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

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Abstract

Did Fintech lenders ease credit access for borrowers underserved by the traditional banking? Are borrowers able to improve their credit outcomes through a personal loan by a Fintech lender? We address these questions using a unique individual-level data providing detailed information about borrowers' credit histories and lenders' identities and the *Madden vs. Midland Funding, LLC* case as source of exogenous variation. We find that Fintech borrowers earn more, live in higher income neighborhoods, are on average younger, and more likely to be professionals. However, we show that Fintech borrowers are significantly more likely to default and exhibit higher indebtedness than similar individuals borrowing from traditional financial institutions. Fintech borrowers tend to carry a significant credit card balance, and are more likely to consume the additional funds rather than using them to consolidate high-cost credit card debt. Overall, these findings suggest that Fintech lenders enable households with a particular desire for immediate consumption to finance their expenses and borrow beyond their means.

Keywords: Fintech, Banking, Innovation, Self-control, Present-bias

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1. Introduction

Financial markets have recently witnessed a disruptive force: the rise of online intermediaries and, more generally, *Fintech* companies, i.e. firms that apply technology to improve financial activities. Fintech companies 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 might 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.[2] This might be because they face significantly lower fixed costs, e.g., they do not have branches, or because they are less strictly regulated, which might allow them to adopt laxer lending standards.[3] Thus, the entry by Fintech lenders might alleviate credit frictions, such as credit rationing due to information asymmetries (Stiglitz and Weiss, 1981) or imperfect competition (Parlour and Rajan, 2001). This might result in access to credit for financially constrained households or lower financing costs for those who switch from traditional banks to new online lenders. On the contrary, the use of different data and tools might enable Fintech lenders to capture the most creditworthy borrowers, which might result in lowering the average quality of the pool of households borrowing from banks.

In addition to these possibilities, Laibson (1997) cautions that financial innovation might enable individuals to *over-borrow*. Fintech, in particular, might be an attractive option for borrowers with self-control issues, because of the fully online application process and the

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

significantly higher speed to being approved and having access to the new funds.[4] The ease with which borrowers have access to additional credit might tempt them to borrow beyond their means, leading to higher default rates and worse financial outcomes for the individuals borrowing from Fintech lenders. Thus, what the overall effect is remains an empirical question.

Ideally, to investigate these issues one would need individual-level data on borrowers' characteristics, including information about their liabilities, recorded not only at the time of the loan application but over time; furthermore, it would be critical to have a benchmark to assess Fintech borrowers' performance, 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 are 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 from traditional banks.

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

The paper has three main sets of findings. The first set of results investigates the *ex-ante* characteristics of the borrowers, by examining whether Fintech lenders substituted banks in underserved areas and whether the households borrowing from Fintech were previously rationed by traditional banks. We show that Fintech borrowers tend to be younger, have higher income, exhibit a better credit history due to lower delinquency rates, live in richer neighborhoods with

[4] Most Fintech lenders advertise their ability to deposit the funds within 48 hours compared to significantly longer delays for traditional financial institutions.
[5] One of the three main credit bureaus, TransUnion, established that Fintech companies have grown from a mere 1% of personal loan originations in 2010 to one-third of the entire market in 2017 (Transunion, 2017).

higher house price appreciation, and are more likely to be professionals. Most of the Fintech borrowers have credit scores in the mid-range between 640 and 720. They are less likely to have a mortgage, but more likely to still have to pay off their student loans. 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 region-times-month fixed effects.

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

The second set of results exploits the panel nature of our data to follow borrowers over time and analyze their *ex-post* performance. Since Fintech borrowers do not seem to be subprime or riskier in general, we would expect them to perform better ex-post. Instead, we show that Fintech loans are about 3% more likely to be in default after just few months post-origination, in addition, the Fintech borrowers are also more likely to be delinquent on any other account after having access to the Fintech loan. These results are driven by the comparison of similar individuals borrowing from banks and Fintech, as we control for all observable characteristics (i.e. borrowers;' credit characteristics and demographics), loan terms as well as borrower fixed effects to absorb any time-invariant borrower characteristic. Furthermore, 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. Finally, these effects are the strongest among least creditworthy individuals, which suggests that rather being able to identify the "invisible prime" borrowers, the Fintech lenders perform worse than traditional institutions.

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

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

Albeit we control in a flexible way for observable characteristics and exploit the panel dimension of our data by using borrower fixed effects, to causally determine whether the access to additional credit through Fintech lenders is responsible for the increase in defaults we observe in the data, we would need a source of exogenous variation affecting the demand or the supply of credit. To this end, we exploit the *Madden vs. Midland Funding LLC* court ruling in May 2015 between a New York-based borrower and a collection agency. The Second Circuit court overseeing New York, Connecticut and Vermont ruled that the National Bank Act's usury-rate preemption would not apply to third party debt-buyers like Midland. This resulted in the interest and principal of these loans to be null and void in the Second Circuit. This decision had important repercussion to Fintech lenders as their loan agreements carry interest rates in excess of the usury limits of 16%. Furthermore, this logic applies beyond the sale of delinquent loans to debt collectors, but includes also secondary sale of loans to non-national bank purchasers through securitization activities, which is the prevalent source of capital for Fintech companies. Then, we exploit this decision as a contraction in credit supply from Fintech lenders in the Second Circuit compared to other states. More specifically, we should expect the contraction to be concentrated among the riskiest borrowers, who should be the ones paying higher interest rates, i.e. above the usury law cutoff.

In a difference-in-differences framework, we first show that the Madden court ruling had a significant effect on the Fintech lenders' supply of credit: riskier borrowers experienced a significant reduction in credit availability from Fintech lenders of about 17%. In contrast, as expected, this decision had no impact on traditional lenders. To further corroborate these results, we show that the average interest rate charged by Fintech lenders declined by about 2% in the aftermath of the lawsuit decision, as Fintech lenders are now effectively capped by the limits imposed by the state laws.

Having established that this was a significant shock for the Fintech lenders, we then analyze the borrowers' ex-post performance. We do this in several ways. First, we look in aggregate at the number of delinquencies in the treated states compared to the control ones, and we find a significant decline among Fintech borrowers. Second, we distinguish between high and low credit score borrowers and find the results to be concentrated among riskier borrowers. Third, we exploit the granularity of our data and explore delinquency at the individual level, and provide further evidence that the contraction in lending resulted in a lower probability to default.

We find no change in the average riskiness of the pool of individuals that borrow from traditional institutions, which suggest that some borrowers are rationed from the credit market as banks are not willing to lend to the same type of borrowers as the Fintech lenders. In other words, there is no substitution from Fintech to banks. Finally, we show that the average level of indebtedness significantly declined for borrowers whose loans originated after the court decision compared to the pre-ruling period. Overall, these results show that the borrowers having access to the additional capital provided by Fintech lenders tend to significantly underperform due to excessive leverage.

