.004) | (0.125) | (0.005) |
| 8-12 Months After | 1.411*** | 0.539*** | 1.708*** | 0.611*** |
| | (0.132) | (0.005) | (0.145) | (0.006) |
| 13-15 Months After | 2.117*** | 0.664*** | 2.402*** | 0.765*** |
| | (0.208) | (0.007) | (0.198) | (0.007) |
| Borrower FE | No | No | Yes | Yes |
| R-Square | 0.030 | 0.011 | 0.031 | 0.012 |
| Observations | 104917 | 23361571 | 104917 | 23361571 |

## Table 9

## Evidence on the Mechanism: Past Inquiries

This table reports the regression results of borrower and loan performance based on loan-level data. The dependent variable is delinquent borrower indicator in Columns (1)-(2), which identifies whether borrower has any delinquent account; and delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017 in Columns (3)-(4). Odd Columns restrict attention to the subsample of borrowers who had at most one credit report hard inquiries in the quarter before the personal loan originated, while even Columns restrict attention to borrowers with more than one inquiries. On the right hand side, we include FinTech loan indicator, relative monthly dummies, interaction of the two, origination year-month fixed effects, and borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Borrowe DLQ | | Loan DLQ x 100 | |
|---|---|---|---|---|
| | Low Inquiries | High Inquiries | Low Inquiries | High Inquiries |
| Fintech Borrower Indicator | | | | |
| x 1-3 Months Before | -0.004*** | 0.002* | -0.002 | 0.089*** |
| | (0.000) | (0.001) | (0.009) | (0.026) |
| x 1 Month After | -0.004*** | -0.007*** | -0.003 | -0.204*** |
| | (0.001) | (0.001) | (0.012) | (0.034) |
| x 2 Months After | -0.002*** | -0.004*** | -0.004 | -0.179*** |
| | (0.001) | (0.001) | (0.013) | (0.035) |
| x 3-7 Months After | 0.006*** | 0.007*** | 0.169*** | 0.272*** |
| | (0.000) | (0.001) | (0.013) | (0.028) |
| x 8-12 Months After | 0.019*** | 0.014*** | 1.060*** | 1.713*** |
| | (0.000) | (0.001) | (0.019) | (0.033) |
| x 13-15 Months After | 0.029*** | 0.017*** | 2.037*** | 2.775*** |
| | (0.001) | (0.001) | (0.025) | (0.043) |
| 1-3 Months Before | -0.003*** | -0.009*** | -0.005 | -0.075*** |
| | (0.000) | (0.001) | (0.004) | (0.010) |
| 1 Month After | -0.005*** | -0.001** | 0.015*** | 0.063*** |
| | (0.000) | (0.001) | (0.005) | (0.011) |
| 2 Months After | -0.002*** | 0.003*** | 0.029*** | 0.099*** |
| | (0.000) | (0.001) | (0.006) | (0.011) |
| 3-7 Months After | 0.011*** | 0.020*** | 0.293*** | 0.492*** |
| | (0.000) | (0.001) | (0.005) | (0.010) |
| 8-12 Months After | 0.024*** | 0.046*** | 0.528*** | 0.861*** |
| | (0.000) | (0.001) | (0.006) | (0.012) |
| 13-15 Months After | 0.033*** | 0.060*** | 0.690*** | 0.999*** |
| | (0.000) | (0.001) | (0.007) | (0.013) |
| Borrower FE | Yes | Yes | Yes | Yes |
| R-Square | 0.007 | 0.011 | 0.011 | 0.015 |
| Observations | 18133067 | 5288732 | 18133067 | 5288732 |

