NBER WORKING PAPER SERIES

FINTECH BORROWERS:
LAX-SCREENING OR CREAM-SKIMMING?

Marco Di Maggio
Vincent Yao

Working Paper 28021
http://www.nber.org/papers/w28021

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020

Fintech Borrowers: Lax-Screening or Cream-Skimming?
Marco Di Maggio and Vincent Yao
NBER Working Paper No. 28021
October 2020
JEL No. G21,G23,G4

ABSTRACT

We study the personal credit market using unique individual-level data covering fintech and traditional lenders. We show that fintech lenders acquire market share by first lending to higher-risk borrowers and then to safer borrowers, and mainly rely on hard information to make credit decisions. Fintech borrowers are significantly more likely to default than neighbor individuals with the same characteristics borrowing from traditional financial institutions. Furthermore, they tend to experience only a short-lived reduction in the cost of credit, because their indebtedness increases more than non-fintech borrowers a few months after loan origination. However, fintech lenders' pricing strategies are likely to take this into account.

Marco Di Maggio
Harvard Business School
Baker Library 265
Soldiers Field
Boston, MA 02163
and NBER
mdimaggio@hbs.edu

Vincent Yao
Georgia State University
J. Mack Robinson College of Business
35 Broad Street NW
Atlanta, GA 30303
wyao2@gsu.edu

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 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) and their market share has been predicted to increase to 20% by 2020 (Transunion, 2017). Therefore, it is important to understand how these new intermediaries affect households' borrowing and consumption decisions. Given their increasing 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.[1] 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 allow them to adopt laxer lending standards.[2] 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 (Ausubel, 1991; Parlour and Rajan, 2001). This might result in access to credit for financially constrained households or lower financing costs for those who switch from traditional institutions 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. Thus, how the market equilibrium looks remains an empirical question.

Ideally, to investigate these issues, one would need individual-level data on borrowers'

[1] 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)

[2] 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).

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, e.g., similar individuals borrowing from other institutions. 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. 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 is a monthly borrower-level panel rather than a cross section of loan applications. Furthermore, in contrast to previous studies, we observe a natural benchmark: individuals borrowing at the same time from traditional lending institutions.

While this data covers multiple types of loans, we focus on unsecured 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 from fintech lenders. Second, these loans are unsecured loans, which make them more easily comparable across lenders, because the contract is standard and the only terms are the loan size, the maturity and the interest rate (each of which we observe).

Since very little is known about the market for consumer credit, we start by investigating its key features and how this market has evolved in the last several years. One key question is how fintech lenders successfully increased their footprint while also facing the competition of significantly more established financial institutions. There are two potentially successful market penetration strategies. New lenders might target credit constraints borrowers, which has the advantage of providing them with more data to improve their credit models and time to increase their brand recognition to attract better borrowers, but it is likely to come at the cost of higher defaults. In contrast, new lenders might try to focus on the most creditworthy borrowers, winning them over by offering them better terms than those offered by traditional banks, this is likely to result in slower volume growth and lower profitability but it can prove to the market the better technology in identifying higher-quality borrowers.

We test this hypothesis by differentiating between lenders based on how much time they have been operating in a specific market, defined at the state level. We find that fintech lenders tend to start with less creditworthy individuals and then increase their market share by extending credit to better borrowers.[3] Most of the fintech borrowers have credit scores in the mid-range between 640 and 720. They tend to have a higher number of accounts and exhibit a higher credit utilization ratio, which suggests that they already have plenty of access to credit, and 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 zip code by month fixed effects.

We can further exploit the granularity of the data to explore the main loan features. In particular, we test whether the loan features offered by fintech and traditional institutions differ significantly. We find that fintech lenders charge on average higher rates, about 3% higher, to lower score borrowers.[4] We investigate whether this pricing difference depends on the fintech lenders' market share and find that the difference in pricing is lower for regions where fintech lenders originate less than 20% of loans, i.e., fintech lenders are more cautious in charging higher rates in areas where they still have room to grow. Instead, we find that fintech lenders offer a better deal than non-fintech to higher score individuals with a 1.5% lower rate. Finally, if data processing is one of the key differences between fintech and traditional lenders, one might think that the rates would differ depending on how much information the credit report contains. We find that the rate differential is the largest for borrowers with thin files, as fintech charge a premium of more than 5% compared to non fintech lenders.

This evidence suggests that the way hard information contained in the credit report is

[3]Alternatively, this result can be demand-driven as at the beginning fintech lenders might only attract borrowers that are not able to obtain credit from other lending institutions. However, once their reputation is established, fintech lenders might be able to attract higher quality borrowers

[4]The rate does not include potential additional fees which we do not observe.

used might be a key factor in explaining the differences in lenders' pricing decisions. However, fintech lenders advertise the use of alternative data not present on the credit report, e.g., rent payment history, utility bills or education, to provide a more accurate assessment of a consumer's financial behavior. We shed some light on this issue by regressing the interest rate on borrowers' characteristics, allowing for both linear and non-linear effects, and controlling for time-varying shocks by including zip-code by month fixed effects. The R^2 from these regressions measures how much of the variation in interest rates is explained by the observable borrower characteristics across lender type. Somewhat surprisingly, we find that the information in the credit report is able to explain most of the variation in interest rates for fintech lenders, while this is not the case for traditional lenders. To our knowledge, this is the first study showing that fintech lenders, much more than traditional lenders, focus their credit decisions on the most salient hard-information figures found on the credit report, suggesting a soft information deficiency for these new lenders.

We then turn to our main results and examine whether fintech loans exhibit different performance than loans granted by traditional institutions in the 15 months following origination. We find that fintech loans are significantly more likely to be in default, even when we include a full set of borrower's credit characteristics, as well as loan features and zip code by month fixed effects. In other words, these results are not driven by time-varying local heterogeneity as we are comparing similar borrowers getting loans from fintech and non-fintech in the same month and zip code with similar terms. The results are also economically meaningful, in fact, we find that the fintech loans exhibit a 1.1% higher default probability, which is large compared to the sample mean of 1.4%. In addition, the relative underperformance persists for our entire time window starting in month five after origination.

One potential concern with this analysis is that borrower heterogeneity between those that have a fintech loan and those who do not might be affecting our findings. We address it in multiple ways. First, we present our results for three more restricted samples for which we match fintech borrowers to non-fintech ones using a propensity score matching, a manual criteria, and an entropy balance methodology. We match on a full set of demographic and credit characteristics pre-origination that are likely to affect the loan performance. All specifications confirm our main findings. Furthermore, we exploit the panel nature of the data and show that the results are robust to the inclusion of borrower fixed effects, which allows us to capture time-invariant observable and unobservable characteristics of the borrower. We also provide results highlighting how this relative underperformance differs based on borrower's characteristics. We find that fintech borrowers default more than matched non-fintech borrowers when they have a low credit score and a thin credit file, suggesting that rather than being able to identify the "invisible prime" borrowers, the identified individuals perform worse than those borrowing from traditional institutions. We show that these results are not driven by one specific period of time in our sample, as they hold even when we distinguish between different cohorts of borrowers.

Next, we analyze what the reason for this higher delinquency probability might be. One possibility is that the fintech borrowers are using the additional funds not to consolidate their debts, but rather to support additional expenditures. We find several pieces of evidence confirming this result. Specifically, both their total indebtedness and revolving balance increase more than their matched individuals borrowing from traditional institutions after loan origination. Also, we find that fintech borrowers are more likely to purchase a car in the first few months after origination. This makes them overextended and more likely to default. In fact, we also find that the delinquency rate on any type of account for fintech borrowers is higher. This type of behavior results in their credit score first increasing, due to the initial partial debt consolidation, but then falling steadily after the first quarter post loan origination.

We also explore the heterogeneity of this result and find that borrowers with low credit score, high interest rate and a thin file are the subgroups where the results are the strongest. The evidence on the soft information deficiency and this heterogeneity based on the length of the credit report further suggests that fintech lenders are exposed to adverse selection. For instance, fintech borrowers might be weaker in their financial management skills which would translate into higher default rates. However, by predominantly relying on hard information, fintech lenders are likely to miss this source of risk and so end up giving credit to borrowers that would have been rejected by a traditional lender.

At this point we can ask whether fintech lenders are likely to take this different behavior into account, e.g., by charging a higher interest rates, which could compensate for the higher default probability. We investigate this issue by examining whether fintech and non-fintech lenders' interest rates are predictors of ex-post loan performance. Specifically, we model defaults as a function of interest rate as well as borrowers' characteristics. The more accurate the interest rates are, the more positively correlated with defaults they should be.[5] We find that this is indeed the case, even when we control for a full set of borrower characteristics. In addition, we show that the rates set by fintech lenders are even better predictors of defaults than those charged by traditional institutions. The difference is considerable since the correlation is at least 20% higher for fintech lenders. This suggests that fintech lenders might be better at pricing on the intensive margin. An additional benefit that is likely to mitigate the adverse effects of defaults on fintech lenders is that once they receive a loan from an online lender, borrowers are more likely to rely on the same lenders, which increases its lifetime value. Thus, higher defaults do not necessarily translate into worse outcomes for fintech lenders as these are likely to be priced in.

Taking stock of our results, the evidence points out that the increased ease and speed with which borrowers can have access to credit is particularly appealing to certain households who tend to use these funds, in conjunction with other forms of credit, to sustain their consumption, which ultimately makes them more financially vulnerable. These results might also inform the debate about the need to provide clearer guidelines and regulatory scrutiny for those new institutions operating in this market. 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 are bound to default.

Our paper contributes to a growing literature examining fintech lending.[6] Vallee and Zeng

[5]This correlation might also be driven by a more severe adverse selection or moral hazard issue present in fintech lending.

[6]See Morse (2015) for an early review of this strand of the literature.

(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), 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. 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 a few recent studies that focus specifically on the consumer credit segment of the market, i.e., unsecured personal loans (see, among others, Liao et al. 2017; Danisewicz and Elard, 2018; De Roure, Pelizzon and Thakor, 2018; Balyuk, 2019).[7] The most related studies are Tang (2019) and Chava, Paradkar and Zhang (2019), which analyze the interaction between traditional and fintech lenders. Specifically, Tang (2019) exploits a regulatory change that caused banks to tighten their lending criteria to study whether banks and P2P lenders are substitutes or complements. The author uses the data made available by Lending Club and variation in exposure to that regulatory change at the county level. The main result is that treated markets experienced a disproportionate increase in P2P loan applications and a deterioration in borrower quality after the regulatory change. These findings are consistent with the hypothesis that P2P platforms operate as substitutes for banks.

Chava, Paradkar and Zhang (2019), instead, look at one marketplace lender (MPL), and show that borrowers who have access to the MPL experience laxer credit constraints as their credit score improves. They argue that these improvements in credit scores cause an increase in credit card limits, which for subprime borrowers ultimately translate into higher default rates. We share similar findings on defaults. However, Chava, Paradkar and Zhang's (2019) main control group is composed of people who got rejected by banks, while ours is borrowers sharing very similar characteristics who do get approved by banks. Then, the interpretation of the increase in defaults is also very different, ours points to the differences in screening

[7] Other related papers in this literature include Iyer et al. (2015), Mariotto (2016), Balyuk (2017), Wolfe and Yoo (2017), and Balyuk and Davydenko (2018).

between lenders.

Finally, while we share with these two papers the focus on the relation between traditional banks and fintech lenders, we differ in the data, the methodology and the main results. Specifically, we exploit the richness of our data covering all the major fintech lenders to provide an in-depth analysis of how the market for consumer lending has evolved in recent years. Then, we take advantage of individual level data comprising both banks and fintech lenders to test whether the performance of fintech lenders differs and what the main drivers are. We find that fintech loans are more likely to default, but this is likely to be taken into account by the fintech lenders' pricing models. We also highlight a soft information deficiency affecting fintech lenders that is consistent with the performance results we uncovered.

The rest of the paper is organized as follows. Section 2 describes the data employed and the construction of the sample. Section 3 describes the key features of the consumer credit market and how it evolved in recent years. Section 4 presents our results on borrowers' performance, and Section 5 examines the lenders' pricing decisions. Section 6 presents additional evidence on the benefits of fintech loans for both borrowers and lenders, while Section 7 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, student loans and credit cards (revolving). It also contains information about the main features of these individual loans, such as date opened, account type, loan size, monthly scheduled payment (for installments only), balance, lender and performance history.[8] It contains more than 200 million consumer credit files and over a billion credit trades, i.e., information about single

[8]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.

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 is not confined to households' balance sheet information but includes other information about the borrowers. For instance, we also observe demographic information, such as the gender, age, marital status and whether the borrower is a college graduate, which is collected by creditors. Overall, we believe our data gives us a unique opportunity to study the consumer loan market, and what distinguishes individuals borrowing from traditional lenders and those relying on the credit granted by fintech ones.

2.2. Sample Design

To create a representative and matched sample, we first identify all the individual loans associated with the fintech companies in the credit tradeline data. We define fintech lenders as those who operate exclusively online and do not have a brick and mortar presence, do not accept deposits, and are not regulated by the Federal Reserve or the Office of the Comptroller of the Currency (OCC). We also require them to be recently founded.[9] We restrict our sample to only the loans with a minimum of $500 loan size, 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. We then identify all unsecured personal loans originated by non-fintech lenders. We randomly draw 25% of all unsecured personal loans originated by fintech lenders and by non-fintech lenders in 2012–2017, excluding loans with missing loan maturity and missing loan size, but include those with missing credit score, debt balances, age of credit and borrower age.[10] For the borrower with year-month panel data, we match all

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

[10] Table A.1 provides several statistics about missing information. Overall, we only have 2.5% of missing observations. Panel A shows the missing rates by variables for the overall sample as well as for fintech vs. non-fintech lenders, showing that the interest rate is the only variable that is missing for fraction of the

loans in our loan-level sample with monthly credit report data from 3 months before through 15 months after the origination of the loan.

2.3. Summary Statistics

Our final sample contains 3,792,757 loans originated during the sample period, 2012-2017. They are for 1,882,286 borrowers who have either fintech or bank loans, which is our main sample. We present key summary statistics in Table 1 about the loan-level data. In the appendix we provide more detailed statistics by subsample (Table A.2). Our main analysis is at the loan level. We start to track the ex post performance of the loan from the month of origination and the borrower's outcomes four months prior to loan origination, both through 15 months after that. Our panel data sample contains over 53 million records and we report the summary statistics in Table A.3. On credit outcomes, we report typical information: the number of accounts, and the balance on all the main accounts (i.e., auto, credit cards, student and mortgage), borrower's credit score which predicts borrower's creditworthiness in the near future (Vantage score), the age of the credit history, delinquent (DLQ) balance and also DLQ rate at the time of origination. We also report information about borrower's credit, demographic and employment characteristics 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 654. Revolving accounts (credit cards) balance is on average about \$10,000, while revolving utilization is on average 43%, although the standard deviation is significant (34%). On average the borrowers in our sample are 49 years old, 8% of the households have jobs in professional, technical and management occupations, and about 20% are high income borrowers, i.e., defined as income above \$100,000.

We are able to match loan size and loan term for almost all the loans in our sample. On average, borrowers take out \$8,492 per loan with a term of 39 months. With scheduled payment, loan term and loan size, we calculate the original note rate to be about 13% on

sample. Panel B shows that there is not important geographic variation across states, while Panel C reports missing information by age of the borrower. Finally, Panel D reports the key statistics for the subsample with and without the interest rate information and shows that the samples are very similar.

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, 21% of the borrowers and 1.4% of the loans in our sample have experienced at least one delinquency.

Panel (a) of Figure 1 plots the number of personal loans originated by fintech lenders and non-fintech lenders. The largest fintech lenders include Lending Club Corporation, GreenSky Financial, SoFi Lending Corp, Avant Credit Corporation, LoanDepot.com, Upstart Network Inc, and Cashcall.[11] Non-fintech lenders include all the other lenders, which are generally major banking institutions. The figure also suggests a non-complete substitution with the traditional banking sector, as the overall market experienced a significant growth in recent years. Fintech lenders were originating only a very small fraction of the personal loan market in 2012, but starting in late 2013 they experienced a significant growth. Panel (b) of Figure 1 shows that the fintech market share doubled from 2014 to 2016, irrespective of whether we measure it based on the number or the volume of loans.

3. Consumer Loan Market

Since very little is known about the market for consumer credit, this section investigates its key features and how this market has evolved in the last several years.

3.1. Fintech Lending over Time

Fintech lenders mainly started in California and New York and then expanded throughout the U.S. Figure 2 plots the growth rate of fintech loans from 2013 to 2017 showing the highest growth rate on the East coast and some of the central states. One question is how they successfully increased their footprint while also facing the competition of significantly more established financial institutions. A market penetration strategy envisions new lenders tar-

[11] We excluded from our final sample all the lenders that specialize in debt settlement, such as OneMain and Freedom Financial. There are no loans originated by Prosper in our data source, because Prosper does not report to all the three credit bureaus.

geting credit constrained borrowers, which would provide them with more data to improve their credit models and time to increase their brand recognition to attract better borrowers. In contrast, new lenders might try to focus on the most creditworthy borrowers, winning them over by offering them better terms than those offered by traditional banks. Figure 3 investigates this question by plotting key borrowers average characteristics based on the year of entry of each lender in each state. That is, the x-axis identifies the numbers of years since the entry in a state.

Panel (a) shows that the average credit score improves as time in the same market passes by, especially for fintech lenders, going from 668 to 703 while for non-fintech lenders it goes from 631 to 679. Panel (b) shows that the average age also increases from 46 years to 51, showing a stronger penetration among older borrowers over time. As another indication of improved performance, panel (c) shows that the prior borrower delinquency declines significantly from 0.12 to 0.06. This is true, to a lesser extent, also for non-fintech lenders. Panel (d) shows that these changes in borrower composition occur while the average loan size stays constant for fintech lenders, but increases for non-fintech lenders. This is consistent with fintech lenders providing more standardized loan menus, while banks might be more prone to increase loan size after establishing lending relationships with local borrowers. More detailed statistics for fintech lenders are provided in Table 2, showing for instance that the number of inquiries tends to decrease, while the maturity of the loan increases as a lender operates in a market for longer. Overall, this evidence suggests that fintech lenders tend to start with less creditworthy individuals and then increase their market share by extending credit to better borrowers. These results are also consistent with a demand-driven explanation. During the first few years of operation, fintech lenders might only attract marginal borrowers, e.g., those that are not able to obtain credit from other lending institutions. However, as fintech lenders establish a reputation and increase customer awareness, they might be able to attract higher quality borrowers.

Another dimension we explore is how fintech lenders extend credit across the credit score distribution, specifically, how much they tend to focus on the left tail, which might not have access to traditional institutions. Figure 4 plots the distribution of loans for both types of lenders by credit score. Panel (a) presents the number of loans, and it shows that over our sample period traditional lenders are more likely to lend to less credit-worthy individuals than fintech lenders. This holds true even when we look at dollars volume in Panel (b). This is consistent with the fact that some of the main fintech lenders have minimum credit score requirements for being considered for a loan. Figure A.1 in the online appendix reports these panels separately by year to investigate whether this result changed over time. It shows that the result was the strongest during the earlier years, when fintech lenders did not seem to grant any loans to individuals with scores below 600. Note that while the fintech borrower credit score distribution remains fairly stable over time, for non-fintech lenders it changes by shifting towards the higher-score borrowers in later years. This is consistent with the fintech loans being more standardized, while the banks might change with regulatory, demand and funding conditions.