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

Our paper contributes to a growing literature examining marketplace lending.[7] Vallee and Zeng (2018), for instance, examines how information provision by a marketplace lender to investors affects their performance, using a sudden reduction in the information about borrowers' characteristics provided by Lending Club after 2014. Hertzberg, Liberman and Paravisini (2018), instead, shows how maturity choice can be used to screen borrowers by exploiting a natural experiment due to changes in the menu of loans offered by Lending Club. Whereas Buchak, Matvos, Piskorski and Seru (2018) and Fuster et al. (2018) study whether there is substitution or complementarity between Fintech lenders and traditional banks in the mortgage market.

There are also few recent studies that focus specifically on the consumer credit segment of the market, i.e. unsecured personal loans. For instance, Tang (2018) takes advantage of a regulatory change resulting in a contraction in the credit supplied by traditional banks to show that peer-to-peer lenders substituted banks for infra-marginal borrowers. Similarly, De Roure, Pelizzon and Thakor (2018) compare banks loans with the ones granted by a German peer-to-peer lender and show that the latter are riskier but exhibit lower risk-adjusted rates. Liao et al. (2017) focus on

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

the largest platform in China and show that it is mainly attracting underserved borrowers. Also related is a recent study by Chava and Paradkar (2018). They exploit panel credit bureau data about a marketplace lender to investigate the extent of misrepresentation in the stated purpose of the loan and to show that some borrowers benefit from these loans by having access to additional credit from traditional lenders. Finally, Danisewicz and Elard (2018) exploit the Madden court decision to show that personal bankruptcy might arise as reversing access to marketplace lenders.

We contribute to this growing literature by taking advantage of the unique features of our data. Specifically, these previous studies have relied upon information provided by a single marketplace lender. Furthermore, the data is usually aggregated at the regional level and is only provided at origination. Our study, instead, uses a comprehensive panel data on Fintech borrowers that allows us to estimate the impact of obtaining a Fintech loan on the borrower's performance, controlling for a wide set of characteristics. In addition, we are able to compare Fintech loans to bank loans directly. Finally, our data include all the major Fintech lenders except Prosper.[8]

Finally, our results also belong to the literature showing how present bias or short-term impatience might explain households' borrowing behavior (e.g. Ausubel, 1991; Laibson, 1997; Heidhues and Koszegi, 2010). The empirical evidence has already uncovered how these behavioral traits might play a role in numerous contexts (e.g. DellaVigna and Malmendier, 2006, Kaur, Kremer and Mullainathan, 2015). However, most related to our findings are the papers by Meier and Sprenger (2010) and Kuchler (2013) directly linking self-control to credit card spending and Laibson, Repetto and Tobacman (2007) and Nakajima (2015) who study the effects of present bias on credit card debt in a life-cycle model. We take advantage of the insights emerged in this literature to uncover evidence corroborating the view that easier access to credit might be misused by present-biased individuals.

The rest of the paper is organized as follows. Section 2 describes the data employed and the construction of the sample. Section 3 explores which characteristics of the borrowers are associated with obtaining a Fintech loan. Section 4 presents our results on borrowers' performance, Section 5 discuss potential mechanisms, while Section 6 presents our results based on the Madden vs. Mdiland Funding decision. Section 7 concludes.

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

2. Data

2.1 Data Sources

Our analysis relies mainly on data available at one of the nation's largest credit bureaus. The credit bureau provides information on households' balance sheets, specifically, monthly payment history of all the borrower's loans, including auto loans, mortgages, home equity lines of credit, student loans and credit cards (revolving). It also contains information about the main features of these individual loans, such as date opened, account type, credit limits, monthly scheduled payment (for installments only), balance, lender and performance history.[9] It contains more than 200 million consumer credit files and over a billion credit trades, i.e. information about single loans, and is updated monthly. Limited versions of this data have been employed in other papers studying households' financial decisions. However, our proprietary version is unique in a few respects.

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

2.2 Sample Design

To create a representative and matched sample, we first identify all the individual accounts associated with the top Fintech companies in the credit tradeline data. We define Fintech lenders

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

those who operate exclusively online and do not have a brick and mortar presence, do not accept deposits, and are not regulated by the Fed or the Office of the Comptroller of the Currency (OCC). We also require them to be recently founded.[10] We restrict our sample to only the trades with a minimum of $500 credit limit, accounts opened since January 1, 2012 when there are at least 100 of these loans originated by these companies in a given month, and borrowers living in Continental USA. After excluding a few credit files with missing information, there are about 2.6 million Fintech loans. We then identify 18 million personal loans originated by banks. We randomly draw 25% of all personal loans originated by Fintech lenders and by non-Fintech lenders, excluding loans with missing origination date, missing loan terms, missing loan limits, missing credit score or those with credit score below 440, missing total balance, missing number of accounts, missing ZIP Code and county, and invalid loan balance (negative or zero). For the borrower by year-month panel data, we match all loans in our loan-level sample with monthly credit report data.

2.3 Summary Statistics

Our final sample contains 3,384,786 loans originated during the sample period, 2012-2016. 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 (Panel A) as well as for the analysis related to the Madden case (Panel B). Our main analysis is at the borrower by year-month level. We start to track the credit outcomes of Fintech borrowers three months prior to when they open up a Fintech account through 15 months after that. For non-Fintech borrowers, we track them around a similar period measured in calendar time. Our panel data sample contains over 53 million records. On credit outcomes, we report typical information: the number of accounts, and the balance on all the main accounts, i.e. auto, student and mortgage, borrower's credit score which predicts borrower's creditworthiness in the near future, the age of the credit history, delinquent (DLQ) balance and also DLQ rate at the time of origination. Panel A also reports information about borrower's credit, demographic and employment characteristics at origination, as well as some regional characteristics such as house prices, unemployment, and median income at origination.

On average, US consumers in our sample have more than 20 financial accounts opened during the sample period and have an average credit score of 658. Revolving accounts (credit

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

cards) balance is on average $10,000, while revolving utilization is on average 49%, although the standard deviation is significant (30%). 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 credit limit and loan term for almost all the loans in our sample. On average, borrowers take out $8,256 per loan with average term of 39 months. With scheduled payment, term and limit, we calculate the original note rate to be about 13% on average for the vast majority of our loans. We also summarize the ex-post borrower and loan performance at the loan level based on the maximal delinquent balance during our observation window on any account and the personal loan, respectively. As of December 2017, 22% of the borrowers and 1.4% of the loans in our sample have experienced at least one delinquency.

Panel B also reports information about the subsample of borrowers we consider for the analysis related to the Madden case. The summary stats show that this sample of borrower is not significantly different from the main sample used in the analysis.