## Table 10

### Evidence on the Mechanism: Revolvers vs Transactors

This table reports the regression results of borrower and loan performance based on loan-level data. The dependent variable is delinquent borrower indicator in Columns (1)-(2), which identifies whether borrower has any delinquent account; and delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017 in Columns (3)-(4). Odd Columns restrict attention to the subsample of borrowers who have been classified as *revolvers* by the credit bureau, while even Columns restrict attention to borrowers who have been classified as transactors. On the right hand side, we include FinTech loan indicator, relative monthly dummies, interaction of the two, origination year-month fixed effects, and borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | Borrower DLQ | | Loan DLQ Indicator x 100 | |
|---|---|---|---|---|
| | Revolver | Transactor | Revolver | Transactor |
| Fintech Borrower Indicator | | | | |
| x 1-3 Months Before | -0.004*** | -0.004*** | 0.004 | 0.003 |
| | (0.001) | (0.001) | (0.009) | (0.023) |
| x 1 Month After | -0.004*** | -0.003*** | -0.025** | -0.011 |
| | (0.001) | (0.002) | (0.012) | (0.031) |
| x 2 Months After | -0.002*** | -0.001 | -0.034*** | -0.005 |
| | (0.001) | (0.002) | (0.013) | (0.031) |
| x 3-7 Months After | 0.005*** | 0.002* | 0.084*** | 0.092*** |
| | (0.000) | (0.001) | (0.010) | (0.024) |
| x 8-12 Months After | 0.020*** | 0.005*** | 0.916 | 0.567*** |
| | (0.001) | (0.001) | (0.013) | (0.029) |
| x 13-15 Months After | 0.033*** | 0.009*** | 1.841*** | 0.972*** |
| | (0.001) | (0.001) | (0.019) | (0.043) |
| 1-3 Months Before | -0.003*** | -0.001 | 0.003 | 0.000 |
| | (0.000) | (0.001) | (0.004) | (0.009) |
| 1 Month After | -0.006*** | -0.004*** | 0.007 | -0.004 |
| | (0.000) | (0.001) | (0.005) | (0.012) |
| 2 Months After | -0.003*** | -0.003*** | 0.017*** | -0.004 |
| | (0.000) | (0.001) | (0.005) | (0.012) |
| 3-7 Months After | 0.010*** | 0.003*** | 0.226*** | 0.152*** |
| | (0.000) | (0.001) | (0.005) | (0.010) |
| 8-12 Months After | 0.022*** | 0.007*** | 0.439*** | 0.276*** |
| | (0.000) | (0.001) | (0.005) | (0.011) |
| 13-15 Months After | 0.030*** | 0.011*** | 0.591*** | 0.346*** |
| | (0.000) | (0.001) | (0.007) | (0.015) |
| Borrower FE | Yes | Yes | Yes | Yes |
| R-Square | 0.008 | 0.002 | 0.011 | 0.005 |
| Observations | 15213280 | 1527849 | 15213280 | 1527849 |

## Table 11

### Evidence on the Mechanism: Payment Spikes and Advertising

This table reports the regression results of specifications where the dependent variable is FinTech loan indicator (0/1) to investigate the characteristics driving individuals to borrow from FinTech lenders. Columns (1)-(3) identifies borrowers whose revolving balance increases more than two SD above the average level during December and January, which captures expenses made in November and December. Column (4) focuses on the advertising broadcast during the 2016 and 2017 Superbowl overtime, while Column (5) focuses on Bank of America and American Express ads in 2014, Suntrust ads in 2016, and US BankCorp ads in 2018. On the right hand side, we include Event indicator, a Post dummy identifying the three months after the event, interaction of the two, origination year-month fixed effects, and borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| | FinTech Loan Indicator | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Event | Payment Shock | | | SoFi Ads | Bank Ads |
| x Post (1-3 months) | 0.0050*** | 0.0030*** | 0.0045*** | 0.038*** | 0.007*** |
| | (0.0003) | (0.0003) | (0.0007) | (0.001) | (0.0003) |
| x Young Borrower | | 0.0036*** | | | |
| | | (0.0005) | | | |
| x High Rev. Utilization | | 0.0007*** | | | |
| | | (0.0004) | | | |
| x Revolver | | | 0.0013*** | | |
| | | | (0.001) | | |
| Borrower FE | Yes | Yes | Yes | Yes | Yes |
| Credit YM FE | Yes | Yes | Yes | Yes | Yes |
| Clustered at | County, Cohort YM | | | | |
| Observations | 431262 | 431262 | 297516 | 868915 | 673189 |
| R-Square | 0.041 | 0.041 | 0.046 | 0.017 | 0.008 |