Next, we explore in more details the ex-ante heterogeneity among individuals borrowing from different types of lenders. We estimate the following baseline specification:

$$Fintech_{i,z,t} \quad = \beta \cdot X_{i,t} + \mu_z + \eta_t + + \varepsilon_{i,z,t} \tag{1}$$

where the main dependent variable is a dummy variable equal to one if the borrower i, living in zip code z, has a fintech loan in month t and 0 otherwise. The main independent variables are the borrower's characteristics $X_{i,t}$. To control for local economic shocks that might affect the propensity to get a fintech loan, we include zip code by year-month fixed effects. Thus, we are comparing the characteristics of neighbor individuals at the same time from different lenders.

Panel A 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. Column (1) shows that each S.D. increase of credit score, about 97 points, is associated with 2% higher likelihood of borrower obtaining a fintech loan on average. The specification is useful to compare the linear effects of credit score, however Figure A.2 plots the coefficients of a similar specification to (1) but with different dummies for different credit score 20-point bins. We find that borrowers with credit scores between 640 and 720 are significantly more likely to have a fintech loan. In other words, even this regression evidence shows that 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) does support this hypothesis, because it shows that the length of the credit history has an economically significant effect. This is consistent with the evidence we shall provide in a later section about the soft information deficiency affecting fintech 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, although the magnitude of the effect is small, since each S.D. increase of credit card utilization, which is equivalent to 30%, is associated with 0.6% higher likelihood of borrower obtaining a fintech loan. One important dimension to explore to shed light on whether fintech lenders are likely to go after borrowers in distress or that would find it difficult to get a loan from a traditional lenders is to check whether prior delinquency matters for fintech lenders. Column (5) shows that borrowers who have defaulted in the past are 4.5% less likely to obtain a fintech loan than a non-fintech one. Thus, fintech lenders are even more cautious when it comes to lending to borrowers with delinquent history.

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 balances 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 (Column

6). Columns (7) and (8) show that these borrowers are also more likely to have a student loan and a mortgage. Column (9) shows very similar results in a multivariate setting. Notably, once we include all variables, the magnitude of the effects of the credit score and the number of accounts decline. Overall, fintech borrowers tend to carry credit card balance, but do not exhibit the usual traits of borrowers that do not have access to financial markets.

We exploit the breadth of our data to investigate whether fintech borrowers are also different on other demographic information. Panel B of Table 3 shows that borrowers with fintech loans are slightly more likely to be male (Column 1) and more likely to be married (Column 2). More importantly, fintech borrowers are more likely to have a college degree (Column 3), while Column (4) shows that high-income borrowers (i.e., those earning more than $100,000) are about 5% more likely to borrow from fintech companies. Column (5) also shows that younger borrowers are 1% more likely to get a fintech loan. Specifically, allowing for non-linearities, Panel (b) of Figure A.2 shows that individuals that are between 30 and 45 years old are significantly more likely to get a fintech loan. 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 4.5% 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 than to traditional institutions for their financial needs.

3.2. Loan Terms

We can further exploit the granularity of the data to explore the main loan features by testing whether the loan features offered by fintech and traditional institutions differ significantly. Table 4 regresses the loan amount, the loan maturity and the interest rate on a fintech loan indicator, which compares them to personal loans granted by non-fintech. This rate does not include potential additional charges, e.g. origination fees, as they are not present in our credit bureau data. Columns (1)-(3) control for the borrower's credit score, age of credit history and age as well as zip code by year-month fixed effect, while Columns (4)-(6) include time and borrower fixed effects. When we analyze the interest rate, we control for the loan size and the maturity of the loan. Effectively, the first three columns compare borrowers that have fintech loans with those having non-fintech loans, while the last three columns take advantage of the subsample of borrowers that have both fintech and non-fintech loans on their credit report.

We find that fintech lenders are more generous about granting larger loans: on average, a fintech loan has a $1,600 higher balance. We also find that usually the maturity of the loan is about ten month longer. Controlling for the loan size and the maturity, we find that fintech lenders charge a 1.5% higher rate on average. As expected, we find that higher credit score is associated with larger loans, longer maturity and significantly lower interest rates. Similarly, a longer credit history is associated with larger loans and longer maturity, but no discernibly different effect on rates. Also, older borrowers have smaller loans, slightly shorter maturity loans and higher rates, although the effects for maturity and rate are economically small, i.e., one third of a month and eight basis points. Column (3) also shows that larger loans tend to feature lower rates, which is likely driven by the fact that larger loans are only granted to more creditworthy individuals, and longer maturity loans feature slightly higher rates.

Interestingly, once we control for borrower fixed effects, which restricts attention to borrowers having both a fintech and a bank personal loan, the result for loan amount increases in magnitude to $2,900, while the maturity of fintech loans becomes about one month shorter than non-fintech. Furthermore, within borrower variation shows that the interest rates charged by fintech lenders are 13 basis point lower than those charged by banks.[12] As expected, borrower fixed effects also absorb most of the effects of the other control variables, likely 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 from the lenders' point of view. These results also motivate why, when we investigate the loan performance of

[12]Due to the growth of fintech lenders, it might be that for a significant fraction of borrowers the non-fintech loan is first. This means that once they borrow from fintech they might be older and wealthier. To check whether this affects our results, appendix Table A.4 presents results where we match borrowers who had first a fintech loan to those with a non-fintech loan first. We find very similar results on loan amounts and interest rates, while we find that the fintech loans are about 3 months shorter in this sample.

fintech and banks loans, we take advantage of multiple approaches, from carefully matching fintech to non-fintech borrowers, to exploiting the panel nature of the data with the inclusion of borrower fixed effects to control for potentially unobserved borrower heterogeneity.

Panel B of Table 4 complements the previous results to shed some light on how interest rates vary within different subsets of borrowers. In fact, the differences between fintech and non-fintech lenders are likely to be more or less accentuated depending on the different target individuals. Columns (1) and (2) report the results for borrowers above and below a credit score of 700. We find that fintech lenders on average charge higher rates, about 2.8% higher, to low score borrowers, while they offer a better deal than banks to higher score individuals with a 1.5% lower rate. Columns (3) and (4) show that fintech lenders offer higher rates irrespective of age, but the difference with non-fintech is larger for older borrowers, i.e., older than 45 years. Columns (5) and (6) relate to Figure 1 (b) as we test whether the difference in pricing is also a function of the fintech lenders' market share defined at the county level, with "high" identifying counties where fintech lenders have at least 20% of the market. We find that the difference in pricing is half for low county share than for high ones. Intuitively, this suggests that the rate is a dimension used to attract new borrowers as fintech lenders are more wary to charge higher rates in areas where their competitive position is weaker.

Finally, one might think that fintech lenders screen applicants not only based on hard information provided in the credit report, but could use alternative data to price the loans. If true, this would suggest that their rates would differ depending on how much information the credit report contains. Columns (7) and (8) test this hypothesis by estimating our specification separately for individuals with "thin credit files," i.e., borrowers with credit history shorter than 48 months. We find that the rate differential is the largest for borrowers with thin files, as fintech charge a premium of more than 5% compared to non fintech lenders while the difference we found in Panel A of about 1.5% remains for those with longer histories.

3.3. Screening

The evidence presented in Table 4 suggests that the hard information contained in the credit report might be an important dimension that drives differences across lenders, potentially, as input to different credit models. Then, we investigate the differences in screening technologies between fintech and traditional lenders in more detail. Fintech lenders advertise the use of alternative data to serve borrowers who may otherwise not be approved for loans. Alternative data may allow a lender to get a more accurate assessment of a consumer's financial behavior that is only partially reflected in traditional credit scores. For instance, lenders may use information about an individual's rent payment history, utility bills or education to assess and price borrowers' riskiness. On the one hand, this alternative data can increase access to credit for individuals with a short credit history or that are priced out of the market; on the other, some of the alternative variables could involuntarily discriminate against some group of borrowers (Bartlett et al., 2017).

This tension has attracted the attention of policy makers including the CFPB. After issuing in 2017 a no-action letter to Upstart Network, Inc., a company that uses alternative data in making credit underwriting and pricing decisions, the CFPB encouraged lenders "to develop innovative means of increasing fair, equitable, and nondiscriminatory access to credit, particularly for credit invisibles and those whose credit history or lack thereof limits their credit access or increases their cost of credit, while maintaining a compliance management program that appropriately identifies and addresses risks of legal violations."[13]

Following Rajan, Seru, and Vig (2015) and Buchak, Matvos, Piskorski, and Seru (2018), we examine whether fintech lenders' use of different information results in different pricing models. We do so by examining how much variation in interest rates is explained by standard borrower characteristics across lenders. We estimate the following specification:

$$Rate_{i,z,t} \quad = \beta \cdot CreditScore_{i,t} + \gamma \cdot LoanSize_{i,t} + \alpha \cdot X_{i,t} + \mu_z + \eta_t + + \varepsilon_{i,z,t} \qquad (2)$$

[13]See https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/.

where we regress the interest rate on the credit score and loan size, as well as, on a number of credit and borrower characteristics. Furthermore, to capture macroeconomic variation and local heterogeneity we include different fixed effects such as zip code and month fixed effects. Finally, we also allow for the effects of these borrowers' characteristics to be non-linear. We estimate the regressions separately for fintech and non-fintech banks. The R^2 from these regressions measures the object of interest - how much of the variation in interest rates is explained by the observable borrower characteristics across lender types- and is presented for different models in Table 5 Panel A.

Somewhat surprisingly, we find that these standard characteristics capture most of the variation in the rates set by fintech lenders. Even just the credit score and the loan size, together with time fixed effects, explain 44% of the variation for fintech lenders, while only 2% for traditional lenders. The regional heterogeneity is an important factor though. In fact, including zip code by month fixed effects increases the R^2 to 77% for fintech and to 57% for traditional lenders. This is also the result of fintech lenders not always operating nationally. Including more variables, such as age or credit history, improves the R^2 by only 2%. Also, when we allow for non-linear effects we see the R^2 increasing to almost 80% for fintech lenders and 59% for non-fintech.

For all of these specifications, we test the significance of the R^2 differences following the test proposed by Erickson and Whited (2002) and find that the R^2 for the fintech lenders is significantly higher than that for traditional lenders. The differences are also economically large as they are at least 15%. As expected, the differences disappear once we control for lender fixed effects as that would capture most of the variation in pricing models.

Overall, these findings show that, contrary to what one could have expected given the recent emphasis on alternative data, we find that the information in the credit report is able to explain most of the variation in interest rates for fintech lenders. Furthermore, we show that this is not the case for traditional lenders, suggesting a potential role for soft information absent in the credit reports. To our knowledge, this is the first study showing that, in contrast to traditional lenders, fintech lenders focus their credit decisions on the most salient hard-information figures found on the credit report, rather than exploiting the predictive power contained in soft information or alternative data. Consistent with this interpretation, we show in Table 5 Panel B that there is significant learning for fintech lenders, as the R^2 declines as lenders operate in the market for longer, i.e., they acquire more soft information, although fintech lenders still rely more on hard information. Finally, in appendix Table A.5, we also find that the larger the market share, the more fintech learn as captured by a lower R^2.

4. Borrower Ex-Post Performance

Having described the differences in the characteristics of the fintech borrowers with respect to the bank borrowers, we can then turn to our main result and investigate how the borrowers perform after obtaining these loans. On the one hand, these personal loans are marketed as a way to consolidate existing higher-cost debts, which suggests that fintech borrowers might be less prone to default as their interest expenses should drop significantly. On the other hand, the ease with which these funds are accessed and the lack of a personal interaction with a loan officer, might lead borrowers to misuse the additional credit by increasing their consumption expenditures, leaving them with too much leverage and unaffordable monthly payments down the road.

To investigate these hypotheses, we examine next whether fintech loans are more or less likely to be in default in the 15 months following origination. We start by comparing cross-sectionally the performance of the different loans in Table 6. Column (1) reports the results controlling for time and county fixed effects and shows that fintech loans are more likely to be in default. Column (2) show that the results also hold once we include a full set of borrower's credit characteristics, as well as loan features, in addition to county and time fixed effects. We find that fintech loans are about 1.1% more likely to be delinquent compared to a sample mean of 1.4%. Intuitively, the credit score as well as the length of credit history and the number of accounts are inversely related to defaults. Columns (3) and (4) present similar results once we control for county by month and zip code by month fixed effects respectively, that is, these results are not driven by time-varying local heterogeneity as we are comparing borrowers getting loans from fintech and non-fintech in the same month and region. Finally, since Table 4 has shown a difference in the size of the loans granted by fintech and non-fintech lenders, which might drive the higher delinquency rate we find, Column (5) allows for the effect of loan size and maturity to be non-linear by controlling for loan size and maturity binds. Even in this restrictive specification we find similar results. Overall these results show that fintech loans severely underperform non-fintech loans for similar borrowers.[14]

Panel B of Table 6 explores this result across borrowers with different credit scores (Columns 1 and 2), based on whether the fintech lender is the main lender (Columns 3 and 4), on the fintech lenders' market share (Columns 5 and 6) and on the length of credit history (Columns 7 and 8). We find that the relative underperformance of fintech loans is concentrated among the borrowers with credit scores less than 700. Having a long-term relationship with the fintech lender might affect the borrowers' perception of the costs of default. Notice that defaulting on a fintech loan has exactly the same negative consequences on the borrower's credit score as defaulting on bank loans though. To analyze whether this is the main force driving our results, we 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 do not find evidence supporting this hypothesis, as the higher default rates of fintech loans are present for both subsamples. We do find that, consistent with the previous evidence that fintech institutions tend to lend to better borrowers as they gain market share, we find that the higher defaults are even more pronounced in low fintech share counties. Finally, we find that, as in the case of interest rates, the defaults are significantly higher among borrowers with thin credit files.

One potential concern with the previous analysis is that borrower heterogeneity between those that have a fintech loan and those who do not might be affecting our findings. We address

[14] In Table A.6, we also report the similar regressions with the missing values of the explanatory variables imputed using predictive mean matching methodology. This allows us to use every observation in our loan sample in the regressions. They yield very similar results as those in Table 6.

this concern in several ways. First of all, Table 7 uses different matching methodologies to find for each fintech loan the closest match among non-fintech. Panel A uses a propensity score matching methodology to match based on zip code location, as well as demographic information, and the full set of credit attributes that we used in Table 3, e.g., credit score, delinquent history, debt balances, etc.[15] This is our preferred specification since it is the most restrictive and the one with the most conservative results. However, we also provide the results with two more methodologies. Columns (1)-(4) of Panel B present the results based on a manually-matched sample based on zip code, age and total indebtedness, as these are likely to drive most of the variation in the loan performance. Finally, Columns (5)-(8) of Panel B estimate our main specification employing a generalization of the propensity score matching, entropy balance weighting, which involves a reweighting scheme that is more flexible than the nearest neighbor matching (Hainmueller, 2012). Although each methodology selects a different sample, we find consistent results across all specifications: fintech loans are significantly more likely to default than similar loans made by non-fintech lenders to extremely similar borrowers.

An additional way in which we can enrich the previous analysis and at the same time make sure that unobservable characteristics of the borrower are not the main drivers of the fintech underperformance is to exploit the panel nature of our data. Specifically, we use the sample identified by the propensity score matching methodology in Table 7 to present the estimates of the following specification:

$$DepVar_{i,t} \;\; = \textstyle\sum_{\tau=-1}^{\tau=+5} \mathbf{1}_{\tau} \cdot Fintech + \Omega \cdot X_{i,t} + \mu_i + \eta_t + + \varepsilon_{i,t} \tag{3}$$

in which, on the left hand side, we estimate borrower's behavior around the loan origination. The main independent variables are the interaction between quarter dummies identifying the periods before and after the loan origination times the fintech borrower indicator, and they are estimated relative to the origination quarter. This dynamic specification allows us to include borrower fixed effects μ_i. In other words, we are comparing our outcome variables for the same

[15]Table A.7 reports the pooled OLS regression results that has similar specification to the regression used in PSM. PSM is done by each zip code.

borrower before and after obtaining the loan relative to the origination quarter for fintech and non-fintech loans. We perform this analysis on the propensity score matched sample.

In Column (1) of Table 8 the dependent variable is loan delinquency, which would then capture whether borrowers are more or less likely to default on fintech loans, while in Column (2) the dependent variable is delinquency on any account. We find that matched fintech loans first perform better than their bank counterparts, but their performance significantly deteriorates starting in the third quarter. Furthermore, their underperformance becomes more pronounced as time from origination increases, in fact, while fintech loans are about 0.30% more likely to be delinquent in the third quarter after origination, they are 1.7% more likely to default in the fifth quarter. Column (2) complements the previous analysis by exploring whether the fintech borrowers are in general more likely to default post-origination on any account. For instance, if access to a fintech loan resulted in total indebtedness that is too high to sustain, these borrowers might find themselves behind on other loan payments, e.g., on their credit card payments. Column (2) shows that, before 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. However, starting already in the first quarter after origination, the likelihood that fintech borrowers default is increasing over time and reaches more than 5% one year after origination. This result is both statistically and economically significant, since this corresponds to about a 25% increase in the likelihood to default relative to the sample mean.

Our matching procedure is likely to account for all the information available to the lenders at the time of origination, however, we are not able to rule out the possibility that borrowers' unobservable time-varying characteristics could affect our results. For instance, borrowers might turn to fintech lenders only when they are not able to get access to credit from traditional banks. Borrower fixed effects would only capture time-invariant characteristics of the borrowers that might be correlated with their willingness to apply to fintech lenders and so it would not be able to capture this situation. The concern is somewhat lessened by the fact that the observable characteristics we match the borrowers on aim to capture, although imperfectly, these instances.

Columns (3) and (4) complement the previous results showing how borrowers differ on other dimensions capturing their financial health depending on whether they borrowed from fintech or non-fintech lenders. Column (3) shows that in the first two quarters after the loan origination their credit score increases by about 10 points, consistent with partial debt repayment, however, it declines over time. This pattern is probably explained not only by the higher probability to default but also by the overall increase in their total debt balances. In fact, Column (4) shows that while there is a decline of about $3,000 in the first quarter after loan origination (relative to the average loan size of $8,400), total indebtedness increases significantly over time by more than the amount of the initial decline.

Figure 5 complements the previous findings by plotting the interaction between the fintech indicator and monthly dummies for the variables in Table 8. Panels (a) and (b) clearly show that individuals borrowing from fintech lenders experience higher loan delinquency and higher default rate on any account after origination than matched non-fintech borrowers. Panels (c) and (d) confirms the dynamic patterns highlighted in Table 8 with credit score first increasing more for fintech borrowers but then rapidly declining 9 months since origination, and total balance first sharply decreasing and then increasing after just four months. One might think that these results could potentially be driven by the earlier cohorts, when the fintech lenders had limited data and might have been more prone to face adverse selection. Panels (e) and (f) of Figure 5 show that this is not the case, in fact, we find that the results are consistent across cohorts, although some years (e.g., 2016) are worse than others (e.g., 2013) especially for loan delinquency, while there is no variation for borrower delinquency.

What might be the reason for this higher delinquency probability? One possibility, suggested by the result on total indebtedness, is that the fintech borrowers are using the additional funds not to consolidate their debts, but rather to support additional expenditures. Our data does not contain explicit measures of consumption, but we can follow Di Maggio et al. (2017) and compute the probability to purchase a car using changes in the auto loan balance, which can be a valuable measure of durable consumption. Column (5) of Table 8 shows that fintech borrowers are indeed 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 0.25%, a 5-percent increase from the sample mean.