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

To describe how this growth has been heterogeneous across states, Figure 2 plots the state fixed effects in a regression where the dependent variable is an indicator for Fintech loans. States on the west coast such as California and Arizona, as well as Florida in the south, and the east coast are the states with the highest number of Fintech loans. To control for the potential differences in

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

demand factors that might have driven the heterogeneity in the rise of Fintech lenders between states, in our analysis we always control for region by time fixed effects.

3. Who Borrows from Fintech Lenders?

Since very little is known about this market and the borrowers that turn to Fintech borrowers, this section explores which borrowers' characteristics are related to entering in a lending relationship with Fintech lenders. That is, before investigating how obtaining a Fintech loan affects borrowers' behavior and credit outcomes, we first explore the ex-ante heterogeneity among individuals borrowing from different types of lenders. In other words, we ask: who borrows from Fintech lenders? Different hypothesis have been proposed. On the one hand, Fintech lenders might be able to serve individuals that have been previously rationed, by being more competitive than traditional banks due to their lower fixed costs and laxer regulatory constraints. On the other hand, Fintech lenders might employ financial innovations, such as machine learning techniques applied to alternative data, to target the most profitable borrowers.

We test these hypotheses by estimating the following baseline specification:

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

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

3.1 Regional Heterogeneity

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

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

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

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

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

3.2 Credit Characteristics

A natural question is whether the Fintech borrowers exhibit different risk profiles. 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. Furthermore, since both our dependent and independent variables are at the borrower level, Column (1) shows that each S.D. increase of credit score, about 84 points, is associated with 2% higher likelihood of borrower obtaining a Fintech loan on average. The specification is useful to compare the linear effects of credit score, but it is also important to understand whether the Fintech lenders focus on one particular segment of the market. For instance, are they targeting the subprime borrowers or are they trying to attract the best-performing customers? An intuitive way of addressing these questions is to run a similar specification to (1) but with different dummies for different credit score bins, and then plot the coefficients. We do so in the top panel of Figure 3 using 20-point bins. We find that borrowers with credit scores between 640 and 720 are the most likely to have a Fintech loan. In other words, the bulk of customers for Fintech lenders is neither in the bottom nor in the very top of the credit score distribution.

Are Fintech lenders strategically focusing on customers with a longer credit history potentially to exploit the higher degree of information available about their profiles? Column (2) does not support this hypothesis, because it shows that the length of the credit history does not have an economically significant effect. Column (3) suggests that Fintech borrowers have also on average a higher number of credit accounts.

Consistent with the intuition that one of the main purposes of obtaining a personal loan is to consolidate existing debts with higher interest rates, Column (4) shows that Fintech borrowers are more likely to have a higher revolving utilization ratio. Each S.D. increase of credit card utilization, 30%, is associated with 3% higher likelihood of borrower obtaining a Fintech loan. However, Column (5) shows that these borrowers are significantly less likely to be delinquent at the time of origination, suggesting that although they might be younger and not super prime borrowers, they are less likely to have defaulted on their debts before.

Another complementary way to assess the borrowers' profiles is to investigate how they manage their current accounts. The credit bureaus classify borrowers in *revolvers* and *transactors*, depending on their use of credit cards. Revolvers are borrowers that carry balance over multiple months, while transactors tend to pay off their credit cards at the end of each month. We find that Fintech borrowers are significantly less likely to be transactors. This evidence is noteworthy as it is one of the findings supporting the view that Fintech borrowers might be present-biased. Columns (7) and (8) show that these borrowers are also more likely to have a student loan but not a mortgage (again consistent with their young age). Column (9) shows the same results in a multivariate setting. It is worth noticing that once we control for the other characteristics, it is even less likely that a borrower who has been late on his existing debts is able to be approved for a Fintech loan, as the coefficient on the delinquency indicator triples in size.

Finally, one possibility is that Fintech lenders attract borrowers with just higher or lower credit score; another possibility is that, even within credit score bins, they are able to cater to more creditworthy borrowers. Panel B of Table 3 explores these hypotheses by separately examining borrowers with credit scores below 700 and above 740. We find that among higher credit scores borrowers, those with a shorter credit history, higher number of accounts, higher utilization and lower score are more likely to borrow from Fintech firms. Whereas among lower credit scores borrowers, those exhibiting utilization and being a transactor are not significantly driving the credit decisions. These findings suggest that the credit score is not the only dimension the Fintech lenders pay attention to, and that within segment of the market, the Fintech lenders consider the borrowers' information somewhat differently.

3.3 Socio-demographic characteristics

We exploit the granularity of our data to investigate whether Fintech borrowers are also different on other demographic information. Panel C of Table 3 shows that borrowers with Fintech loans are more likely to be male (Column 1), and less 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 3% more likely to borrow from Fintech companies. We complement the previous analysis with information about the borrowers' occupations: technician, management, cleric worker, laborer, student, homemaker, retired, or business owner. We find that professionals are significantly more likely to have a Fintech loan. These findings further suggest that the more educated borrowers and those with higher-paying jobs are more likely to turn to Fintech lenders for their financial needs. Finally, the bottom panel of Figure 3 plots the fixed effects for different individual ages. It shows that Fintech borrowers are more likely to be in their mid-thirties to mid-forties. This is consistent with the hypothesis that Fintech borrowers are in general younger than those borrowing from traditional lenders.

3.4 Loan Terms

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

We find that Fintech are more generous about granting larger loans: on average, a Fintech loan has a $3,800 higher balance. We also find that usually the maturity of the loan is about one month shorter. A larger loan and a shorter maturity come at the expense of a 3.6% higher interest rate on average.

Interestingly, once we control for borrower fixed effects and restrict attention to borrowers having both a Fintech and a bank personal loan, the results for credit balance and loan maturity are similar, although the magnitude changes to $2,600 and two months respectively, but the interest rate differential changes significantly to just 30 bps difference between Fintech and bank loans. This is probably because the borrower fixed effect is capturing most of the variation in the borrower's riskiness profile, and that is the main dimension that drives variation in the interest rate from the institutions' point of view.

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

To investigate these hypotheses, we examine next whether Fintech loans are more or less likely to be in default. To do so, in Table 5 Panel A we exploit the loan-level data which also allows us to take advantage of within-borrower variation as we observe multiple loans for the same borrower. Column (1) reports the results controlling for a full set of borrower's credit characteristics, the loan terms (including the rate, maturity and the amount), in addition to county and time fixed effects. We find that Fintech loans are about 2.4% more likely to be delinquent. Column (2) shows similar results once we control for ZIP Code by month fixed effects, 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 zip code with the same terms.