Another way in which we can measure consumption is with total revolving debt as it includes spending using credit cards as well as retail cards, e.g., Macy's card or Best Buy's card. Intuitively, borrowers might initially use the additional funds to repay their credit cards, but then start financing their expenditures with these credit cards again, which results in a greater total indebtedness and higher financial fragility. Column (6) shows that while there is an initial decline in the first two quarters, we see a rapid and persistent increase during the following year. This evidence corroborates the view that part of the reason for the increase in defaults is the higher propensity of the fintech borrowers to spend the additional funds rather than using them to achieve a healthier financial situation. Figure 6 confirms these findings by plotting the coefficients on the interaction term of fintech loan indicator and relative monthly dummies from a regression examining the probability to purchase a car and revolving debt as dependent variables.

We complement the previous results by exploring whether these findings reside also in the subsamples where the key interpretation suggests they should reside: for borrowers facing a high ex ante interest rate; those with low credit score, and in the subsample where the borrower's credit history is "thin." We report the results for these three subsamples in appendix Table A.8. The results are even stronger than our baseline in these subsamples. Specifically: We find that borrowers with high interest rate are about 40% more likely to be delinquent (coefficient is 8.4 vs. 5.8 four quarters after the loan), their credit score declines more (-12 points vs. -0.9), and their total indebtedness increases by $8,390 after four quarters, which is larger than the average $5,355. The borrower's revolving debt increases by $1,547, which is substantially more than the baseline $367. We do not find a large difference for car purchases for this group. Low credit score individuals experience even larger effects on delinquency, i.e,. coefficient on borrower delinquency is about double the average, and on credit score. Their total debt increases about 20 percent more than for the average borrower.

Finally, the borrowers with a thin credit file are those where we find the strongest results for borrower delinquency and decline in credit score. These heterogeneity results fit well with the interpretation that fintech lenders do not appear to use much information outside the most salient hard-information figures to set rates (i.e., they don't use much soft information) which is the main insight from Table 5. Taken together, the evidence in Table 5 and the results on the borrowers' delinquency suggests that fintech lenders are likely to be exposed to adverse selection. For instance, fintech borrowers might be weaker in their financial management skills which would translate into higher default rates. However, by predominantly relying on hard information, fintech lenders are likely to miss this source of heterogeneity and risk and so end up giving credit to borrowers that would have been rejected by a traditional lender.

Overall, these results provide evidence that even when controlling for potential differences in creditworthiness, fintech borrowers are significantly more likely to be in default both on the personal loan as well as on other accounts. The results also seem to be concentrated in the less creditworthy segment of the market. Hence, although Fintech companies advertise their superior ability in identifying the "invisible prime" and the "underserved borrowers," we find evidence that their loans perform significantly worse than traditional lenders in that segment mainly because the borrowers' behavior after origination is different.

5. Loan Pricing and Defaults

The previous findings have established that fintech borrowers are more likely to default than neighbor non-fintech borrowers with very similar characteristics. However, that does not mean that fintech lenders are losing money. In fact, the higher interest rates could compensate for the higher default probability. Furthermore, fintech screening technologies might perform worse than traditional institutions on the extensive margin, but be more accurate on the intensive margin.

We shed some lights on this issue by examining whether fintech or non-fintech lenders' interest rates are better predictors of ex-post performance in terms of default. Table 4 showed that fintech lenders charge higher rates for similar borrowers, while Table 5 has shown that fintech lenders rely more heavily on hard information provided in the credit report for the pricing decisions. We can then complement those results by noting that if lenders are using more data or better pricing algorithms to set interest rates, then these interest rates should be more correlated with ex-post performance (Rajan, Seru, and Vig, 2015). Formally, we estimate the following specification:

$$DLQ_{i,z,t} = \beta \cdot Rate_{i,t} + \gamma \cdot Rate_{i,t} \cdot Fintech + \alpha \cdot X_{i,t} + \mu_{z,t} + \varepsilon_{i,z,t} \tag{4}$$

where the dependent variable is the loan default probability. The main coefficients of interests are β, which captures how correlated the interest rate is to default, and γ, which captures whether this correlation is stronger or weaker for fintech lenders. Note that a higher correlation can also be driven by a more severe adverse selection or moral hazard issue in fintech lending. To mitigate this concern, we also include a full vector of controls that should be correlated with defaults. In addition, in the most conservative specifications, Columns (5) and (6) also include zip code by month fixed effects. Column (1) of Table 9 shows a positive and significant coefficient for the interest rate in absence of any other controls. Column (2) shows that the interaction with the fintech lender indicator is also positive and significant. These results hold true even once we include the other controls in Columns (3) and (4). Intuitively, the controls do matter, as they are significant and have the expected sign. For instance, credit score is strongly negatively correlated with defaults, as is the length of credit history, the number of accounts and the borrower age. By far the largest coefficient is the credit score though. Finally, Column (5) and (6) show that zip code by month fixed effects increase the R^2 considerably, but the main coefficients of interest remain economically and statistically significant.

Overall, these results show that interest rates are indeed correlated with defaults, and are even more so for fintech lenders. The difference is considerable since the correlation is at least 20% higher for fintech lenders. This is consistent with the hypothesis that the higher defaults are likely not to translate to lower profits for the lenders as fintech lenders seem to be better at pricing than traditional institutions.

6. Fintech Borrowers

The findings discussed in the previous section highlighted that higher defaults do not necessarily translate into worse outcomes for fintech lenders as these are likely to be priced in. This section provides evidence that there are also other benefits for both lenders and borrowers in creating a new lending relationship with a fintech institution.

The first hypothesis we test is whether borrowers tend to be loyal to their fintech lenders. Intuitively, if a borrower feels the fintech lender provided access to credit that was not available at other traditional institutions, it is likely that they will return to these lenders in the future. This would be beneficial for the lenders because of the lower customer acquisition costs and the more data available about these returning borrowers' behavior.

We test this hypothesis by checking whether borrowers who got a fintech loan in the past are more likely to stay with a fintech lender for the next loan. Table 10 shows that this is the case. Columns (1)-(3) provide the baseline result controlling for zip code by month fixed effects as well as demographic and credit attributes of the borrower. In all specifications, we find that those borrowers who got a previous fintech loan have a 60% likelihood to get another fintech loan.[16]

If this loyalty is driven by the fact that fintech lenders provided a loan while other traditional institutions would not, we should see these effects to be stronger for more credit constrained borrowers. Column (4) tests this hypothesis by interacting the previous fintech indicator with an indicator identifying borrowers with lower credit score. We find that lower credit individuals are 15% more likely to stay with the fintech lender (i.e., interaction coefficient of 0.089 relative to a baseline of 0.556). Another important dimension capturing access to credit is whether the borrower has a thin credit file. Column (5) shows that indeed

[16] As a comparison, we report the results of a similar test for non-fintech borrowers in appendix Table A.9. We find that these borrowers stay with the non-fintech lender with only 14 percent probability.

borrowers with these characteristics tend to rely on fintech lenders for multiple loans. Finally, Column (6) tests whether being the main lender of the borrower influences whether the borrower keeps obtaining credit from the lender. We show that this is the case, in fact, the probability increases by an additional 30% when the lender was the main one. Then, we can conclude that fintech lenders are rewarded by taking some risk and lend to less creditworthy borrowers as these tend to be loyal and increase their lifetime value.

To further test in which ways fintech lenders can be filling a gap in the market, we can also check whether these lenders might be helpful in smoothing negative shocks. Thus, we complemented the existing data with information about individuals who lost their job due to involuntary layoffs. This is an additional dataset that is matched by the credit bureau to credit report data and provides information about individuals who lost their jobs and the reason leading to the layoff. This provides a unique opportunity to examine whether the demand for credit post unemployment is met differently by fintech and traditional lenders.

Specifically, we use this information to test whether individuals who experience unemployment shocks are more or less likely to get a loan in the quarter after job loss, and whether they are more likely to get it from a fintech or a traditional institution. We do so in Table 11 where the dependent variable is an indicator for whether the loan is originated in a given month. $Postjobloss$ is an indicator that takes 1 for individuals with job loss after their job loss date. Unemployment is an indicator for the individuals with job loss during our sample period. The specifications in Columns (1) and (2) are based on fintech loans only. Columns (3) and (4) present the results based on non-fintech loans, while the results for the pool sample are presented in Columns (5) and (6). Intuitively, we can compare the propensity of accessing credit for those individuals who lose their job to those who do not, and then we can also compare this difference for fintech and non-fintech loans. We control for county by time fixed effects in Columns (1), (3), (5) and control for individual and time fixed effects in the other specifications.

Overall, we show that after the job loss individuals are more likely to get a loan from a fintech lender. Columns (3) and (4) show that this is not the case for non-fintech lenders, once we control for borrower fixed effects. Finally, the last two columns confirm that the higher propensity to get a loan post job loss from a fintech lender is statistically higher than getting it from a non-fintech lender. This evidence is consistent with the view that fintech lenders are less stringent than non-fintech lenders on employment status. The appendix Table A.10 compares outcomes for the unemployed individuals that receive a fintech loan to those that do not. While we find that their delinquency increases, their total indebtedness as well as their revolving debit decline. We also find that these individuals are more likely to experience a growth of their income greater than 5 percent.

7. Conclusion

The growing importance of fintech lenders in the consumer lending market poses several questions about the market as well as the practices adopted by fintech lenders to quickly expand and compete with traditional financial institutions. We first show that fintech lenders tend to first lend to less creditworthy individuals, but over time the quality of their pool of borrowers significantly improves. We also show that, for similar borrowers, the terms offered by fintech lenders are different. Specifically, average loan size tends to be larger, and interest rates higher. We then examine whether the screening technologies between types of lenders differ significantly. We find, somewhat surprisingly, that fintech lenders rely more on the hard information provided in the credit report which suggests a soft information deficiency. As time passes by, fintech lenders seem to learn more about the local markets and rely less on the hard information contained in the credit report.

The main result of the paper is that fintech loans are significantly more likely to default. Also, borrowers' outcomes worsen in the months following the fintech loan origination compared to similar individuals borrowing from non-fintech lenders. Since selection is an important concern, we exploit the granularity of our data to match borrowers based on a number of characteristics at origination using multiple methodologies and confirm the robustness of these results. The underlying mechanism suggested by our findings is that borrowers spend the additional funds rather than consolidating their debts. In other words, even when borrowers use the personal loan to consolidate their credit card debt, we find that their revolving balance increases again a few months after origination. The new level of total indebtedness then becomes harder to sustain.

The evidence on the underlying screening technology and the results on the borrowers' delinquency suggest that fintech lenders are likely to be exposed to adverse selection. Specifically, due to the lack of soft information available to them, fintech lenders might end up giving credit to borrowers that would have been rejected by a traditional lender who might be able to detect weaker financial management skills.

However, we find that the higher likelihood to default is not likely to hurt the fintech lenders and the borrowers. First of all, fintech lenders seem to price their loans better, because the interest rate they charge is more correlated with the loan default probability. Furthermore, in addition to larger payments, the lifetime value of the borrower is also likely to be higher for fintech lenders. We find that fintech borrowers are loyal, as they tend to get multiple loans from fintech lenders over time, which is especially true for those less creditworthy borrowers. From the point of view of the borrowers, we also find that borrowers are more likely to obtain more credit when they need it the most, e.g., once they lose their job. This suggests that the additional credit available from fintech lenders might provide a significant relaxation of their credit constraints.

This trade-off poses some challenges for policy makers: curbing the credit provided by fintech lenders could negatively impact the most credit-constrained borrowers. However, 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 and the way these additional funds are actually used by the borrowers.

References

Ausubel, L.M., 1991. The failure of competition in the credit card market. *American Economic Review*, 50-81.

Balyuk, T. 2019. Financial innovation and borrowers: Evidence from peer-to-peer lending. Rotman School of Management Working Paper No. 2802220.

Balyuk, T. and Davydenko, S.A., 2018. Reintermediation in Fintech: Evidence from Online Lending.

Bartlett, R.P. and Morse, Adair and Stanton, Richard H. and Wallace, Nancy E., 2017 Consumer lending discrimination in the finTech era. UC Berkeley Public Law Research Paper.

Buchak, G., Matvos, G., Piskorski, T., Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3), 453-483.

Chava, S., Paradkar, N., and Zhang, Y. 2019. Winners and losers of marketplace lending: Evidence from borrower credit dynamics. Georgia Tech Scheller College of Business Research Paper 18-16.

De Roure, C., Pelizzon, L., and Thakor, A. V. 2018. P2P lenders versus banks: Cream skimming or bottom fishing?

Danisewicz, Piotr and Elard, Ilaf, The Real Effects of Financial Technology: Marketplace Lending and Personal Bankruptcy (July 5, 2018). Available at SSRN: https://ssrn.com/abstract=3208908.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11), 3550-88.

Erickson, T., Whited, T. M., 2002. Two-step GMM estimation of the errors-in-variables model using high-order moments. *Econometric Theory*, 18, 776–799.

Federal Reserve Bank of New York, 2018. Quarterly Report on Household Debt and Credit.

Fuster, A., Plosser, M., Schnabl, P. and Vickery, J., 2018. The role of technology in mortgage lending. *The Review of Financial Studies*, forthcoming.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25-46.

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

Iyer, R., Khwaja, A.I., Luttmer, E.F. and Shue, K., 2015. Screening peers softly: Inferring the quality of small borrowers. *Management Science*, 62(6), 1554-1577.

Liao, L., Z. Wang, H. Xiang, and X. Zhang. 2017. P2p lending in china: An overview.

Mariotto, C. (2016). Competition for lending in the Internet era: The case of Peer-to-Peer Lending Marketplaces in the USA. Available at SSRN 2800998.

Morse, A., 2015. Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending. *Annual Review of Financial Economics*, 7, 463-482.

Parlour, Christine A., and Uday Rajan, 2001. Competition in loan contracts. *American Economic Review*, 91(5), 1311-1328.

Rajan, Uday, Amit Seru, and Vikrant Vig. 2015. The failure of models that predict failure: Distance, incentives, and defaults. *Journal of financial economics* 115(2), 237-260.

Stiglitz, Joseph E., and Andrew Weiss, 1981. Credit rationing in markets with imperfect information. *American economic review*, 71(3), 393-410.

Tang, H., 2019. Peer-to-Peer Lenders versus Banks: Substitutes or Complements? *The Review of Financial Studies*, 32(5), 1900-1938.

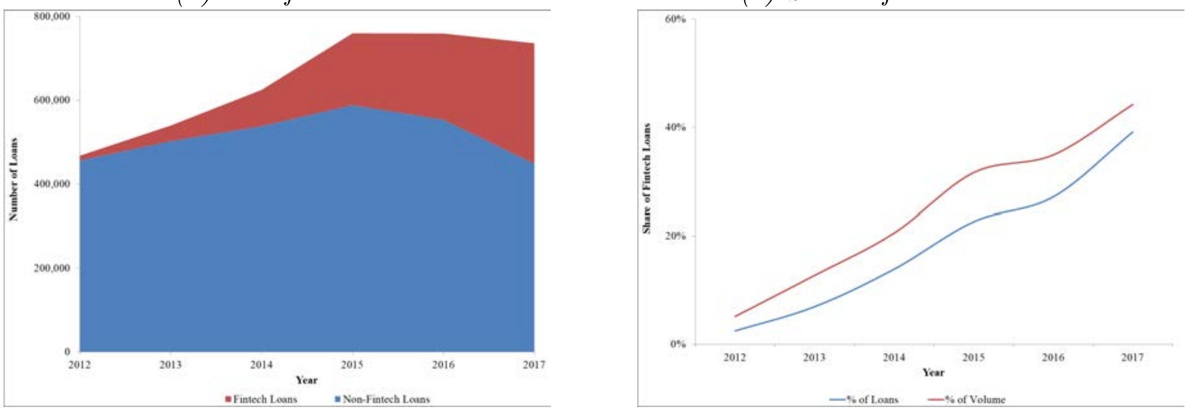
Transunion, 2017. Fact versus Fiction: Fintech Lenders. available at https://newsroom.transunion.com /Fintechs-taking-larger-share-of-personal-loan-market-while-increasing-portfolio-risk-return-performance.

Vallee, B. and Zeng, Y., 2018. Marketplace Lending: A New Banking Paradigm?. *The Review of Financial Studies*, forthcoming.

Wolfe, B., and W. Yoo. 2017. Crowding out banks: Credit substitution by peer-to-peer lending.

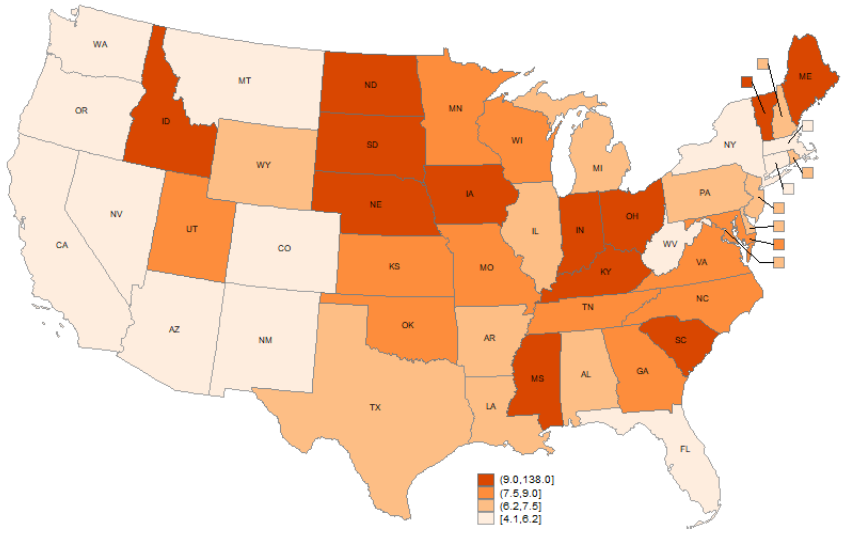
Figure 1. Fintech Loan Market

(a) No of Loans *(b) Share of Fintech Loans*



Notes: This figure plots number of loans originated by fintech lenders and non-fintech lenders based on our loan sample. The largest fintech lenders include LendingClub Corporation, Greensky Financial, SOFI Lending Corp, Avant Credit Corporation, and Upstart Network Inc. Non-fintech lenders include all the other lenders among top 100 lenders in the unsecured personal loan market based on their origination volume in 2012–2017. The data is a random sample of all personal loans reported to one of the main credit bureaus.