However, this result could be driven by unobservable borrower characteristics between those that have a Fintech loan and those who do not. Then, Column (3) includes borrower fixed effects, which allows us to compare whether a borrower with a Fintech loan is more or less likely to default on its Fintech loan rather than on the other loans. We find that the Fintech loan is about 1.3% more likely to be in default. This is noteworthy because, although the economic magnitude decreases, controlling for borrower fixed effects make sure that the higher delinquency is not exclusively driven by potential adverse selection that might drive borrowers away from traditional banks and towards new lenders.

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

These results are noteworthy given the initial findings on the better ex-ante characteristics of the Fintech borrowers. To further examine the performance of these loans, we can analyze how the borrowers' performance changes over time since the loan origination. Specifically, in Table 5 Panel B we estimate the following specification:

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

in which, on the left hand side, we estimate the loan delinquency dynamics around the loans origination. The main independent variables are the interaction between time dummies identifying the periods before and after the loan origination times the Fintech borrower indicator with exact month when the Fintech loan is originated omitted as the reference bucket. This dynamic specification allows us to include borrower fixed effects δ_i as well as county-by-month fixed effects $\xi_{c,t}$. In other words, we are comparing delinquency for Fintech and bank loans before and after obtaining the loan for the same borrower relative to the month when the borrower obtained the loan controlling for changes in local economic conditions.

In Columns (1)-(3) the dependent variable is loan delinquency, which would then capture whether borrowers are more or less likely to default on Fintech loans, while in Columns (4)-(6) the dependent variable is delinquency on any account. Column (1) reports the results for the whole sample, while the second and the third column distinguish between high and low credit score. We find that Fintech loans are also more likely to be delinquent by 1.3% within 12 months since origination, while they are 2.7% more likely to default between 12 and 15 months after origination. Columns (2) and (3) analyze separately the borrowers with credit score below 700 and above 740, which are the two thresholds commonly used in credit industry to delineate borrower quality. They further confirm that low credit score borrowers are the ones performing the worst in the aftermath of the Fintech loan origination. In fact, low credit score borrowers start being delinquent already within six months since origination, and their likelihood to default is more than ten times larger after one year compared to high credit score borrowers.

Column (4)-(6) complement the previous analysis by exploring whether the Fintech borrowers are in general more likely to default post-origination on any account. Column (1) shows that, until seven months after origination, the likelihood of having an account in default is slightly lower for the borrowers with Fintech loans compared to those with bank loans, controlling for borrower fixed effects. However, starting in month 8 the likelihood that Fintech borrowers default is increasing over time and reaches 1.5% one year after origination. This corresponds to about a 10% increase in the likelihood to default. Columns (2) and (3) report the same specification but looking at the two subsamples based on credit score. The evidence clearly shows that, although the effects are statistically significant for both subsamples, the magnitude of the effects is greater for the low credit score borrowers. In fact, one year after origination, low-credit-score Fintech borrowers are about 1.5% more likely to default than bank borrowers, compared to 0.6% for high credit score individuals.

Figure 4 and 5 complement the previous findings by plotting the delinquency dynamics for different subsamples. Figure 4 reports the results for the whole sample, and for the high and low credit score subsamples. The panels clearly show that Fintech loans to less creditworthy borrowers are significantly more likely to be in default than bank loans to similar borrowers. Figure 5 also shows that a similar insight holds for borrower delinquency, i.e. Fintech borrowers tend to be more delinquent on any account after the loan origination. One might think that these results might potentially be driven by the earlier cohorts, when the Fintech lenders had limited data and might have been more prone to face adverse selection. The right panel of Figure 5 shows that this is not the case, in fact, we find that the results are consistent across cohorts, although some years (e.g. 2014 and 2015) are worse than others (e.g. 2012 and 2016).

Overall, these results provide evidence that albeit Fintech borrowers seem to be more creditworthy than borrowers obtaining loans from other institutions, they 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 banks in that segment. The next section explores different reasons for why this might be the case.

5. Discussion

What might be the reason for this higher delinquency probability? One possibility is that the Fintech borrowers are using the additional funds not to consolidate their debts, but rather to support additional expenditures. Table 6 Panel A shows evidence supporting this view. Specifically, Columns (1) and (2) show that total debt starts significantly increase more for Fintech borrowers since the third month after the origination. The effects are quite large, as the Fintech borrowers' indebtedness increases by almost five thousand dollars one year after origination. Intuitively, borrowers might use the additional funds to repay their credit cards, but then might start financing their expenditures with these credit cards again, which results in a greater total indebtedness and higher financial fragility.

Our data does not contain explicit measures of consumption, but we can follow Di Maggio et al. (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. Columns (3) and (4) show that Fintech borrowers are more likely to purchase a car in the months following the loan origination, with the highest spike in the first two months by as high as 0.5%. This evidence corroborates the view that part of the reason for the increase in defaults is the propensity of the Fintech borrowers to spend the additional funds rather than using them to achieve financial responsibility.

Figure 6 complements the previous findings by plotting the coefficients on the interaction term of Fintech loan indicator and relative monthly dummies from a regression with credit score as dependent variable. It shows a sudden and more substantial increase in credit score in the aftermath of the Fintech loan origination compared to bank loans, but within the first year since origination, Fintech borrowers are more likely to experience sharp declined in their credit worthiness. This is consistent with the hypothesis that the Fintech borrowers tend to only experience short-term benefits from access to extra credit.

These results suggest that another hypothesis consistent with both our results on delinquency and the results on increasing indebtedness and consumption after the loan origination is that Fintech borrowers are more likely to be present-biased. To investigate whether this hypothesis is supported by the data, we take inspiration from the existing works showing that, even controlling for credit and demographic characteristics, present-biased individuals are more likely to have credit card debt and to have significantly higher amounts of credit card debt (see Meier and Sprenger, 2010 and Kuchler, 2013). This suggests that Fintech borrowers should be more likely to be revolvers and the increased fragility due to higher leverage should be concentrated among this type of borrowers, as these are more likely to exhibit self-control issues.

Table 6 Panel B shows that this is indeed what we find in the data. Columns (1) and (2) investigate any delinquency, while Columns (3) and (4) analyze loan delinquency. The effects are more than twice as large for the revolvers as for transactors. For instance, after 12 months, Fintech borrowers that are revolvers are 1.2% more likely to default than bank borrowers, while for Fintech borrowers that are transactors the difference is 0.7%. For loan delinquency, one year after origination, the revolvers are 2.8% while the transactors are 1.2% more likely to be delinquent on the personal loan than bank borrowers.

In addition to these behavioral explanations, another non-mutually exclusive possibility that could explain the worse performance of the Fintech loans, is that not 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 can report our loan and borrower delinquency results by differentiating between the cases in which the Fintech and the bank that are providing the personal loan are the main lenders and those in which they are not. We define as main lenders the institution providing the largest loan to the borrower. We report the results in Panel C of Table 6 for these two subsamples.

Odd columns report the results for the non-main lenders, while even columns analyze whether the effects are different for the main lenders. We find that for both subsamples the Fintech borrowers are more likely to default, irrespective of whether the Fintech institution is the main lender or not. If anything, we find that the magnitude of the effects is significantly higher for the case in which the loans are originated by the main lender.

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

6. Madden vs. Midland Funding, LLC

To provide further evidence that borrowing from Fintech lenders affects the borrowers' creditworthiness, we exploit an exogenous credit supply shock. This supply shock is the result of the Second Circuit court in favor of Saliha Madden against Midland Funding LLC, a debt-collection agency. Madden defaulted on a Bank of America credit card that charged a 27% interest rate in 2011 and her debt was transferred to Midland Funding, one of the country's largest purchasers of unpaid debts. However, at that point, the borrower claimed that under the Fair Debt Collection Practices Act the debt was effectively illegal, because the 27% interest rate was in violation of New York State's 16% usury rate. The argument was that while Bank of America as a national bank is regulated by the National Bank Act which preempts these constraints, Midland did not have the same rights as a bank to override New York's state usury laws. While she lost in 2013 at the district court level, she won the appeal two years later.

The court ruled that the National Bank Act's usury-rate preemption would not apply to third party debt-buyers like Midland. This resulted in the interest and principal of these loans to be null and void in the Second Circuit.[12] This decision had important repercussion to Fintech lenders as they extensively deal in consumer and credit cards loans, and their loan agreements carry interest rates in excess of 16%. Furthermore, this logic applies beyond the sale of delinquent loans to debt collectors, but might also include the secondary sale of loans to non-national bank purchasers through securitization activities, which is the prevalent source of capital for Fintech companies.

The importance of such decision for the Fintech industry is corroborated by the intense lobbying that, after the Supreme Court refused to review the case, has pushed the Congress to propose the Protecting Consumers Access to Credit Act in 2017, which while has been approved by the House, it has not passed in the Senate yet. This bill aimed to enforce the validity of a loan after it is bought by a non-bank, in accordance with the "valid when made" doctrine.[13]

Our empirical methodology exploit this event occurred in May 2015 as a negative shock to the credit supply by Fintech lenders. We then use this shock to trace whether in response to this

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[12] The Second Circuit court covers New York, Connecticut, and Vermont but in Vermont only the interest above the usury level is to be considered null. For our purposes, since the number of loans originated in Vermont is too small, we will only consider New York and Connecticut as our treatment states.

[13] For further details about the Madden case, see Danisewicz and Elard (2018) as well as https://lending-times.com/2017/11/22/madden-vs-midland-funding-llc/ and https://www.americanbanker.com/opinion/bill-to-correct-madden-ruling-would-benefit-consumers.

shock, the likelihood of borrowers defaulting has declined significantly. We start by estimating the first stage, that is, the effects of this court ruling on the supply of credit with the following difference-in-differences specification:

$$Origination\ Volume_{c,t} = Treated\ States \times Post\ + \mu_c + \xi_t + \varepsilon_{i,c,t}$$

where the dependent variable is the log of origination volume in each month by Fintech lenders, and the sample period is January to December 2015. We only consider the 2015 origination year, because in the later part of the sample, the Fintech lenders figured out that by retaining a portion of the loan on their balance sheet they would be able to overcome the constraints introduced by the Madden ruling. So we expect the effect to be temporary.

Table 7 presents evidence based on a zip-month level dataset. Column (1) consider the total volume originated in 2015 and while the coefficient is negative, it is not statistically significant. However, Columns (2) and (3) differentiate between loans above and below 680, which is the cutoff in the data that is most frequently associated with loans above the usury law threshold. We find statistical and economical significant results that the Fintech lenders reduced by more than 17% their credit supply to riskier borrowers. Whereas, the supply of credit to high credit score borrowers was unaffected, which is consistent with the hypothesis that the contraction is driven by the court ruling and not by a general decline in credit demand. Panel A of Figure 7 complements the previous findings by showing that even at the individual level, there is a sudden decrease post May 2015 in the propensity to obtain a loan by Fintech lenders, while there is no difference between states in the pre-period. Panel B of Table 7 presents a placebo where we look at the loans originated by non-Fintech lenders and find no different before and after the ruling, further confirming our identification assumption.

Table 8 shows that the Second Circuit states exhibited a significant decline in their interest rates both when we equal weight and volume weight (Columns 1 and 2). Intuitively, after the court ruling, the rates are capped by the newly enforced usury laws. Furthermore, as before, the effects are only present in the low credit score segment. The effects are also economically significant as the rate declined by almost 2%.

Having established that the Madden case resulted in a contraction in lending by Fintech institutions, we can then see whether this affected the average borrower performance in those states. Table 9 provides evidence that the borrower's delinquency in the treated states for the low credit score segment declined by 1.5% (Column 1), while there is no effect for the non-Fintech borrowers. In addition, the results are concentrated among low score individuals as shown by the significantly lower magnitude of the coefficient in Column (3).

Similarly, to what we have shown in Table 6, we can distinguish between revolvers and transactors and explore whether as expected the most fragile borrowers are the most affected. Panel B of Table 9 shows that the loan delinquency of the revolvers declined by 1.6% in the aftermath of the Madden case, whereas we find smaller effects for transactors (Column 2), and no effect at all for the non-Fintech lenders. In sum, these results suggest that the Madden case has actually increased the quality of the pool of Fintech borrowers, without negatively affecting the banks' borrowers.

To further corroborate this result, we can exploit the individual level data in Panel C of Table 9. Columns (1) and (2) focus on Fintech lenders while Columns (3) and (4) report the results for the non-Fintech. We can test whether the borrowers taking a loan in the months before the Madden ruling performed significantly different from the ones taking a loan afterwards, controlling for the borrowers' characteristics (Column 1 and 3) and for individual fixed effects (Column 2 and 4). Consistent with the aggregate evidence, we find that individuals obtaining a loan after the Madden case were about 70 basis points less likely to default. The effects on non-Fintech are positive but very small, about 5 basis points. These results suggest that even controlling for time-invariant unobservable characteristics that might drive the decision to borrow from a Fintech or traditional lender, the Madden case improved performance of the Fintech borrowers.

Finally, we show that the mechanism through which the Madden case alleviated Fintech borrowers' worse performance is by limiting the scope for over-indebtedness. Table 10 reports the total borrowing by Fintech borrowers in a specification similar to the one presented in Table 9. If the Madden case resulted in rationing from the credit market borrowers that tended to take excessive leverage, we should find that it resulted in a decline in the borrowing amount for Fintech individuals. That is exactly what we find: after the Madden case, Fintech borrowers tend to have lower leverage, while there is no change in the pool of non-Fintech borrowers.