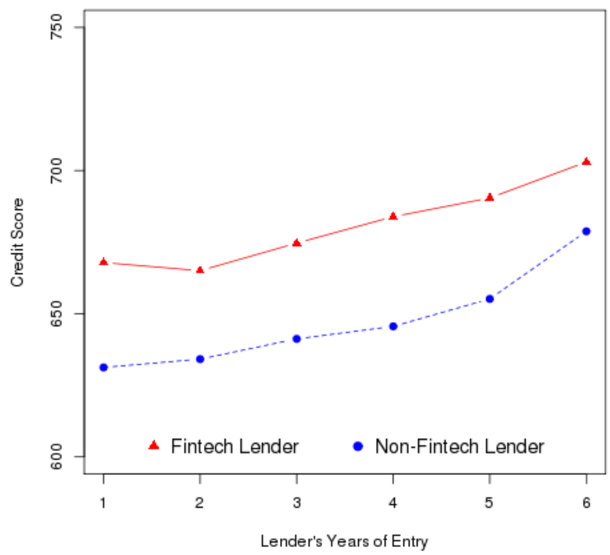
Figure 2. Fintech Volume Growth from 2013 to 2017



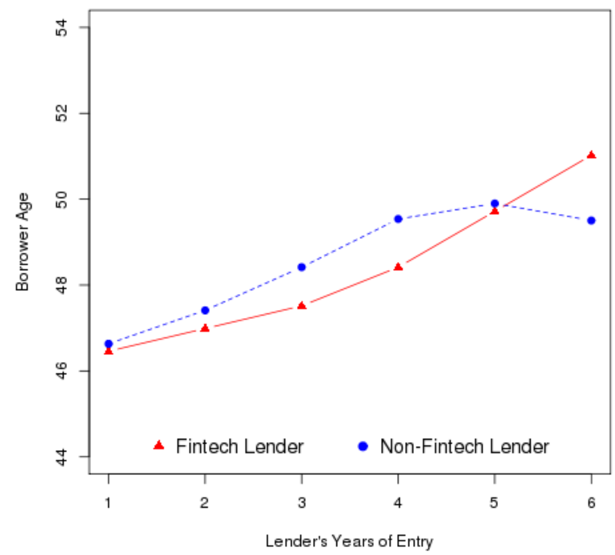
Notes: This figure plots the growth rate of fintech loan origination volume from 2013 to 2017. Total origination volume of fintech loans based on our sample is $453 million in 2013 and $3.7 billion in 2017, i.e., an eight-fold increase.

Figure 3. Evolution of Borrower Profile After Market Entry

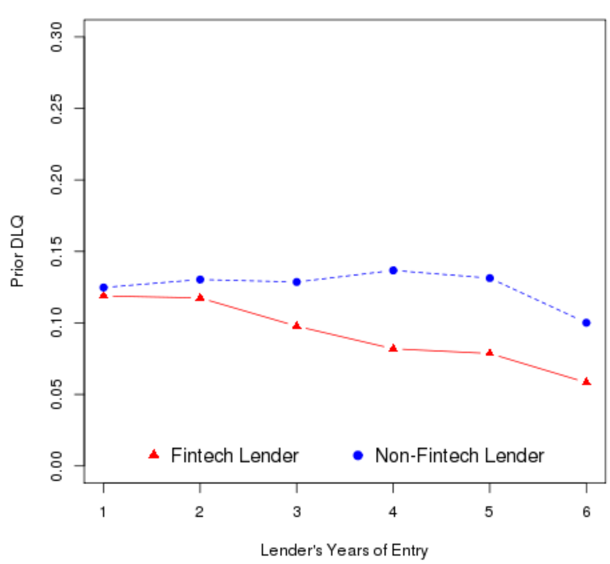
(a) Credit Score



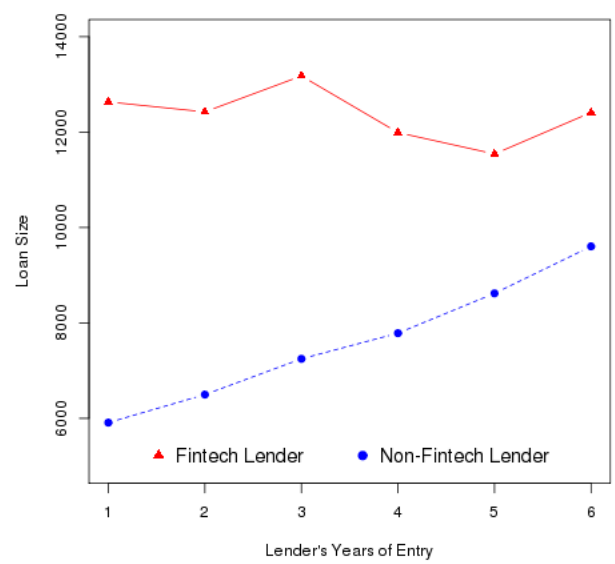
(b) Borrower Age



(c) Prior DLQ Indicator



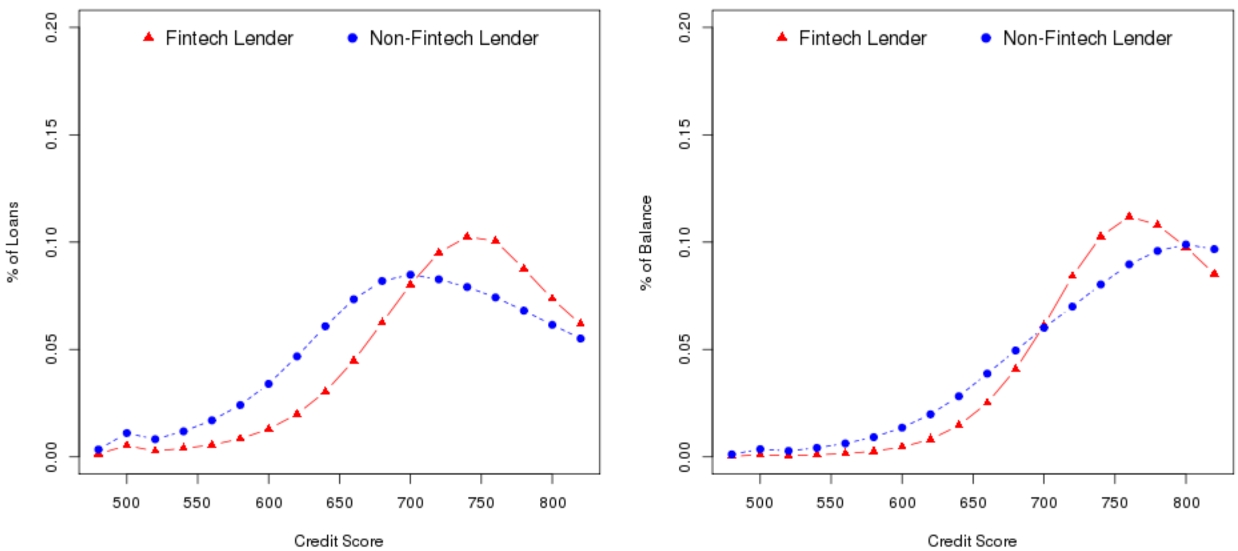
(d) New Loan Size



Notes: This figure plots average values of consumer and loan attributes by lender's years of entry. Lender's years of entry is defined based on number of years from the first loan originated by each lender in a given state. We report the statistics separately for fintech and non-fintech loans in each Panel. The statistics are based on all loans in our loan sample summarized in Table 1.

Figure 4. Evolution of Credit Score Distribution

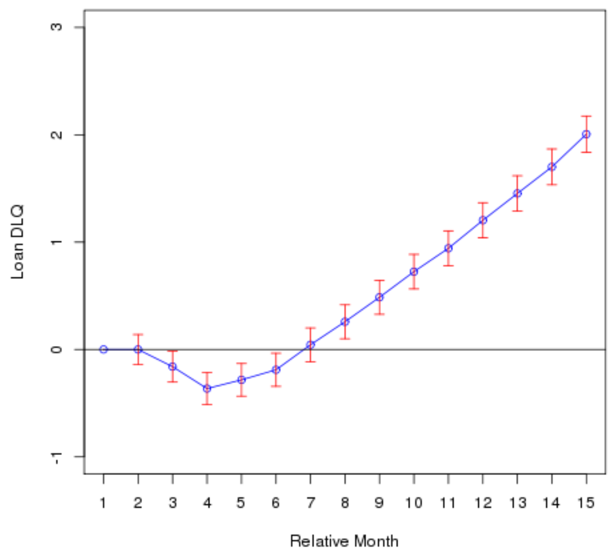
(a) Number of Loans *(b) Balance*



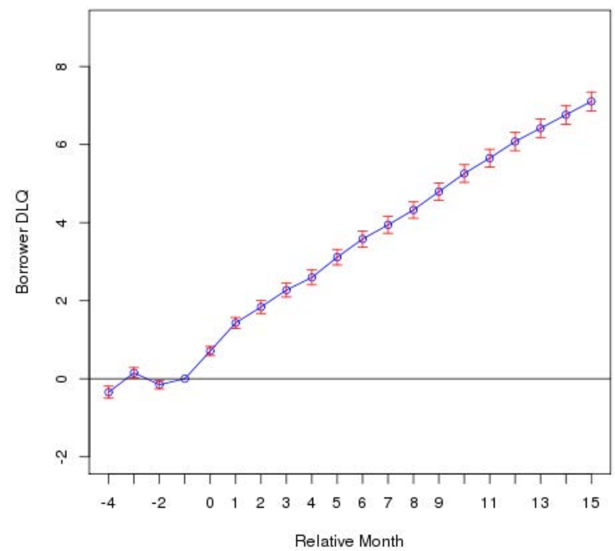
Notes: This figure plots relative frequency of loans over borrower's credit score between the fintech and non-fintech loans based on our loan sample. Panel (a) plots the frequency based on number of loans and Panel (b) plots share of loan balance in each credit score bins. Fintech and non-fintech loans are defined based on the lender names.

Figure 5. Dynamics of Loan and Borrower Performance

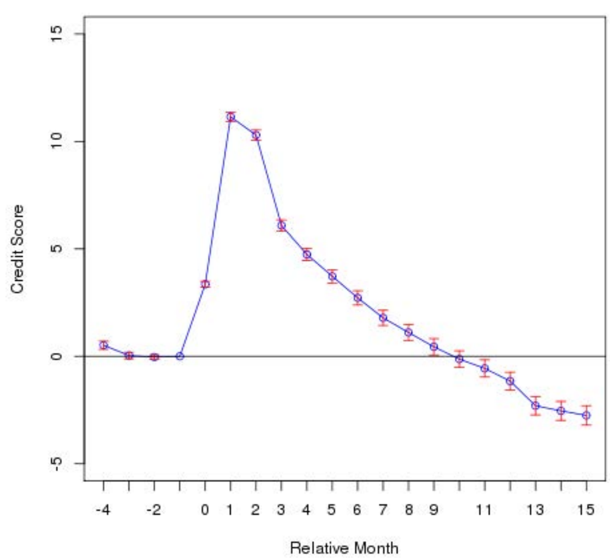
(a) Loan DLQ



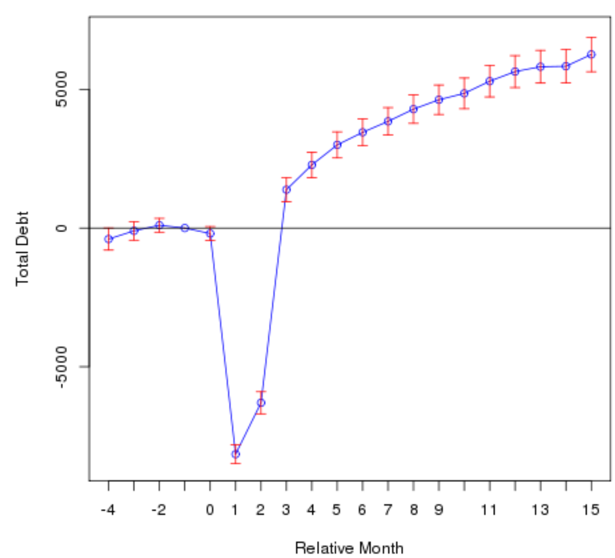
(b) Borrower DLQ



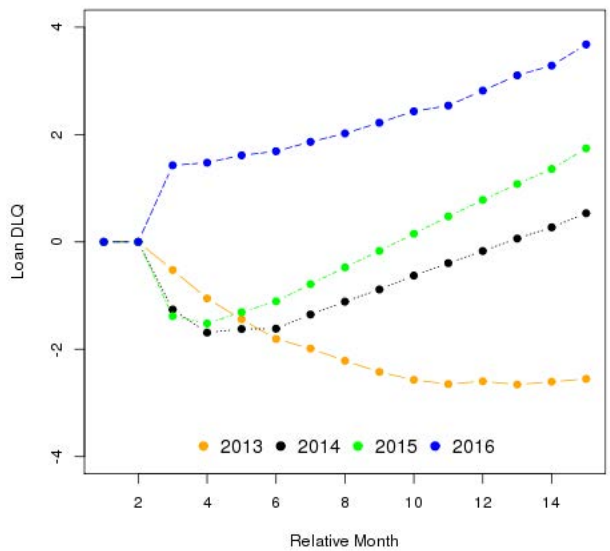
(c) Credit Score



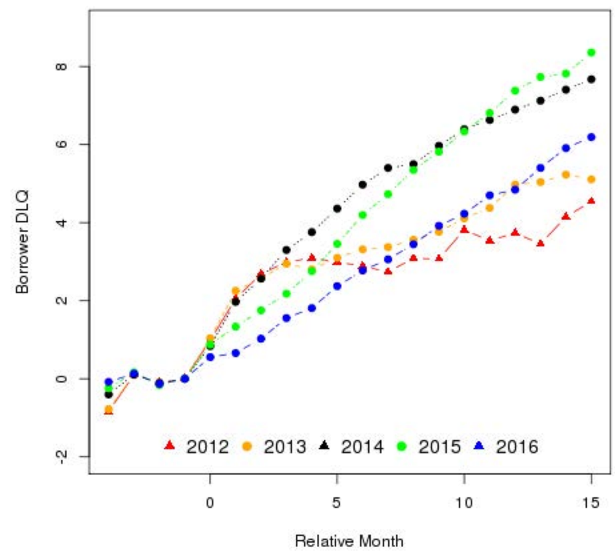
(d) Total Debt



(e) Loan DLQ by Origination Year



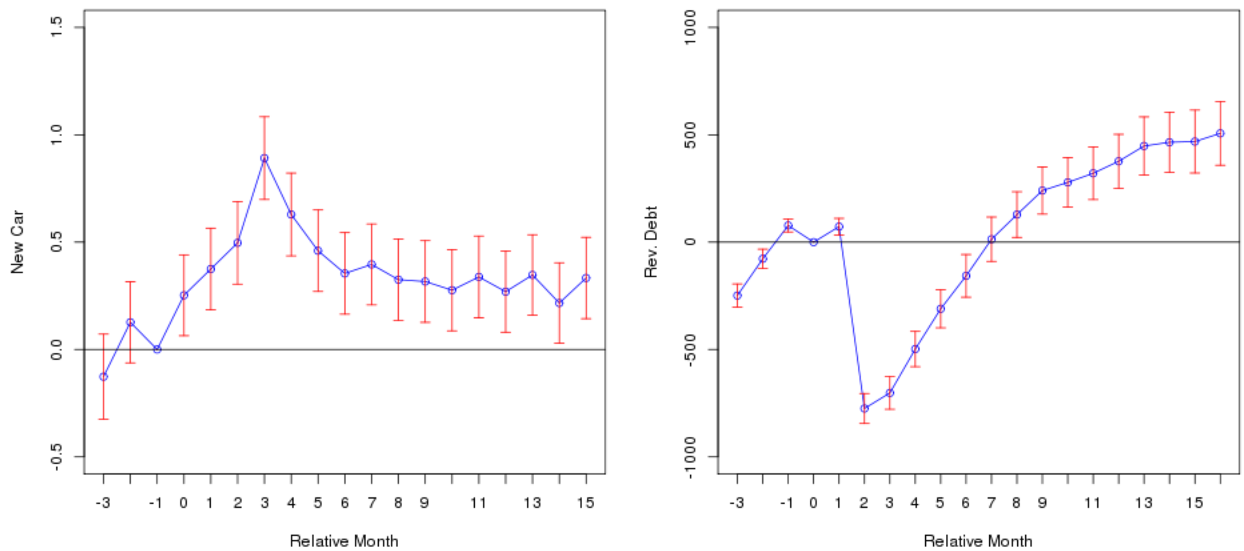
(f) Borrower DLQ by Origination Year



Notes: The figure plots the coefficient on the interaction of fintech loan indicator and relative month dummies from the regressions that examine the difference in the performance dynamics between the fintech and non-fintech loans in our sample. The regression is based on the loan-month panel from 3 month before through 15 months after the loan origination, restricted to the loans in the PSM–matched sample. The dependent variable for each chart is the figure title. We control for individual loan, calendar time and relative month fixed effects. Standard errors are double clustered at county and origination year-month levels. Panels (e) and (f) plot the coefficients from regressions of loan delinquency and borrower delinquency, respectively, but based on the subsample of loans originated in each year.

Figure 6. Dynamics of Borrower Consumption

(a) New Car *(b) Revolving Debt*



Notes: The figure plots the coefficient on the interaction of fintech loan indicator and relative month dummies from the regression examining the difference in the spending dynamics between the fintech and non-fintech borrowers in our sample. The regression is based on the loan-month panel from 3 month before through 15 months after the origination of the loan, restricted to the loans in the PSM–matched sample. The dependent variable for each chart is the figure title. We control for individual loan, calendar time and relative month fixed effects. Standard errors are double clustered at county and origination year-month levels.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Fintech Loan Indicator	3,792,757	0.208	0.406	0	0	0	0	1
Loan Size	3,792,757	$8,492	$11,822	$1	$1,575	$5,446	$11,869	$5,850,000
Maturity	3,792,757	39.185	26.26	1	13	36	60	999
Note Rate	2,218,740	13.108	9.818	0	7.033	11.55	18.818	49.996
Borrower DLQ Indicator	3,792,757	21.495	41.079	0	0	0	0	100
Loan DLQ Indicator	3,792,757	1.452	11.964	0	0	0	0	100
No of Accounts	3,709,883	22.878	13.12	0	13	21	30	91
Total Balance	3,709,883	$106,986	$146,034	$ -	$13,490	$45,595	$157,011	$8,857,760
Auto Balance	3,709,883	$11,739	$16,168	$ -	$ -	$5,731	$18,650	$1,997,020
Revolving Balance	3,709,883	$9,749	$24,402	$ -	$456	$3,550	$10,754	$6,089,626
Student Balance	3,709,883	$8,061	$25,897	$ -	$ -	$ -	$ -	$980,313
Mortgage Balance	3,709,883	$73,061	$128,126	$ -	$ -	$ -	$117,168	$8,175,626
Student Indicator	3,792,757	0.281	0.449	0	0	0	1	1
Mortgage Indicator	3,792,757	0.532	0.499	0	0	1	1	1
Credit Score	3,791,076	653.836	97.873	0	596	658	722	840
Inquiries	3,709,883	1.253	1.611	0	0	1	2	74
Age of Credit	3,709,883	188.407	100.958	0	122	170	240	1050
Revolving Utilization	3,672,635	0.434	0.344	0	0.079	0.419	0.74	1.111
Age	3,637,150	48.785	14.323	14	38	48	59	99
Young Indicator	3,792,757	0.412	0.492	0	0	0	1	1
Male Indicator	3,792,757	0.515	0.5	0	0	1	1	1
Married Indicator	3,792,757	0.573	0.495	0	0	1	1	1
College Indicator	3,792,757	0.238	0.426	0	0	0	0	1
Professional Indicator	3,792,757	0.084	0.277	0	0	0	0	1
High Income Indicator	3,792,757	0.209	0.406	0	0	0	0	1
Prior DLQ Indicator	3,709,883	0.168	0.374	0	0	0	0	1
Transactor Indicator	3,782,705	0.067	0.251	0	0	0	0	1

Notes: This table reports summary statistics of loan-level data. Our loan sample is a random sample of all unsecured personal loans originated by fintech and by non-fintech lenders from 2012–2017. The (original) note rate is calculated using scheduled payment, loan term and loan size. Borrower DLQ indicator is defined as an indicator for the borrowers who have any positive delinquent balance on their credit report. 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 loan indicator is defined as an indicator for loans originated by one of the fintech lenders. Fintech share is computed based on all loans in our loan sample originated in the prior three months in a given county.