Taken together, these results provide evidence that the results presented in Table 5 about the loan performance of Fintech borrowers do not seem to driven by unobservable heterogeneity among borrowers, but rather, by the Fintech lenders' propensity to lend to individuals who tend to be more likely to take on excessive leverage.

7. Conclusion

The growing importance of Fintech lenders in the consumer lending market poses the question of whether they provide credit access to borrowers who were underserved by traditional banks or whether these financial innovations are just a vehicle for borrowers to finance higher consumption expenditures. We find evidence supporting the latter hypothesis. In fact, borrowers exhibit good credit scores at origination, are less likely to have been delinquent on an account in the past, have numerous credit accounts with traditional institutions, and are more likely to live in prosperous neighborhoods. However, their credit outcomes significantly worsen in the months following the Fintech loan origination compared to similar individuals borrowing from non-Fintech lenders.

The underlying mechanism seems to be the borrowers' tendency to use the additional credit to finance consumption rather than improve their financial situation. While we do not expect to have a single explanation for these results, we do present several tests showing that these results seem to be driven by consumers with present bias and short-term impatience exploiting the credit access ease of the Fintech lenders to borrow excessively to support their consumption. Intuitively, as an increase in interest rate attracts less creditworthy borrowers, an increase in the origination speed advertised by Fintech lenders is likely to attract borrowers with an immediate need for the loan; or whose financial conditions are going to deteriorate in the near future, which might be detected by the slower-moving traditional financial institutions.

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

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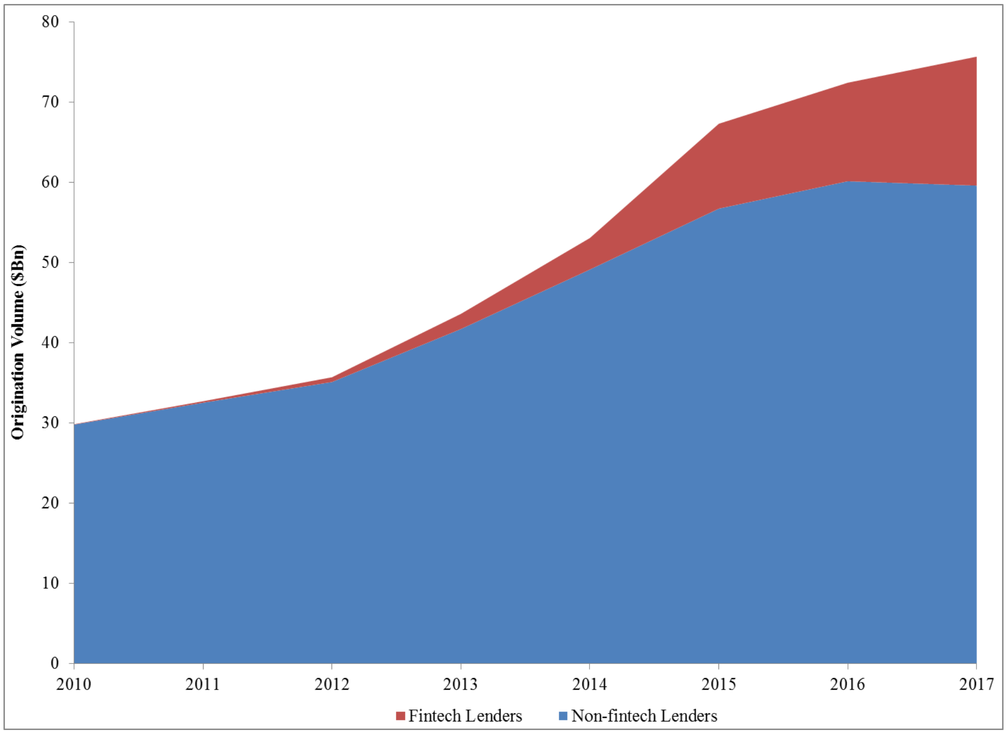


Figure 1

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

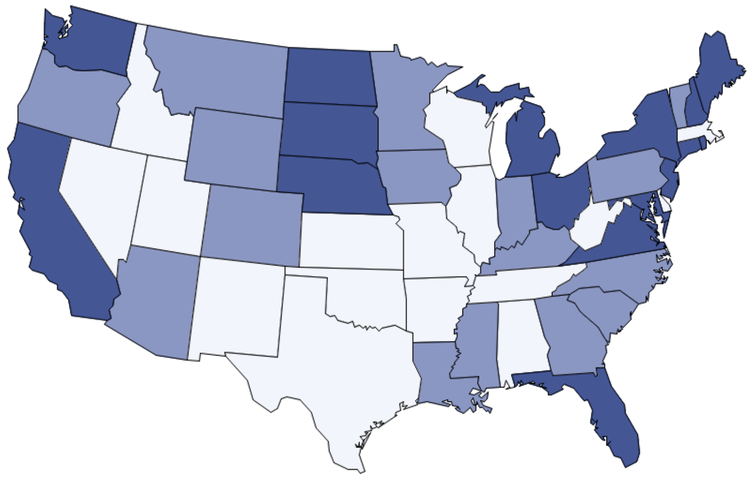
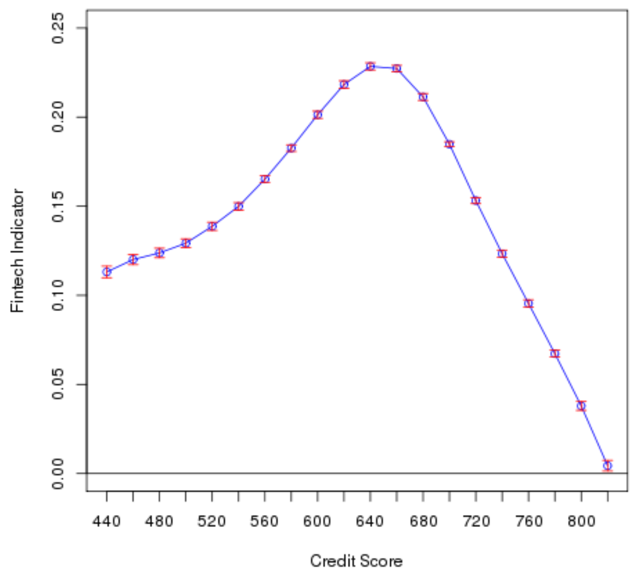