Table 2: Evolution of Fintech Loan Attributes

	Fintech Lender's Years of Entry in Each State					
	1	2	3	4	5	6
Age	46.46	46.988	47.517	48.416	49.717	51.023
% Age $\leq$ 45	0.488	0.473	0.456	0.429	0.388	0.354
% Professional	0.111	0.112	0.114	0.114	0.116	0.119
Credit Score	667.9	665.0	674.7	683.9	690.4	703.0
% Credit Score $\leq$ 620	0.3	0.3	0.2	0.2	0.2	0.1
Age of Credit	196.6	199.1	204.8	213.6	220.1	230.2
No of Accounts	23.6	23.0	23.3	23.0	22.7	23.3
Total Balance	$146,406	$144,227	$144,776	$141,573	$143,742	$158,996
Rev Utilization	0.498	0.516	0.484	0.467	0.442	0.409
No of Inquiries	1.212	1.037	0.947	0.792	0.712	0.625
Prior DLQ	0.12	0.12	0.10	0.08	0.08	0.06
Loan Size	$12,633	$12,424	$13,177	$11,991	$11,542	$12,411
Maturity	47.0	47.7	52.2	53.0	56.0	59.6
Note Rate	15.35	17.41	17.50	15.67	15.93	15.23

Notes: This table presents average values of the consumer and loan attributes of fintech loans by lender's years of entry. Lender's years of entry is defined based on number of years from the first loan originated by each lender in a given state. The statistics are based on all loans in our loan sample summarized in Table 1.

Table 3: Individual Characteristics of Fintech Borrowers

Panel A: Credit Attributes

Dep Var	I(Fintech$_i$)$\times$ 100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit Score	0.019***								0.007***
	(0.001)								(0.001)
Age of Credit History		0.020***							0.014***
		(0.000)							(0.000)
No of Accounts			0.011***						0.001***
			(0.000)						(0.000)
Rev. Utilization				0.006***					0.008***
				(0.000)					(0.000)
Prior DLQ Indicator					-0.045***				-0.036***
					(0.001)				(0.001)
Transactor Indicator						0.039***			0.030***
						(0.001)			(0.001)
Student Loan Indicator							0.043***		0.046***
							(0.001)		(0.001)
Mortgage Indicator								0.041***	0.024***
								(0.001)	(0.001)
ZIP $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3791076	3709883	3709883	3672635	3709883	3782705	3792758	3792758	3663667
R^2	0.382	0.383	0.382	0.381	0.382	0.381	0.382	0.382	0.387

Panel B: Demographics

Dep Var	I(Fintech$_i$)$\times$ 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Male Indicator	0.004***						0.001**
	(0.001)						(0.001)
Married Indicator		0.016***					0.009***
		(0.001)					(0.001)
College Indicator			0.042***				0.031***
			(0.001)				(0.001)
High Income Indicator				0.046***			0.038***
				(0.001)			(0.001)
Young Indicator					0.010***		0.012***
					(0.001)		(0.001)
Professional Indicator						0.045***	0.031***
						(0.001)	(0.001)
ZIP $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3792757	3792757	3792757	3792757	3792757	3792757	3792757
R^2	0.38	0.38	0.381	0.382	0.38	0.381	0.383

Notes: These tables report the linear probability regression results of specifications where the dependent variable is the fintech loan indicator (0/1). In Panel A and B, we report results on borrower's credit attributes and demographic characteristics, respectively. Student loan and mortgage indicators are defined to be 1 for individuals who have positive balance of student loans and mortgages, respectively. 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 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 our loan-level sample. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 4: Loan Terms

Panel A: Overall Sample

Sample	Borrowers that have Fintech or Bank Loans			Borrowers that have Fintech and Bank Loans		
Dep Var	Loan Size	Loan Term	Note Rate	Loan Size	Loan Term	Note Rate
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Loan Indicator	1,562.587***	10.506***	1.498***	2,939.567***	-1.176***	-0.135**
	(30.610)	(0.096)	(0.062)	(38.299)	(0.082)	(0.054)
Loan Size			-1.338***			-0.103***
			(0.024)			(0.020)
Maturity			0.082***			0.051***
			(0.002)			(0.003)
FICO	3,129.673***	8.658***	-2.815***	15.639***	0.040***	-0.036***
	(16.015)	(0.040)	(0.028)	(0.922)	(0.002)	(0.002)
Age of Credit	1,031.716***	1.970***	0.019	1.036***	0.002	-0.001*
	(9.682)	(0.021)	(0.013)	(0.344)	(0.001)	(0.001)
Age	-739.777***	-0.378***	0.088***			
	(7.896)	(0.022)	(0.013)			
Time FE	No	No	No	Yes	Yes	Yes
ZIP × Time FE	Yes	Yes	Yes	No	No	No
Individual FE	No	No	No	Yes	Yes	Yes
N	3559985	3559985	2079676	253,695	253,695	163,436
R^2	0.371	0.526	0.565	0.704	0.576	0.765

Panel B: By Borrower Attributes

Dep Var	Note Rate							
	Credit Score		Age		County Fintech Share		Thin Credit	
Sample	High	Low	Old	Young	High	Low	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fintech Loan Indicator	-1.563***	2.794***	2.506***	1.153***	1.425***	0.719***	1.404***	5.436***
	(0.040)	(0.103)	(0.130)	(0.055)	(0.085)	(0.091)	(0.061)	(1.373)
Loan Size	-0.035**	-2.828***	-2.465***	-0.950***	-0.732***	-1.646***	-1.265***	-5.216***
	(0.015)	(0.044)	(0.049)	(0.029)	(0.019)	(0.050)	(0.023)	(0.828)
Maturity	0.003***	0.155***	0.171***	0.026***	0.020***	0.119***	0.078***	0.236***
	(0.001)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.025)
Credit Score	-4.192***	-1.061***	-2.178***	-3.659***	-5.089***	-2.017***	-2.896***	-0.106
	(0.036)	(0.034)	(0.038)	(0.034)	(0.057)	(0.029)	(0.028)	(0.172)
Age of Credit	-0.052***	0.220***	0.055***	-0.120***	-0.239***	0.132***	-0.032***	0.74
	(0.015)	(0.019)	(0.021)	(0.017)	(0.021)	(0.015)	(0.013)	(0.740)
Age	0.217***	-0.018	0.057***	0.320***	0.370***	-0.025*	0.111***	-0.304***
	(0.017)	(0.016)	(0.018)	(0.018)	(0.021)	(0.015)	(0.013)	(0.091)
ZIP × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	730390	1349286	931309	1148367	704991	1343393	1988624	91052
R^2	0.653	0.674	0.718	0.617	0.525	0.594	0.564	0.939

Notes: The table reports the regression results examining the difference in the loan terms between the fintech and non-fintech loans in our sample. The dependent variable in Panel A is reported in the column title: loan size, loan term and note rate. The dependent variable in Panel B is note rate of the loan. Note rate is calculated using scheduled payment, loan term and loan size. In Panel B, the regressions are based on split samples by borrower attributes (credit score, age, county fintech share and age of credit). High credit score is defined as the borrowers with a high score above 700. Young is defined as borrowers younger than 45 at the time of loan origination. County is defined to have high fintech share if the fintech share in previous three months is above 20%. Borrowers are considered to have thin credit file if their credit history is shorter than 48 months. In addition to the Fintech loan indicator, we also control for borrowers' credit score, age of credit history and age. For the regression of note rate in Panel A, we also control for loan size and maturity. For regressions reported in Columns (1)-(3) in Panel A as well as those in Panel B, we control for zip code by origination year-month fixed effects. Regressions in Columns (4)-(6) Panel A are based on special sample that includes borrowers who have borrowed from both fintech and non-fintech lenders in 2012–2017. In these regressions, 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. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 5: Soft Information: R^2 of Different Specifications Explaining Interest Rates

Panel A: R^2 based on Overall Sample

Specification				R^2			
				Sample			Fintech -
Controls	Time FE	ZIP-Time FE	Lender	All	Fintech	Non-Fintech	Non-Fintech
Credit Score	Yes	No	No	0.033	0.437	0.014	0.423***
Credit Score, Size	Yes	No	No	0.034	0.445	0.019	0.426***
Credit Score, Size	Yes	No	No	0.533	0.768	0.576	0.192***
All	Yes	No	No	0.211	0.49	0.281	0.209***
All	Yes	No	No	0.580	0.79	0.645	0.145***
Nonlinear	No	Yes	No	0.256	0.505	0.324	0.181***
Nonlinear	No	Yes	No	0.597	0.796	0.597	0.199***
Nonlinear	No	Yes	Yes	0.833	0.855	0.861	-0.006

Panel B: R^2 by Years of Entry

Specification		Sample			Fintech -
Controls	ZIP-YM FE	Years of Entry	Fintech	Non-Fintech	Non-Fintech
Nonlinear	Yes	1	0.975	0.748	0.227***
Nonlinear	Yes	2	0.980	0.741	0.239***
Nonlinear	Yes	3	0.969	0.726	0.243***
Nonlinear	Yes	4	0.918	0.686	0.232***
Nonlinear	Yes	5	0.868	0.591	0.277***
Nonlinear	Yes	6	0.787	0.533	0.254***

Notes: This table shows the R^2 for different specifications of a regression similar to Table 4. Data includes all loans in our loan-level sample. Panel A shows pooled regressions based on entire sample, non-fintech, and fintech subsamples, respectively. In addition to credit score and loan size, we also control for loan maturity, length of credit history, number of accounts, revolving utilization, prior DLQ indicator, transactor indicator, mortgage indicator, student loan indicator and age in the 'All' specification. Nonlinear regressions include nonlinear splines of credit score and loan Size. Tests of significance of R^2 differences follow Erickson and Whited (2002). Panel B shows regressions based on subsample sample separated by years since individual lender's entry to a state, non-fintech, and fintech subsamples, respectively. In addition to nonlinear splines of credit score and loan size, we also control for loan maturity, length of credit history, number of accounts, revolving utilization, prior DLQ indicator, transactor indicator, mortgage indicator, student loan indicator and age. Tests of significance of R^2 differences follow Erickson and Whited (2002). Asterisks denote significance levels (***=1%, **=5%, *=10%)..

Table 6: Loan Performance based on Entire Loan Sample

Panel A: Overall Sample

Dep Var	I(Loan DLQ$_i$)$\times$ 100				
	(1)	(2)	(3)	(4)	(5)
Fintech Loan Indicator	0.845***	1.132***	1.157***	1.212***	1.209***
	(0.027)	(0.029)	(0.029)	(0.037)	(0.037)
Loan Size		-0.105***	-0.095***	-0.098***	
		(0.017)	(0.016)	(0.018)	
Maturity		0.001	-0.001*	-0.001	
		(0.000)	(0.000)	(0.001)	
Credit Score		-1.336***	-1.354***	-1.350***	-1.401***
		(0.014)	(0.014)	(0.017)	(0.017)
Age of Credit		-0.033***	-0.041***	-0.051***	-0.066***
		(0.008)	(0.008)	(0.010)	(0.010)
No of Accounts		-0.278***	-0.276***	-0.276***	-0.223***
		(0.007)	(0.007)	(0.009)	(0.009)
Age		-0.080***	-0.071***	-0.078***	-0.058***
		(0.008)	(0.008)	(0.010)	(0.010)
Time FE	Yes	Yes	No	No	No
County FE	Yes	Yes	No	No	No
County $\times$ Time FE	No	No	Yes	No	No
ZIP $\times$ Time FE	No	No	No	Yes	Yes
Loan Size Bin FE	No	No	No	No	Yes
Maturity Bin FE	No	No	No	No	Yes
N	3,792,757	3,559,985	3,559,985	3,559,985	3,559,985
R^2	0.007	0.017	0.041	0.235	0.237

Panel B: By Borrower Attributes

Dep Var	I(Loan DLQ$_i$)$\times$ 100							
	Credit Score		Main Lender		County Fintech Share		Thin Credit	
	High	Low	No	Yes	High	Low	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fintech Loan Indicator	0.029	2.186***	1.109***	1.103***	0.828***	1.497***	1.138***	5.847***
	(0.026)	(0.068)	(0.069)	(0.047)	(0.057)	(0.049)	(0.036)	(1.593)
Loan Size	0.005	-0.621***	-0.116***	-0.090***	-0.054*	-0.100***	-0.093***	-0.654
	(0.017)	(0.056)	(0.042)	(0.024)	(0.028)	(0.015)	(0.018)	(0.703)
Maturity	-0.001**	0.011***	0.005***	-0.006***	0.003***	-0.002***	-0.001	0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.016)
Credit Score	-0.527***	-1.548***	-0.997***	-1.799***	-2.147***	-1.063***	-1.329***	-1.340***
	(0.029)	(0.029)	(0.024)	(0.029)	(0.039)	(0.017)	(0.017)	(0.265)
Age of Credit	-0.004	-0.183***	-0.095***	-0.053***	-0.070***	-0.036***	-0.018*	-1.476
	(0.013)	(0.017)	(0.016)	(0.017)	(0.022)	(0.011)	(0.010)	(1.347)
No of Accounts	-0.066***	-0.285***	-0.151***	-0.280***	-0.294***	-0.255***	-0.257***	-0.17
	(0.013)	(0.012)	(0.012)	(0.018)	(0.023)	(0.010)	(0.009)	(0.243)
Age	0.065***	-0.126***	-0.081***	-0.009	-0.005	-0.108***	-0.072***	-0.273**
	(0.014)	(0.015)	(0.015)	(0.017)	(0.023)	(0.011)	(0.01)	(0.139)
ZIP $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1183605	2376380	1613759	1946226	1076085	2431632	3407831	152154
R^2	0.429	0.313	0.353	0.347	0.256	0.22	0.241	0.815

Notes: The table reports the regression results examining the difference in the ex post performance between the fintech and non-fintech loans in our sample. The dependent variable in all regressions is an indicator whether the loan has ever become delinquent from origination through 15 months after the origination. Regressions in Panel A are based on entire sample and those in Panel B are based on split samples by borrower attributes (credit score, main lender, county fintech share and thin credit). High credit score is defined as the borrowers with a high score above 700. Young is defined as borrowers younger than 45 at the time of loan origination. County is defined to have high fintech share if the fintech share in previous three months is above 20%. Borrowers are considered to have thin credit file if their length of credit history is less than 48 months. In addition to the fintech loan indicator, we also control for loan size and loan maturity, borrowers' credit score, age of credit history, no of accounts, and borrower age, as well as 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%).

Table 7: Loan Performance based on Matched Samples

Panel A: PSM–Matched Sample

Dep Var	$I(\text{Loan DLQ}_i) \times 100$				
	(1)	(2)	(3)	(4)	(5)
Fintech Loan Indicator	1.739***	0.690***	0.576***	0.558***	1.102***
	(0.061)	(0.059)	(0.065)	(0.142)	(0.149)
Loan Size		-0.339***	-0.293***	-0.244	
		(0.085)	(0.084)	(0.196)	
Maturity		0.009***	0.011***	0.014***	
		(0.001)	(0.001)	(0.003)	
Credit Score		-3.723***	-3.784***	-4.144***	-3.832***
		(0.063)	(0.065)	(0.134)	(0.117)
Age of Credit		-0.212***	-0.203***	-0.285***	-0.261***
		(0.029)	(0.031)	(0.071)	(0.070)
No of Accounts		-0.444***	-0.500***	-0.540***	-0.412***
		(0.040)	(0.042)	(0.090)	(0.083)
Age		0.135***	0.145***	0.196**	0.163**
		(0.034)	(0.036)	(0.080)	(0.080)
Time FE	Yes	Yes	No	Yes	No
County FE	Yes	Yes	No	No	No
County × Time FE	No	No	Yes	No	No
ZIP × Time FE	No	No	No	Yes	Yes
Loan Size Bin FE	No	No	No	No	Yes
Maturity Bin FE	No	No	No	No	Yes
N	418,626	418,626	418,626	418,626	418,626
R^2	0.012	0.048	0.134	0.55	0.553

Panel B: Two Alternative Samples

Dep Var	I(Loan DLQ$_i$)$\times$ 100							
	Manually Matched				Entropy Balancing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fintech Loan Indicator	1.583***	1.548***	1.645***	1.713***	2.241***	2.215***	2.358***	2.422***
	(0.054)	(0.057)	(0.096)	(0.104)	(0.037)	(0.038)	(0.051)	(0.052)
Loan Size	-0.415***	-0.365***	-0.311***		-0.041**	-0.049**	-0.083***	
	(0.026)	(0.027)	(0.044)		(0.018)	(0.020)	(0.026)	
Maturity	0.008***	0.007***	0.007***		-0.001**	-0.001**	-0.001	
	(0.001)	(0.001)	(0.002)		(0.001)	(0.001)	(0.001)	
Credit Score	-2.376***	-2.409***	-2.402***	-2.373***	-1.851***	-1.859***	-1.786***	-1.849***
	(0.039)	(0.041)	(0.061)	(0.061)	(0.022)	(0.023)	(0.027)	(0.028)
Age of Credit	-0.203***	-0.188***	-0.209***	-0.196***	-0.159***	-0.157***	-0.144***	-0.159***
	(0.025)	(0.027)	(0.047)	(0.047)	(0.013)	(0.014)	(0.018)	(0.018)
No of Accounts	-0.287***	-0.322***	-0.300***	-0.273***	-0.221***	-0.231***	-0.232***	-0.179***
	(0.025)	(0.026)	(0.044)	(0.044)	(0.013)	(0.013)	(0.017)	(0.016)
Age	-0.001	0.001	-0.008	0.025	0.028**	0.027*	-0.016	-0.003
	(0.027)	(0.028)	(0.050)	(0.050)	(0.014)	(0.014)	(0.018)	(0.018)
Time FE	Yes	No	No	No	Yes	No	No	No
County FE	Yes	No	No	No	Yes	No	No	No
County $\times$ Time FE	No	Yes	No	No	No	Yes	No	No
ZIP $\times$ Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Loan Size Bin FE	No	No	No	Yes	No	No	No	Yes
Maturity Bin FE	No	No	No	Yes	No	No	No	Yes
N	681,274	681,274	681,274	681,274	2,937,580	2,937,580	2,937,580	2,937,580
R^2	0.028	0.1	0.438	0.44	0.025	0.068	0.354	0.356

Notes: The table reports the regression results examining the difference in the ex post performance between the fintech and non-fintech loans in three different samples. Panel A reports results using a matched sample based on the propensity score matching methodology. Details of the PSM are discussed in the paper. Columns 1-4 of Panel B report regressions using a manually–matched sample requiring fintech and non-fintech loans to be originated in the same zip code and origination year with difference in borrower age no more than 4 years and difference in borrower's total indebtedness smaller than $2,000 at the time of origination. Columns 5-8 of Panel B report regressions weighted by the weights assigned by Entropy Balancing procedure following Hainmueller (2011). The dependent variable in all regressions is an indicator whether the loan has ever become delinquent from origination through 15 months after the origination. We also control for loan size and loan maturity, borrowers' credit score, age of credit history, no of accounts,and borrower age, as well as different levels of fixed effects. Standard errors are double clustered at county and origination year-month levels. The regressions are based on the loan-level data. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 8: Dynamic Effect

Dep Var	Loan DLQ	Borrower DLQ	Credit Score	Total Debt	New Car	Revolving Debt
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Rel Qtr = -1		-0.148**	0.051	109.927	-0.022	-7.941
		(0.061)	(0.068)	(93.669)	(0.048)	(13.368)
Fintech × Rel Qtr = 1		2.042***	7.438***	-3,212.081***	0.061	-669.683***
		(0.060)	(0.124)	(163.740)	(0.045)	(33.921)
Fintech × Rel Qtr = 2	-0.241***	3.288***	3.445***	3,007.067***	0.250***	-163.694***
	(0.031)	(0.082)	(0.171)	(227.405)	(0.044)	(46.62)
Fintech × Rel Qtr = 3	0.297***	4.543***	0.833***	4,347.042***	0.101**	202.527***
	(0.042)	(0.093)	(0.197)	(248.564)	(0.044)	(54.295)
Fintech × Rel Qtr = 4	0.987***	5.849***	-0.894***	5,355.385***	0.039	367.762***
	(0.050)	(0.100)	(0.214)	(274.700)	(0.045)	(62.229)
Fintech × Rel Qtr = 5	1.746***	6.946***	-2.808***	6,058.412***	0.032	465.642***
	(0.055)	(0.107)	(0.232)	(295.757)	(0.044)	(70.935)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Relative Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,457,382	8,374,729	8,374,729	8,354,735	7,941,055	8,354,735
R^2	0.603	0.608	0.879	0.924	0.062	0.916

Notes: The table reports the difference in the dynamics of several credit attributes between the fintech and non-fintech loans in our sample. The regression is based on the loan-month panel from 3 month before through 15 months after the origination of the loan, restricted to the loans in the PSM–matched sample. The dependent variable is the column title. Our main explanatory variable is the fintech loan indicator interacted with the relative quarter dummies. In all regressions, we control for individual, calendar time and relative quarter fixed effects. Standard errors are double clustered at county and origination year-month levels. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 9: Pricing and Ex Post Performance

Dep Var	I(Loan DLQ$_i$)$\times$ 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Note Rate	0.058***	0.054***	0.054***	0.051***	0.051***	0.048***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
x Fintech Loan Indicator		0.020***		0.012***		0.010***
		(0.002)		(0.002)		(0.003)
Loan Size			0.018*	0.009	0.018	0.012
			(0.009)	(0.009)	(0.016)	(0.015)
Maturity			-0.008***	-0.008***	-0.008***	-0.008***
			(0.001)	(0.001)	(0.001)	(0.001)
Credit Score			-0.846***	-0.834***	-0.961***	-0.952***
			(0.015)	(0.015)	(0.023)	(0.023)
Age of Credit			-0.029***	-0.029***	-0.054***	-0.054***
			(0.009)	(0.009)	(0.014)	(0.014)
No of Accounts			-0.144***	-0.146***	-0.143***	-0.144***
			(0.009)	(0.009)	(0.012)	(0.012)
Age			-0.044***	-0.042***	-0.030**	-0.028**
			(0.009)	(0.009)	(0.014)	(0.014)
Time FE	Yes	Yes	Yes	Yes	No	No
ZIP Time FE	No	No	No	No	Yes	Yes
N	2,218,740	2,218,740	2,079,676	2,079,676	2,079,676	2,079,676
R^2	0.008	0.008	0.015	0.015	0.314	0.314

Notes: The table reports the regression results examining the difference in the relationship between ex post performance and pricing between the fintech and non-fintech personal loans in our sample. The dependent variable in all regressions is an indicator whether the loan has become delinquent after the origination. Our main explanatory variable is the interest rate on the loan at origination as well as its interaction with the fintech indicator. We also control for loan size and loan maturity, borrowers' credit score, age of credit history, no of accounts, and borrower age, as well as 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. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 10: Repeat Borrowers

Dep Var	I(Fintech$_i$)$\times$ 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Indicator for Last Loan	0.623***	0.621***	0.615***	0.556***	0.614***	0.609***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
× Low Credit				0.089***		
				(0.004)		
× Thin Credit					0.094***	
					(0.011)	
× Main Lender						0.272***
						(0.007)
Male Indicator		0.002***	0.003***	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married Indicator		0.001**	-0.002***	-0.002***	-0.002***	-0.002***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College Indicator		0.012***	0.010***	0.010***	0.010***	0.010***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High Income Indicator		0.019***	0.015***	0.016***	0.016***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Young Indicator		0.004***	0.004***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Professional Indicator		0.010***	0.008***	0.009***	0.008***	0.008***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	No	No	Yes	Yes	Yes	Yes
ZIP × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,695,511	1,695,510	1,650,172	1,650,172	1650172	1650172
R^2	0.689	0.689	0.689	0.69	0.689	0.69

Notes: The table report the regression results of likelihood of fintech borrowers taking another fintech loan in the future based on loan-level data. The dependent variable is the fintech loan indicator. Main explanatory variable is whether borrower's last loan is a fintech loan. We also interact this variable with indicators for low credit score ($\leq$ 700), thin credit file (length of credit history shorter than 48 months), and whether the fintech lender was the main borrower's lender (highest loan balance). We also control for all the demographic (male, married, college, high income, young, professional) and consumer credit attributes at the time of origination, as well as 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. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 11: Job Loss and Fintech Loans

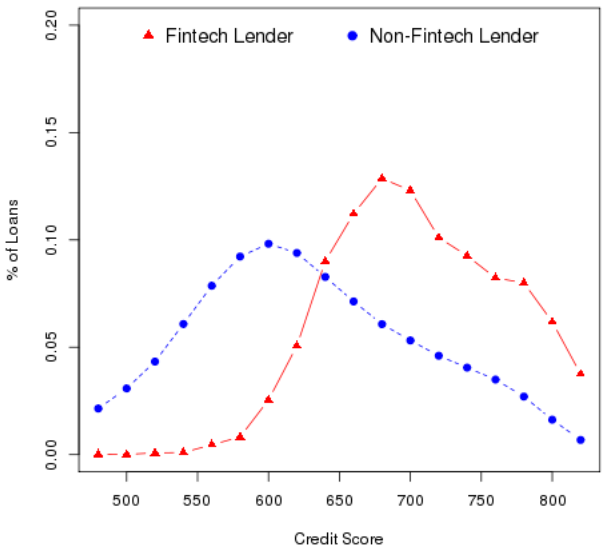
Dep Var	$I(\text{Fintech}_{i,t}) \times 100$		$I(\text{Non-Fintech}_{i,t}) \times 100$		$I(\text{Any Loan}_{i,t}) \times 100$	
Sample	Fintech Borrowers		Non-Fintech Borrowers		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Job Loss$_t$	0.404**	0.260***	0.138**	-0.154***	0.097	-0.216***
	(0.104)	(0.109)	(0.061)	(0.065)	(0.061)	(0.065)
$\times$ Fintech$_i$					0.397***	0.656***
					(0.121)	(0.127)
Fintech$_i \times$ Unemployed$_i$					-0.329***	
					(0.089)	
Unemployed$_i$	0.020**		0.210***		0.247***	
	(0.075)		(0.049)		(0.049)	
County Time FE	Yes	No	Yes	No	Yes	No
Borrower FE	No	Yes	No	Yes	No	Yes
Calendar Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,935,265	6,935,265	23,622,976	23,622,97	30,558,241	30,558,241
R^2	0.031	0.053	0.023	0.058	0.021	0.057

Notes: The table reports the regression results examining the relationship between job loss and personal loan origination. The regression is based on our loan-month panel data matched with individual job loss data. We restrict the individuals with job loss to 3 months before and 3 months after their job loss date. Those with no job loss are the same as our loan-month panel. The dependent variable is an indicator for whether the loan (fintech, non-fintech or both) is originated in a given month. Post job loss is an indicator that takes 1 for individuals with job loss after their job loss date. Unemployment is an indicator for the individuals with job loss during our sample period. Regressions in Columns (1) and (2) are based on fintech borrowers only. Regressions in Columns (3) and (4) are based on non-fintech borrowers only. Regressions in Columns (5) and (6) are based on both fintech and non-fintech borrowers. In addition, we control for county and time fixed effects in Columns (1), (3), (5) and control for individual and time fixed effects in other regressions. Standard errors are double clustered at county and origination year-month levels. Asterisks denote significance levels (***=1%, **=5%, *=10%).

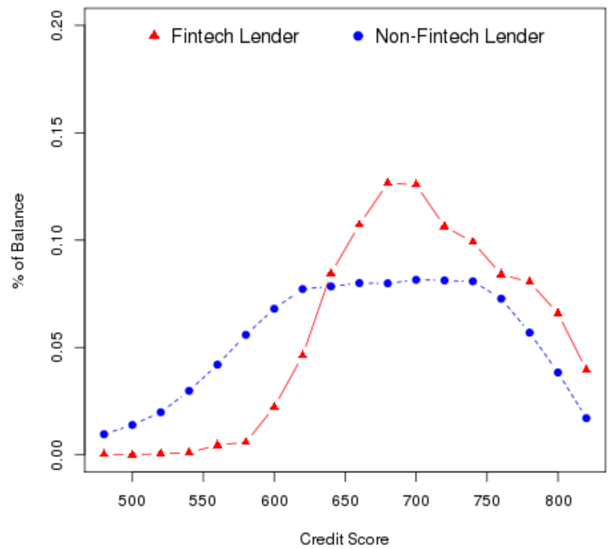
Appendix

Figure A.1. Evolution of Credit Score Distribution (Loan-Level)