Figure 2

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

Panel A



Panel B

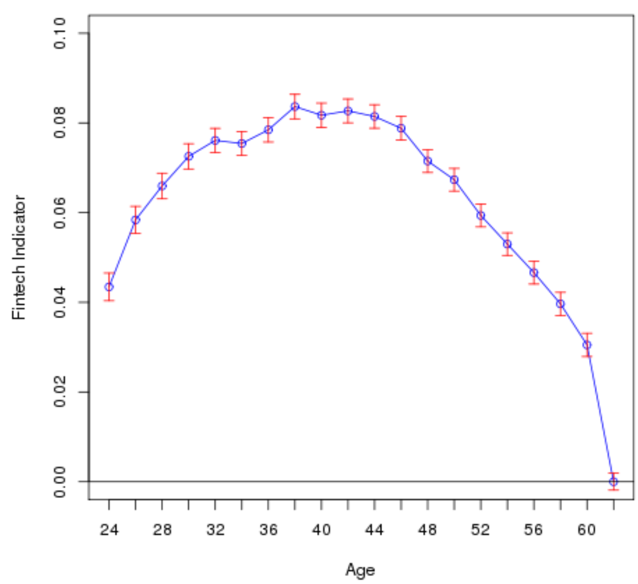


Figure 3

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

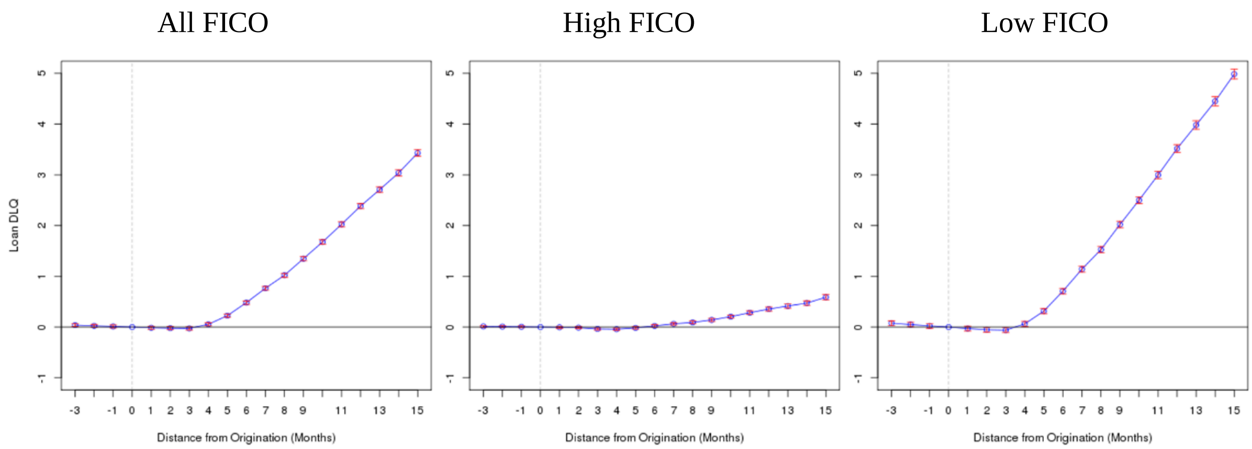


Figure 4

These figure plots the coefficients on the interaction term of Fintech loan indicator and relative monthly dummies from regressions of consumer credit outcomes. Relative monthly dummies are defined as the interval, in months, from origination date of the Fintech loan. The dependent variables is an indicator for loan delinquency. Left figure plots coefficients for the whole sample while central (right) figure plots coefficients for high (low) FICO sub-samples. FICO refers to the Vantage risk score that has a distribution from 350 to 850. We control for borrower fixed effects, Fintech loan indicator, relative monthly dummies and origination year-month-Zip Code fixed effects. Standard errors are double clustered at Zip Code and origination year-month cohort level. The regression is based on panel data for our random sample of personal loans.

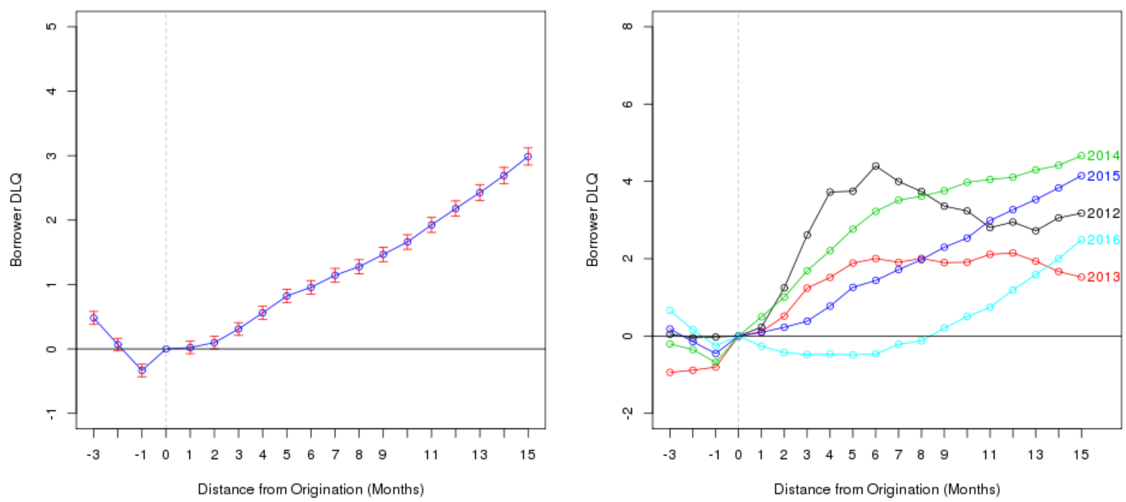


Figure 5

These figure plots the coefficients on the interaction term of Fintech loan indicator and relative monthly dummies from regressions of consumer credit outcomes. Relative monthly dummies are defined as the interval, in months, from origination date of the Fintech loan. The dependent variable is an indicator for borrower delinquency which is equal to one if the borrower has a positive delinquent balance in that month. The left figure of plots coefficients for the whole sample, while the right figure plots coefficients by origination year. We control for borrower fixed effects, Fintech loan indicator, relative monthly dummies and origination year-month-Zip Code fixed effects. Standard errors are double clustered at Zip Code and origination year-month cohort level. The regression is based on panel data for our random sample of personal loans.