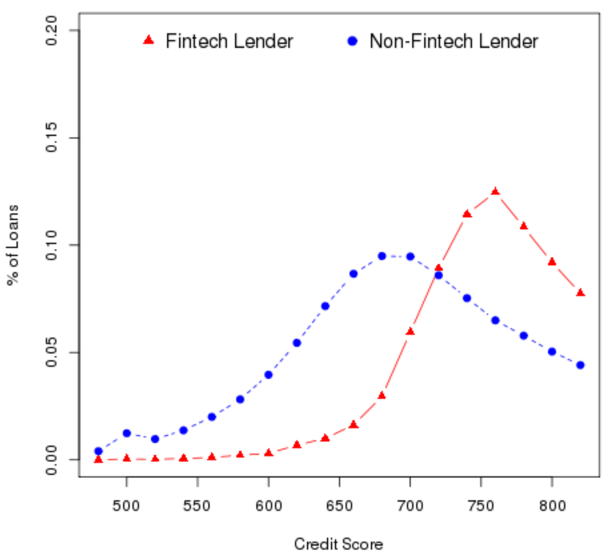
(a) 2012: Number of Loans



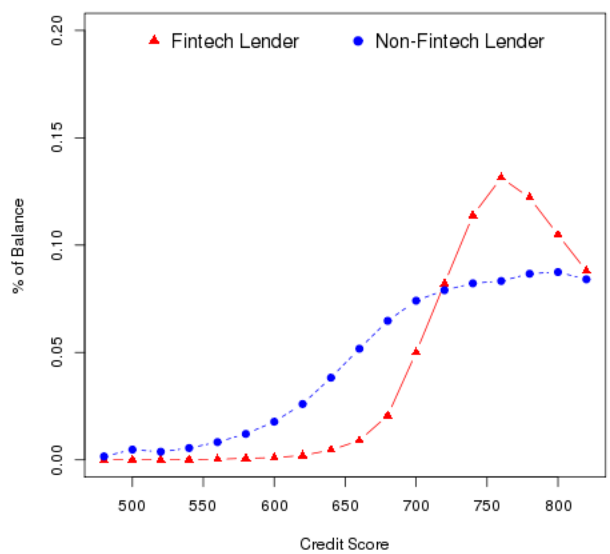
(b) 2012: Balance



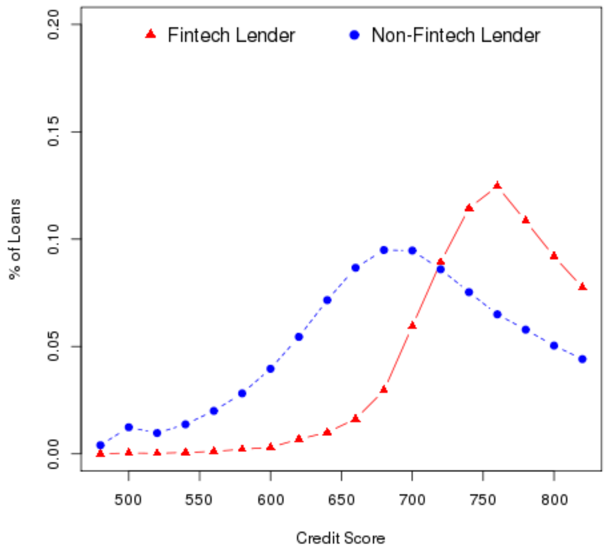
(c) 2013: Number of Loans



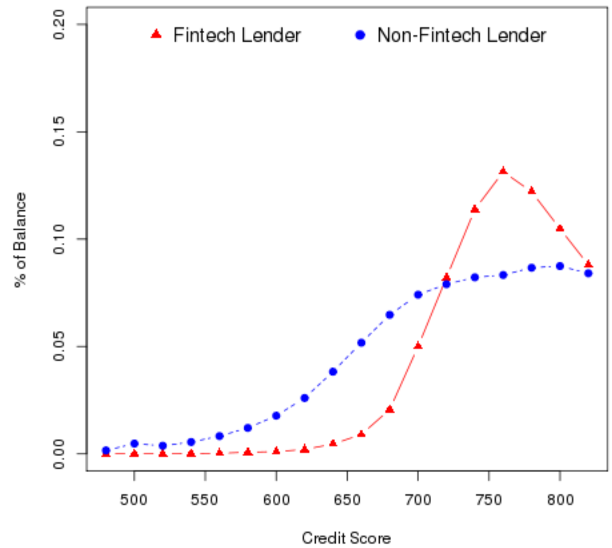
(d) 2013: Balance



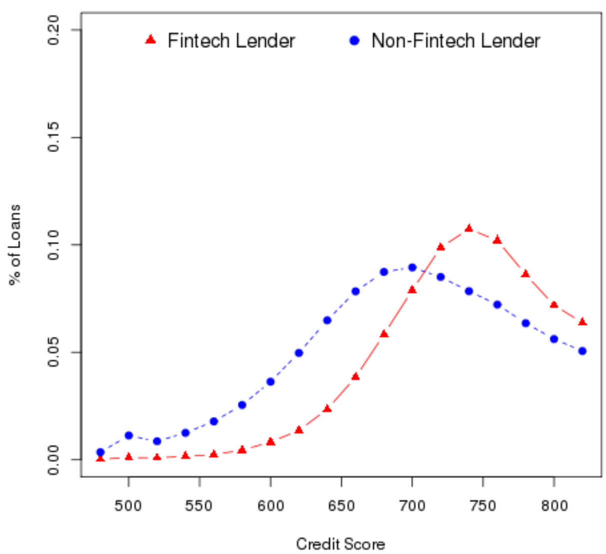
(e) 2013: Number of Loans



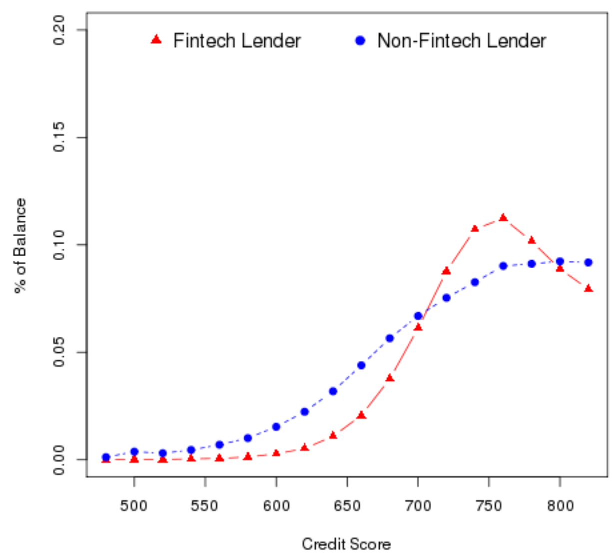
(f) 2013: Balance



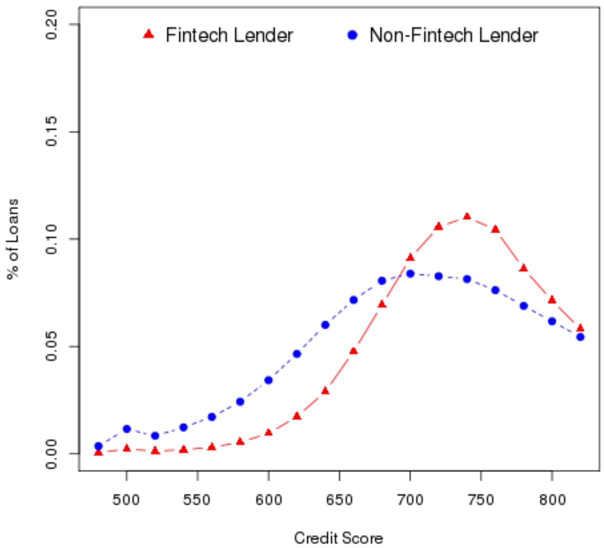
(g) 2014: Number of Loans



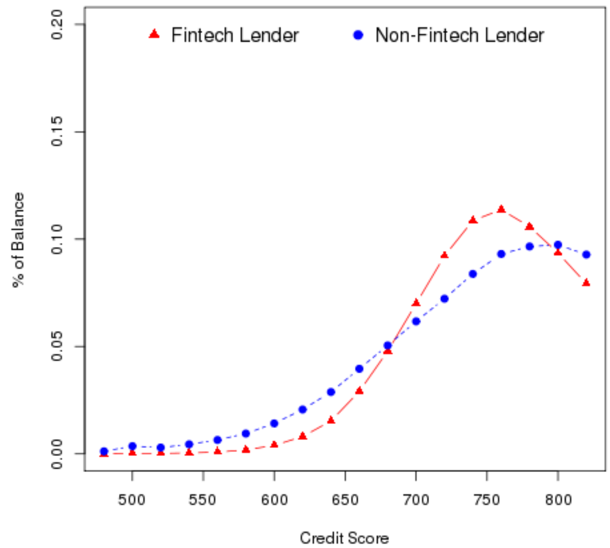
(h) 2014: Balance



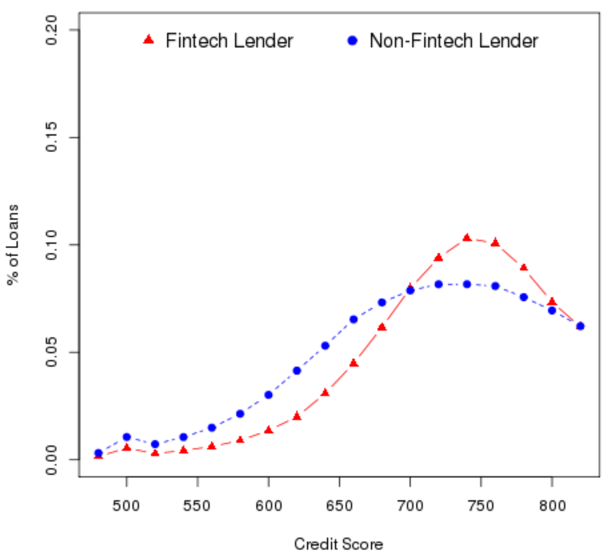
(i) 2015: Number of Loans



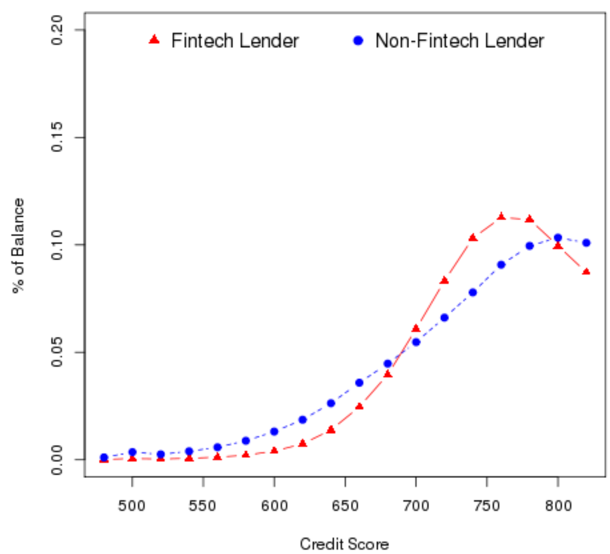
(j) 2015: Balance



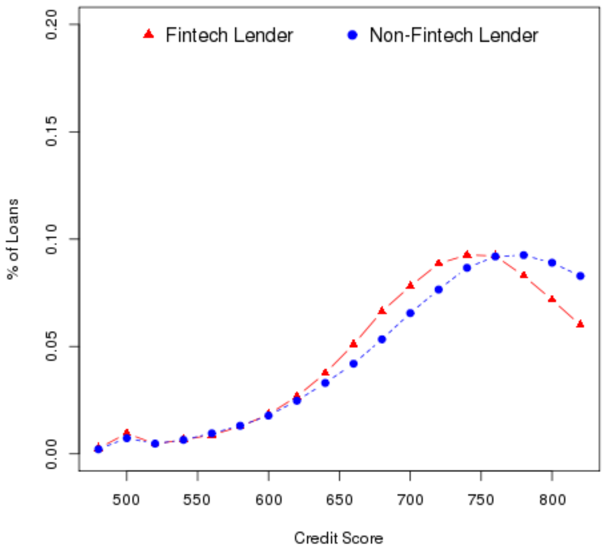
(k) 2016: Number of Loans



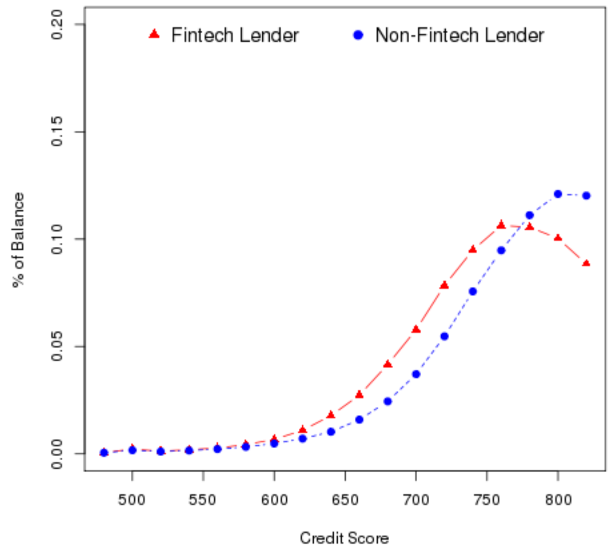
(l) 2016: Balance



(m) 2017: Number of Loans



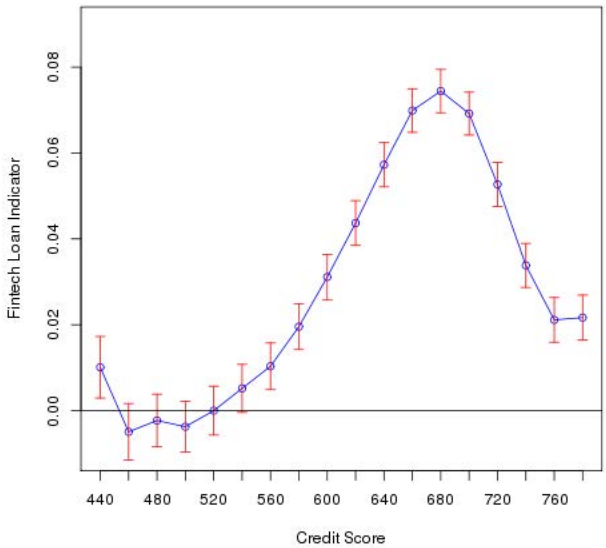
(n) 2017: Balance



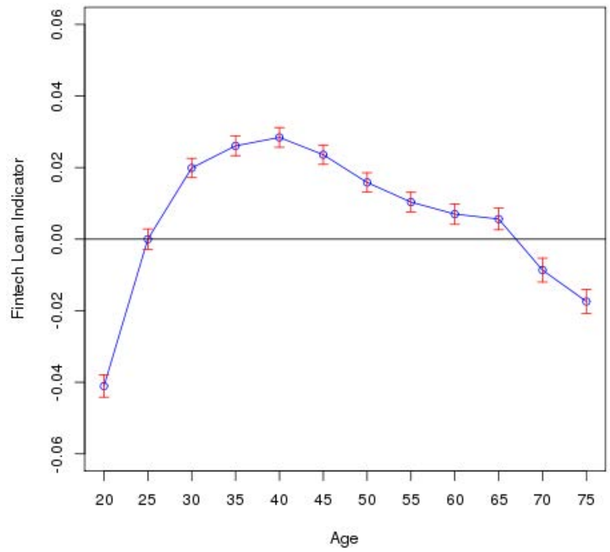
Notes: The figure plots relative frequency of number of loans and share of loan balance over original credit score bins. Original credit score bins are every 20 points from 460 to 840. Those with score below 460 are grouped to 460 and those above 840 are grouped to 840.

Figure A.2. Nonlinear Coefficients

(a) Credit Score



(b) Borrower Age



Notes: This figure plots coefficients on credit score bins at (Panel A) and borrower age bins (Panel B) at time of the origination from the regression results of specification similar to Table 3 Panel A. The dependent variable is the fintech loan indicator (0/1). In addition to credit score or age, 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.

Table A.1: Missing Credit Information

Panel A: Missing Values

Variable	All			Fintech			Non Fintech Loans		
	Obs	Missing Obs	% Missing	Obs	Missing Obs	% Missing	Obs	Missing Obs	% Missing
Loan Size	3,792,974	-	0.0%	761,773	-	0.0%	3,031,201	-	0.0%
Maturity	3,792,974	-	0.0%	761,773	-	0.0%	3,031,201	-	0.0%
Note Rate	2,218,839	1,574,135	41.5%	400,748	361,025	47.4%	1,818,091	1,213,110	40.0%
Borrower DLQ	3,792,974	-	0.0%	761,773	-	0.0%	3,031,202	-	0.0%
Loan DLQ	3,792,975	-	0.0%	761,773	-	0.0%	3,031,202	-	0.0%
No of Accounts	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Total Balance	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Auto Balance	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Rev. Balance	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Student Balance	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Mortgage Balance	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Student	3,710,092	82,882	2.2%	761,773	-	0.0%	3,031,202	-	0.0%
Mortgage	3,710,092	82,882	2.2%	761,773	-	0.0%	3,031,202	-	0.0%
Credit Score	3,791,293	1,681	0.0%	761,712	61	0.0%	3,029,581	1,620	0.1%
Inquiries	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Age of Credit	3,710,092	82,882	2.2%	756,724	5,049	0.7%	2,953,368	77,833	2.6%
Rev. Utilization	3,672,841	120,133	3.2%	753,851	7,922	1.0%	2,918,990	112,211	3.7%

Panel B: % Missing Credit Information by State

State	Random Sample	All Loans			Fintech Loans			Non Fintech Loans		
	% Missing	Obs	# Missing	% Missing	Obs	# Missing	% Missing	Obs	# Missing	% Missing
AL	0.4%	79,671	1,992	2.5%	6,723	47	0.7%	72,948	1,970	2.7%
AR	0.4%	31,298	1,064	3.4%	5,337	32	0.6%	25,961	1,038	4.0%
AZ	0.3%	64,006	1,024	1.6%	22,844	91	0.4%	41,162	947	2.3%
CA	0.3%	380,005	7,980	2.1%	116,693	1,400	1.2%	263,312	6,583	2.5%
CO	0.3%	65,663	854	1.3%	20,381	102	0.5%	45,282	770	1.7%
CT	0.3%	26,896	215	0.8%	11,853	36	0.3%	15,043	181	1.2%
DC	0.3%	7,460	142	1.9%	1,662	13	0.8%	5,798	128	2.2%
DE	0.3%	11,181	257	2.3%	2,778	39	1.4%	8,403	227	2.7%
FL	0.3%	237,000	4,029	1.7%	61,701	247	0.4%	175,299	3,857	2.2%
GA	0.3%	104,929	1,679	1.6%	23,478	117	0.5%	81,451	1,629	2.0%
IA	0.3%	16,186	259	1.6%	1,889	8	0.4%	14,297	243	1.7%
ID	0.3%	32,247	1,193	3.7%	3,092	28	0.9%	29,155	1,166	4.0%
IL	0.3%	165,479	4,964	3.0%	38,658	425	1.1%	126,821	4,566	3.6%
IN	0.3%	67,328	1,145	1.7%	15,538	93	0.6%	51,790	1,036	2.0%
KS	0.3%	15,080	226	1.5%	5,102	46	0.9%	9,978	180	1.8%
KY	0.3%	39,633	753	1.9%	6,303	38	0.6%	33,330	700	2.1%
LA	0.4%	49,838	1,296	2.6%	6,271	56	0.9%	43,567	1,263	2.9%
MA	0.3%	46,915	422	0.9%	19,821	79	0.4%	27,094	325	1.2%
MD	0.3%	97,129	1,166	1.2%	20,535	82	0.4%	76,594	996	1.3%
ME	0.3%	7,345	81	1.1%	1,569	3	0.2%	5,776	81	1.4%
MI	0.3%	72,481	1,232	1.7%	21,365	107	0.5%	51,116	1,176	2.3%
MN	0.2%	41,147	453	1.1%	16,247	97	0.6%	24,900	349	1.4%
MO	0.3%	65,612	2,362	3.6%	9,433	94	1.0%	56,179	2,247	4.0%
MS	0.4%	31,296	908	2.9%	1,710	19	1.1%	29,586	888	3.0%
MT	0.3%	4,014	68	1.7%	871	2	0.2%	3,143	69	2.2%
NC	0.3%	217,684	5,007	2.3%	23,884	119	0.5%	193,800	4,845	2.5%
ND	0.3%	937	6	0.6%	171	-	0.0%	766	6	0.8%
NE	0.3%	14,264	143	1.0%	3,090	9	0.3%	11,174	123	1.1%
NH	0.2%	17,204	206	1.2%	4,220	13	0.3%	12,984	195	1.5%
NJ	0.3%	86,120	689	0.8%	28,812	86	0.3%	57,308	630	1.1%
NM	0.3%	61,062	1,710	2.8%	4,727	38	0.8%	56,335	1,690	3.0%
NV	0.3%	36,814	994	2.7%	10,259	41	0.4%	26,555	956	3.6%
NY	0.3%	183,683	3,123	1.7%	40,193	121	0.3%	143,490	3,013	2.1%
OH	0.3%	127,162	1,399	1.1%	31,278	125	0.4%	95,884	1,246	1.3%
OK	0.4%	107,713	3,555	3.3%	6,389	64	1.0%	101,324	3,445	3.4%
OR	0.3%	28,703	373	1.3%	9,767	68	0.7%	18,936	322	1.7%
PA	0.3%	154,932	2,479	1.6%	31,057	124	0.4%	123,875	2,354	1.9%
RI	0.3%	8,521	60	0.7%	3,900	16	0.4%	4,621	46	1.0%
SC	0.3%	76,342	2,138	2.8%	11,411	91	0.8%	64,931	2,013	3.1%
SD	0.3%	2,901	35	1.2%	724	4	0.6%	2,177	30	1.4%
TN	0.3%	213,606	6,835	3.2%	16,095	161	1.0%	197,511	6,715	3.4%
TX	0.3%	332,047	9,297	2.8%	33,637	303	0.9%	298,410	9,251	3.1%
UT	0.3%	59,886	2,096	3.5%	7,416	52	0.7%	52,470	2,046	3.9%
VA	0.3%	145,573	1,892	1.3%	20,753	83	0.4%	124,820	1,872	1.5%
VT	0.2%	2,474	20	0.8%	1,120	3	0.3%	1,354	16	1.2%
WA	0.3%	56,858	682	1.2%	15,544	62	0.4%	41,314	578	1.4%
WI	0.3%	87,726	3,860	4.4%	13,420	121	0.9%	74,306	3,790	5.1%
WV	0.4%	6,277	113	1.8%	923	3	0.3%	5,354	112	2.1%
WY	0.3%	4,646	70	1.5%	1,129	7	0.6%	3,517	63	1.8%
All	0.3%	3,710,092	92,883	2.5%	761,773	5,049	0.7%	3,031,201	77,834	2.6%

Panel C: % Missing Credit Information by Age Cohort

Age Cohort	All			Fintech			Non Fintech Loans		
	Obs	# Missing	% Missing	Obs	# Missing	% Missing	Obs	# Missing	% Missing
≤ 24	91,994	6,072	6.6%	6,774	41	0.6%	85,220	6,051	7.1%
24–34	583,455	13,419	2.3%	112,045	672	0.6%	471,353	13,198	2.8%
35–44	798,590	15,972	2.0%	179,938	1,080	0.6%	618,592	14,846	2.4%
45– 54	900,136	17,103	1.9%	194,764	1,169	0.6%	705,332	16,223	2.3%
55–64	719,591	14,392	2.0%	143,364	1,004	0.7%	576,198	13,253	2.3%
≥ 65	543,587	10,328	1.9%	99,869	899	0.9%	443,701	9,318	2.1%
Missing	155,622	5,758	3.7%	24,988	225	0.9%	130,620	5,486	4.2%

Panel D: Comparison between Loans With and Without Missing Note Rate

Variable	Note Rate Missing			Note Rate Not Missing		
	Obs	Mean	St. Dev.	Obs	Mean	St. Dev.
Loan Size	1,574,134	$7,736	$13,810	2,218,839	$9,029	$10,144
Maturity	1,574,134	37.951	27.859	2,218,839	40.061	25.027
Note Rate				2,218,839	13.108	9.818
Borrower DLQ	1,574,135	22.856	41.99	2,218,839	20.53	40.392
Loan DLQ	1,574,135	1.836	13.424	2,218,839	1.181	10.801
No of Accounts	1,541,224	23.171	13.483	2,168,875	22.67	12.852
Total Balance	1,541,224	$100,795	$141,765	2,168,875	$111,386	$148,837
Auto Balance	1,541,224	$11,396	$16,049	2,168,875	$11,982	$16,247
Rev. Balance	1,541,224	$8,974	$24,750	2,168,875	$10,299	$24,136
Student Balance	1,541,224	$7,240	$24,097	2,168,875	$8,644	$27,088
Mortgage Balance	1,541,224	$68,706	$125,266	2,168,875	$76,155	$130,032
Student	1,574,135	0.263	0.44	2,218,839	0.293	0.455
Mortgage	1,574,135	0.534	0.499	2,218,839	0.531	0.499
Credit Score	1,573,470	649.835	98.472	2,217,822	656.674	97.347
Inquiries	1,541,224	1.289	1.632	2,168,875	1.227	1.595
Age of Credit	1,541,224	188.076	101.995	2,168,875	188.643	100.214
Rev. Utilization	1,523,687	0.44	0.354	2,149,164	0.429	0.336

Notes: The table reports the number of % of observations with missing data. We report the information on missing values for all the variables in Panel A. In Panels B and C, we report the information on missing credit report data, where missing is defined to include any missing value in number of accounts, total balance, auto balance, student loan balance, mortgage balance, credit score and age of credit. In Column (1) of Panel B, we also report the % of individuals with missing number of accounts, total balance, auto balance, student loan balance, mortgage balance, credit score and age of credit based on a a random sample of 14,000,000 consumers pulled with 2016 credit reports. In Panel D, we report summary statistics of all other variables between loans with and without missing note rate based on our loan sample.

Table A.2: Summary Statistics based on Split Samples

	Fintech Loans			Non-Fintech Loans			Fintech -
	N	Mean	St. Dev.	N	Mean	St. Dev.	Non-Fintech
Loan Size	761,773	$12,295	$11,014	3,031,201	$7,537	$11,825	$4,758
Maturity	761,773	53.908	29.604	3,031,201	35.486	23.968	18.422
Note Rate	400,748	16.041	9.398	1,818,091	12.462	9.791	3.579
Borrower DLQ	761,773	13.488	34.16	3,031,202	23.508	42.405	-10.02
Loan DLQ	761,773	2.257	14.854	3,031,202	1.25	11.111	1.007
No of Accounts	756,724	23.087	11.325	2,953,368	22.824	13.541	0.263
Total Balance	756,724	$146,716	$172,765	2,953,368	$96,807	$136,505	$49,909
Auto Balance	756,724	$13,407	$16,863	2,953,368	$11,311	$15,956	$2,096
Rev. Balance	756,724	$13,994	$28,931	2,953,368	$8,661	$22,972	$5,334
Student Balance	756,724	$12,579	$34,003	2,953,368	$6,903	$23,230	$5,677
Mortgage Balance	756,724	$102,628	$154,626	2,953,368	$65,486	$119,225	$37,142
Student	761,773	0.361	0.48	3,031,202	0.26	0.439	0.101
Mortgage	761,773	0.634	0.482	3,031,202	0.507	0.5	0.127
Credit Score	761,712	684.284	83.877	3,029,581	646.18	99.637	38.104
Inquiries	756,724	0.821	1.34	2,953,368	1.364	1.655	-0.543
Age of Credit	756,724	214.042	102.463	2,953,368	181.84	99.511	32.202
Rev. Utilization	753,851	0.461	0.304	2,918,990	0.427	0.353	0.034
Age	736,785	48.778	13.458	2,900,568	48.787	14.535	-0.009
Young	761,773	0.419	0.493	3,031,201	0.411	0.492	0.008
Male	761,773	0.537	0.499	3,031,201	0.51	0.5	0.027
Married	761,773	0.592	0.491	3,031,201	0.568	0.495	0.024
College	761,773	0.352	0.478	3,031,201	0.21	0.407	0.142
Professional	761,773	0.115	0.319	3,031,201	0.076	0.265	0.039
High Income	761,773	0.313	0.464	3,031,201	0.182	0.386	0.131
Prior Borrower DLQ	756,724	0.086	0.28	2,953,368	0.189	0.391	-0.103
Transactor	761,115	0.096	0.295	3,021,807	0.06	0.238	0.036
County HP Growth	761,773	0.015	0.014	3,031,201	0.011	0.017	0.004
County Home Value	761,504	$248,557	$145,855	3,030,956	$187,776	$122,001	$60,781
County Unemp Rate	761,773	6.254	1.231	3,031,202	6.587	1.714	-0.333
County % College	761,773	30.007	6.314	3,031,202	27.505	8.095	2.502
County Median Income	761,773	$59,773	$13,158	3,031,202	$54,233	$13,312	$5,540
County HP Decline	761,773	-0.239	0.177	3,031,201	-0.163	0.184	-0.076
County Fintech Share	760,414	0.219	0.096	2,976,508	0.116	0.102	0.103
County Bank Rate	760,414	13.882	3.284	2,976,506	12.257	5.482	1.625
County $ Internet	761,773	0.765	0.061	3,031,202	0.744	0.073	0.021

Notes: This table reports summary statistics of loan-level data split between fintech and by non-fintech loans. We draw a random sample of all unsecured personal loans originated by fintech and by non-fintech lenders from 2012–2017, excluding loans with missing origination date and invalid loan balance (negative or zero), but including loans with missing borrower credit report information (debt balances, age of credit and credit score). Borrower DLQ indicator is defined as an indicator for the borrowers who have any positive delinquent balance. 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. We also report 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. Fintech share 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.

Table A.3: Summary Statistics based on Consumer Credit Panel Sample

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Loan DLQ Indicator	38,248,189	0.76	8.684	0	0	0	0	100
Borrower DLQ Indicator	56,684,460	20.681	40.502	0	0	0	0	100
Credit Score	56,684,460	647.859	96.274	0	586	651	719	841
Total Debt	56,684,460	$105,194	$142,581	$ -	$14,708	$45,913	$152,492	$9,190,885
Revolving Debt	56,684,460	$9,083	$23,553	$ -	$300	$3,036	$9,923	$6,095,354
New Car Indicator	56,684,459	4.389	20.486	0	0	0	0	100
Unemployed Indicator	30,558,241	0.025	0.158	0	0	0	0	1
Post Job Loss Indicator	30,558,241	0.014	0.118	0	0	0	0	1

Notes: This table reports summary statistics of loan-month panel data that is associated with the borrowers in the loan sample. We restrict the credit history to 3 months before through 15 months after the origination of the personal loan. The two job loss variables are available in a subset of our loan-month panel matched with job loss data. We restrict the individuals with job loss to 3 months before and 3 months after their job loss date while those with no job loss are the same as our loan-month panel.

Table A.4: Loan Terms based on Matched Sample

Sample	Matched Borrowers that have Fintech and Bank Loans		
Dep Var	Loan Size	Loan Term	Note Rate
	(1)	(2)	(3)
Fintech Loan First	1,869.183***	-3.779***	1.070**
	(421.440)	(0.902)	(0.456)
Loan Size			-0.095***
			(0.007)
Terms			0.050***
			(0.008)
Credit Score	73.700***	0.055***	-0.079***
	(1.653)	(0.002)	(0.002)
Age of Credit	11.672***	0.006***	-0.005***
	(1.682)	(0.001)	(0.001)
Age	-60.256***	-0.053***	0.031***
	(7.316)	(0.013)	(0.006)
County $\times$ Time FE	Yes	Yes	Yes
N	116,544	116,544	74,388
R^2	0.655	0.752	0.832

Notes: The table reports the regression results examining the difference in the loan terms between the fintech and non-fintech loans in our sample. The dependent variable is reported in the column title: loan size, loan term and note rate. In addition to the Fintech loan indicator, we also control for borrowers' credit score, age of credit history and age. For the regression of note rate, we also control for loan size and maturity. Regressions are based on a subset of the sample that includes borrowers who have borrowed from both fintech and non-fintech lenders in 2012–2017. We first separate the sample based on whether they had a fintech-was-first loan or not. We then match the two subsamples using state and origination year and month of the first loan. In these regressions, we include county $\times$ year-month fixed effects. Standard errors are double clustered at county and origination year-month levels. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A.5: Soft Information: R^2 by Market Share

Specification		Sample				Fintech -
Controls	ZIP-YM FE	Market Share Quartile	Year	Fintech	Non-Fintech	Non-Fintech
Nonlinear	Yes	1	2013	0.735	0.964	-0.229***
Nonlinear	Yes	1	2014	0.947	0.908	0.039***
Nonlinear	Yes	1	2015	0.878	0.936	-0.058***
Nonlinear	Yes	1	2016	0.922	0.913	0.009***
Nonlinear	Yes	1	2017	0.639	0.946	-0.307***
Nonlinear	Yes	2	2013	0.871	0.865	0.006***
Nonlinear	Yes	2	2014	0.773	0.844	-0.071***
Nonlinear	Yes	2	2015	0.88	0.871	0.009***
Nonlinear	Yes	2	2016	0.71	0.931	-0.221***
Nonlinear	Yes	2	2017	0.799	0.853	-0.054***
Nonlinear	Yes	3	2013	0.865	0.718	0.147***
Nonlinear	Yes	3	2014	0.473	0.611	-0.138***
Nonlinear	Yes	3	2015	0.866	0.7	0.166***
Nonlinear	Yes	3	2016	0.844	0.674	0.170***
Nonlinear	Yes	3	2017	0.769	0.593	0.176***
Nonlinear	Yes	4	2013	0.926	0.564	0.362***
Nonlinear	Yes	4	2014	0.665	0.548	0.117***
Nonlinear	Yes	4	2015	0.517	0.494	0.023***
Nonlinear	Yes	4	2016	0.534	0.366	0.168***
Nonlinear	Yes	4	2017	0.524	0.351	0.173***

Notes: This table shows the R^2 for the full specification of a regression similar to Table 5 Panel B based on subsamples separated by individual lender's market share in a state in prior year and origination year. Lender's market share is grouped into quartiles for fintech and non-fintech lenders separately. Data includes all loans in our loan-level sample. In addition to nonlinear splines of credit score and loan size, we also control for loan maturity, length of credit history, number of accounts, revolving utilization, prior DLQ indicator, transactor indicator, mortgage indicator, student loan indicator and age. Tests of significance of R^2 differences follow Erickson and Whited (2002). Asterisks denote significance levels (***=1%, **=5%, *=10%)..

Table A.6: Loan Performance Using the Imputed Values

Dep Var	I(Loan DLQ$_i$)$\times$ 100				
	(1)	(2)	(3)	(4)	(5)
Fintech Loan Indicator	0.845***	1.121***	1.152***	1.211***	1.204***
	(0.027)	(0.029)	(0.029)	(0.037)	(0.037)
Loan Size		-0.144***	-0.132***	-0.131***	
		(0.021)	(0.020)	(0.023)	
Maturity		-0.001***	-0.003***	-0.003***	
		(0.001)	(0.001)	(0.001)	
Credit Score		-1.118***	-1.131***	-1.126***	-1.154***
		(0.013)	(0.013)	(0.015)	(0.015)
Age of Credit		-0.092***	-0.099***	-0.109***	-0.116***
		(0.008)	(0.008)	(0.010)	(0.010)
No of Accounts		-0.257***	-0.255***	-0.253***	-0.201***
		(0.007)	(0.007)	(0.009)	(0.009)
Age		-0.074***	-0.067***	-0.071***	-0.058***
		(0.008)	(0.008)	(0.010)	(0.010)
Time FE	Yes	Yes	No	No	No
County FE	Yes	Yes	No	No	No
County Time FE	No	No	Yes	No	No
ZIP $\times$ Time FE	No	No	No	Yes	Yes
Loan Size Bin FE	No	No	No	No	No Yes
Maturity Bin FE	No	No	No	No	Yes
N	3,792,757	3,792,757	3,792,757	3,792,757	3,792,757
R^2	0.007	0.016	0.039	0.225	0.226

Notes: The table reports the regression results examining the difference in the ex post performance between the fintech and non-fintech loans in our sample. The dependent variable in all regressions is an indicator whether the loan has even become delinquent from origination through 15 months after the origination. we also control for loan size and loan maturity, borrowers' credit score, age of credit history, no of accounts, revolving utilization ratio, prior borrower delinquent indicator at the time of loan origination and borrower age, as well as ZIP Code by origination year-month fixed effects. In Column (5), we also include loan rate as additional control. All the missing values in borrowers' credit score, age of credit history, age and loan note rate are imputed using the predictive mean matching methodology. Missing values are imputed to values randomly drawn from the distribution of the variable. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A.7: PSM First-Stage Regression

Dep Var	Fintech Loan Indicator		
	(1)		
Male Indicator	0.023***	No of Accounts	0.059***
	(0.001)		(0.001)
Married Indicator	-0.020***	Inquiries	-0.027***
	(0.001)		(0.000)
College Indicator	0.010***	Rev Utilization	0.031***
	(0.001)		(0.000)
High Income Indicator	0.015***	Prior DLQ Indicator	-0.003
	(0.001)		(36.030)
Young Indicator	0.022***	Change in Borrower DLQ	0.002
	(0.001)		(36.030)
Professional Indicator	0.004***	Transactor Indicator	-0.023***
	(0.001)		(0.001)
Total Balance	-0.010***	Student Indicator	0.021***
	(0.000)		(0.001)
Credit Score	-0.117***	Mortgage Indicator	-0.017***
	(0.001)		(0.001)
Age of Credit	-0.007***	Prior Auto Purchase Indicator	0.0001***
	(0.000)		(0.000)
ZIP FE	Yes		
Orig Time FE	Yes		
N	1,083,058		
R^2	0.189		

Notes: The table reports the results of pooled OLS regressions used in PSM. The dependent variable is the fintech loan indicator. PSM is done by ZIP Code based on our loan sample to construct the matched sample. We first restrict the sample to ZIP Codes that have at least 5 fintech and 5 non-fintech loans in our loan sample. Within each ZIP Code, we estimate a Logit regression of fintech loan indicator on all the covariates, including all the demographic (male, married, college, high income, young, professional) and consumer credit attributes (credit score, age of credit history, no of accounts, no of inquiries, revolving utilization rate, prior delinquency indicator, change in the borrower delinquency in the past 3 months, whether the borrower is a transactor, whether borrower have any student loan or mortgage, whether the borrower had an auto purchase in the 3 months before the origination) at the time of origination, as well as origination year-month fixed effects. Loans are matched between fintech and non-fintech loans using the nearest neighbor criteria.

Table A.8: Dynamic Effect based on Subsamples

Panel A: Borrowers Facing a High Ex Ante Interest Rate

Dep Var	Loan DLQ	Borrower DLQ	Credit Score	Total Debt	New Car	Revolving Debt
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Rel Qtr = -1		0.250**	-0.564***	-465.957	6.390***	-539.651***
		(0.126)	(0.131)	(312.648)	(0.427)	(37.651)
Fintech × Rel Qtr = 1		1.940***	6.640***	-3,711.414***	0.225***	88.066
		(0.122)	(0.208)	(323.960)	(0.087)	(66.291)
Fintech × Rel Qtr = 2	0.259***	4.206***	-2.476***	5,233.862***	0.219**	823.812***
	(0.039)	(0.166)	(0.281)	(426.729)	(0.086)	(80.811)
Fintech × Rel Qtr = 3	0.469***	6.276***	-7.701***	6,947.230***	0.043	1,307.554***
	(0.055)	(0.197)	(0.346)	(497.158)	(0.086)	(92.608)
Fintech × Rel Qtr = 4	0.844***	8.477***	-12.161***	8,390.635***	-0.082	1,547.387***
	(0.070)	(0.218)	(0.400)	(562.532)	(0.087)	(106.946)
Fintech × Rel Qtr = 5	1.424***	10.559***	-17.241***	9,093.286***	-0.151*	1,603.531***
	(0.085)	(0.242)	(0.453)	(640.469)	(0.089)	(116.792)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Relative Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,189,358	1,736,926	1,736,926	1,736,926	1,707,472	1,736,926
R^2	0.437	0.569	0.881	0.928	0.231	0.929

Panel B: Borrowers with Low Credit Score

Dep Var	Loan DLQ	Borrower DLQ	Credit Score	Total Debt	New Car	Revolving Debt
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Rel Qtr = -1		-1.065***	-1.402***	-724.681***	7.385***	-275.797***
		(0.144)	(0.131)	(194.675)	(0.306)	(19.718)
Fintech × Rel Qtr = 1		5.474***	12.243***	-2,860.107***	0.489***	-1,677.513***
		(0.143)	(0.171)	(194.882)	(0.065)	(29.426)
Fintech × Rel Qtr = 2	-0.420***	7.229***	5.192***	4,000.650***	0.614***	-769.520***
	(0.062)	(0.189)	(0.257)	(254.190)	(0.063)	(36.908)
Fintech × Rel Qtr = 3	0.043	9.083***	1.716***	5,417.106***	0.385***	-120.522***
	(0.083)	(0.212)	(0.313)	(293.185)	(0.063)	(42.221)
Fintech × Rel Qtr = 4	0.897***	11.175***	-1.052***	6,763.696***	0.324***	233.911***
	(0.096)	(0.225)	(0.345)	(333.425)	(0.065)	(48.676)
Fintech × Rel Qtr = 5	1.912***	12.772***	-4.018***	7,830.457***	0.379***	438.327***
	(0.106)	(0.239)	(0.378)	(370.938)	(0.066)	(56.564)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Relative Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,768,020	4,276,368	4,276,368	4,276,368	4,204,149	4,276,368
R^2	0.593	0.593	0.744	0.909	0.229	0.924

Panel C: Borrowers with Thin Credit Files

Dep Var	Loan DLQ	Borrower DLQ	Credit Score	Total Debt	New Car	Revolving Debt
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech × Rel Qtr = -1		-0.236	0.34	-104.073	6.278***	-269.992***
		(0.366)	(0.591)	(447.192)	(1.218)	(28.762)
Fintech × Rel Qtr = 1		2.977***	11.796***	-3,721.400***	-0.039	-324.585***
		(0.413)	(0.826)	(634.923)	(0.279)	(51.946)
Fintech × Rel Qtr = 2	-0.14	6.935***	-5.150***	697.006	0.06	446.975***
	(0.295)	(0.634)	(1.247)	(833.541)	(0.257)	(81.401)
Fintech × Rel Qtr = 3	2.309***	10.608***	-15.963***	850.578	-0.005	765.243***
	(0.406)	(0.770)	(1.589)	(952.169)	(0.261)	(103.657)
Fintech × Rel Qtr = 4	5.538***	14.472***	-23.610***	390.147	-0.152	842.961***
	(0.495)	(0.875)	(1.839)	(1,095.455)	(0.266)	(112.979)
Fintech × Rel Qtr = 5	8.775***	17.797***	-30.812***	-157.472	-0.385	691.858***
	(0.561)	(0.976)	(2.023)	(1,221.238)	(0.276)	(129.962)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Relative Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
N	116,952	174,109	174,109	174,109	170,889	174,109
R^2	0.614	0.512	0.751	0.843	0.123	0.709

Notes: The table reports the difference in the dynamics of several credit attributes between the fintech and non-fintech loans in three subsamples. The regression is based on the loan-month panel from 3 month before through 15 months after the origination of the loan, restricted to the loans in the PSM–matched sample and borrower credit attributes. Panel A is based on a subsample of borrowers whose loan rate is higher than the average rate of the loans originated in the same county, year month and similar credit score (20-point bins) in our sample. Panel B is based on a subsample of borrowers whose credit score is below 700 at time of origination. Panel C is based on a subsample of borrowers whose length of credit history is less than 48 months at time of origination. The dependent variable is the column title. Our main explanatory variable is the fintech loan indicator interacted with the relative quarter dummies. In all regressions, we control for individual, calendar time and relative quarter fixed effects. Standard errors are double clustered at county and origination year-month levels. Asterisks denote significance levels (***=1%, **=5%, *=10%).

.

Table A.9: Repeat Bank Borrowers

Dep Var	$I(\text{Bank}_i) \times 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Indicator for Last Loan	0.140***	0.139***	0.136***	0.146***	0.138***	0.136***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
× Low Credit				-0.014***		
				(0.001)		
× Thin Credit					-0.169***	
					(0.006)	
× Main Lender						-0.002**
						(0.001)
Male Indicator		0.0005	-0.002***	-0.003***	-0.002***	-0.002***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married Indicator		0.001	0.004***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College Indicator		-0.023***	-0.019***	-0.019***	-0.018***	-0.019***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
High Income Indicator		-0.034***	-0.029***	-0.029***	-0.028***	-0.029***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Young Indicator		-0.015***	-0.012***	-0.012***	-0.012***	-0.012***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Professional Indicator		-0.021***	-0.017***	-0.017***	-0.017***	-0.017***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls	No	No	Yes	Yes	Yes	Yes
ZIP × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,695,511	1,695,510	1,650,172	1,650,172	1,650,172	1,650,172
R^2	0.546	0.548	0.551	0.551	0.553	0.551

Notes: The table report the regression results of likelihood of bank (non-fintech) borrowers taking another bank loan in the future based on loan-level data. The dependent variable is the bank loan indicator. Main explanatory variable is whether borrower's last loan is a bank loan. We also interact this variable with indicators for low credit score (≤ 700), thin credit file (length of credit history shorter than 48 months), and whether the fintech lender was the main borrower's lender (highest loan balance). We also control for all the demographic (male, married, college, high income, young, professional) and consumer credit attributes at the time of origination, as well as 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. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A.10: Fintech Loans and Outcomes of the Unemployed Borrowers

Dep Var	Loan DLQ	Borrower DLQ	Credit Score	Total Debt	New Car	Revolving Debt	Log(Income)	I(Income $\leq$ 5%)	Log(Base Income)	Log(Other Income)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post Job Loss	0.027	-0.076	-0.051	182.669*	0.037	65.092***	-0.05	-0.278	-0.07	0.357
	(0.023)	(0.099)	(0.130)	(94.225)	(0.053)	(12.969)	(0.093)	(0.220)	(0.092)	(0.920)
$\times$ Post Fintech	0.004	0.347***	-0.257	-912.969***	-0.332***	-308.380***	-0.073	1.588***	0.003	-2.238
	(0.062)	(0.119)	(0.189)	(232.130)	(0.082)	(33.044)	(0.149)	(0.337)	(0.151)	(1.520)
Post Fintech	1.426***	1.308***	0.017	9,243.88***	-3.589***	-55.399*	0.377***	-1.153***	0.321**	5.620***
	(0.099)	(0.097)	(0.169)	(205.788)	(0.085)	(32.456)	(0.131)	(0.298)	(0.131)	(1.275)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,085,902	3,039,183	3,039,183	3,039,183	3,007,083	3,039,183	689,833	549,273	685,753	685,640
R^2	0.436	0.559	0.82	0.908	0.05	0.904	0.955	0.385	0.954	0.877

Notes: The table reports the regression results examining the relationship between fintech loan origination and borrower outcomes for those that lost their jobs. The regression is based on our loan-month panel data matched with individual job loss data. We restrict the sample to borrowers who lost their job at some point. We restrict the borrower by year-month panel to 12 months before and 12 months after the job loss date. Dependent variables are column titles: those in the first six columns are similar those in Table 8; logarithm of total annual income in Column (7); an indicator whether borrower's total income has increased more than 5% from last quarter in Column (8); logarithm of base income in Column (9); logarithm of variable income in Column (10). Regressions in Columns (7)-(10) are based on only individuals with income available. Post job loss is an indicator that takes 1 for individuals with job loss after their job loss date. Post fintech is an indicator that takes 1 for fintech borrowers after their loan origination date. We control for individual and time fixed effects in all regressions. Standard errors are double clustered at county and origination year-month levels. Asterisks denote significance levels (***=1%, **=5%, *=10%).