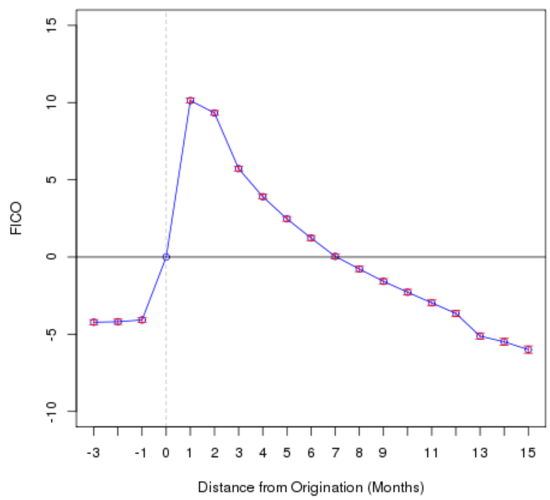
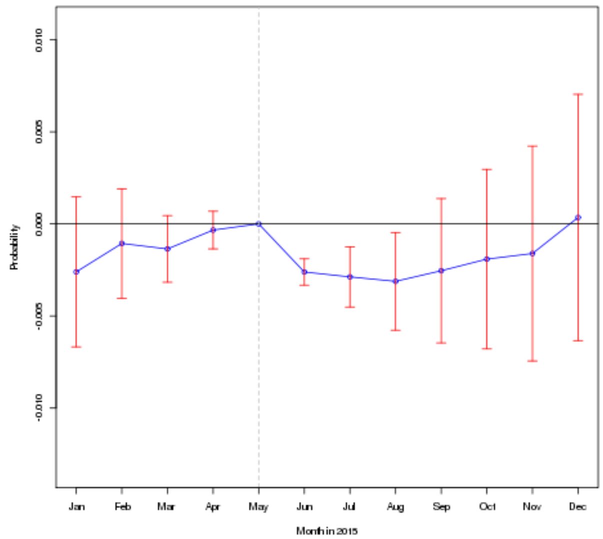


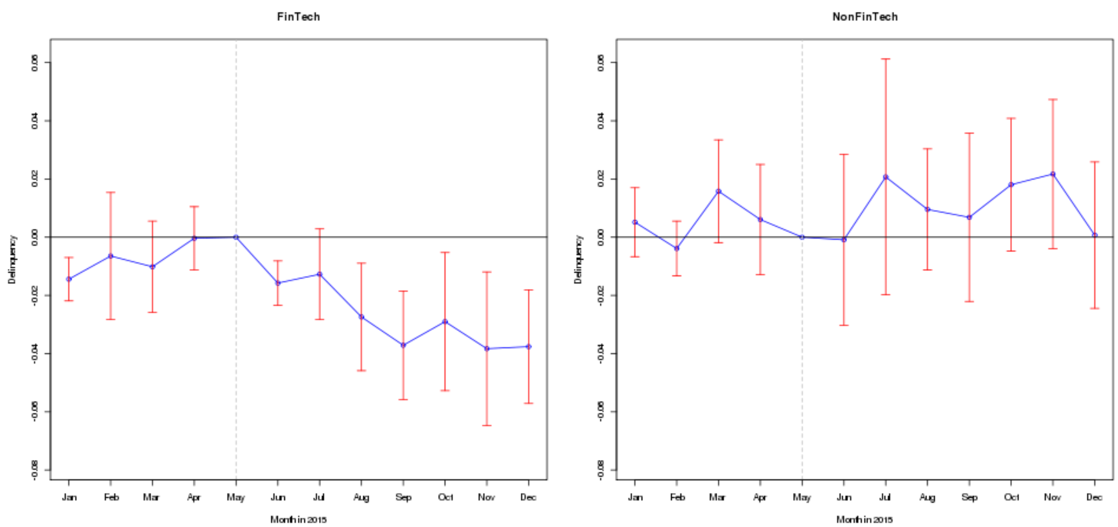
Figure 6

These figure plots the coefficients on the interaction term of Fintech loan indicator and relative monthly dummies from regressions of consumer credit score. FICO refers to the Vantage risk score that has a distribution from 350 to 850. We control for borrower fixed effects, Fintech loan indicator, relative monthly dummies and origination year-month-Zip Code fixed effects. Standard errors are double clustered at Zip Code and origination year-month cohort level. The regression is based on panel data for our random sample of personal loans.

Panel A



Panel B



Panel C

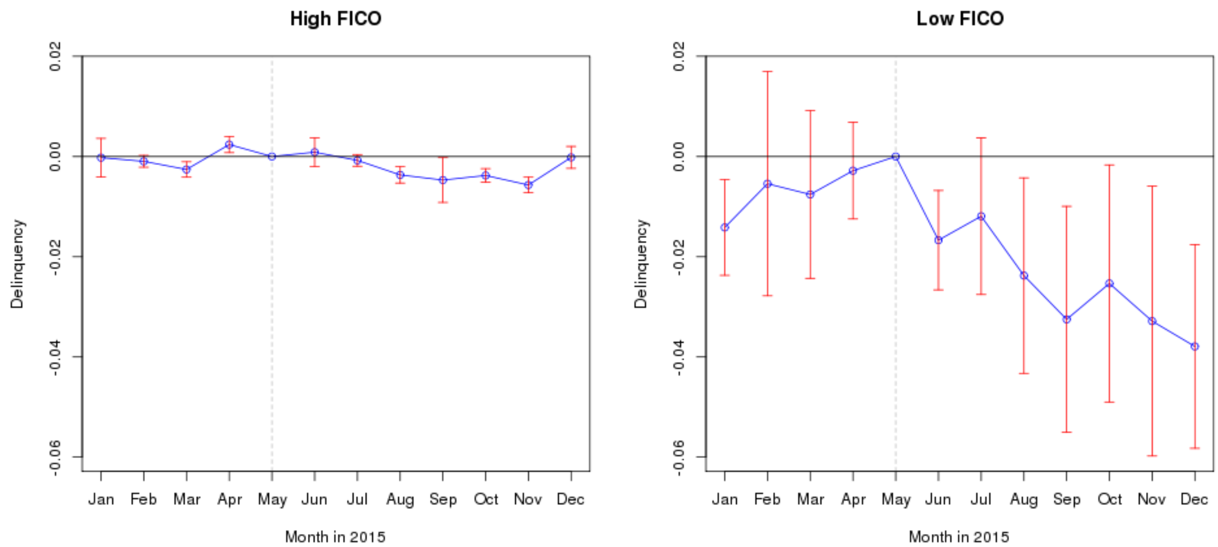


Figure 7

These figure plots the coefficients on the interaction term of New York/Connecticut origination indicator and origination month dummies from regressions of consumer credit outcomes. Origination month dummies are defined as the interval, in months, from January to December of 2015. Dependent variables are the probability of getting a Fintech loan (Panel A) and log number of delinquent loans aggregated at Zip Code-origination month (Panel B). Left figure of Panel B plots the coefficients for the log number of delinquent Fintech loans aggregated at Zip Code-origination month, while the right figure plots the coefficients for the log number of delinquent Non-Fintech loans. Left figure of Panel C plots the coefficients for the log number of delinquent Fintech loans to high FICO borrowers while the right figure plots the coefficients for the log number of delinquent Fintech loans to low FICO borrowers. Delinquency indicator equals one if the borrower has a positive delinquent balance in that month. FICO refers to the Vantage risk score that has a distribution from 350 to 850. In Panel A, we control for credit limit, FICO, loan terms and include county fixed effects and origination month fixed effects. In Panel B and C, we control for county fixed effects and origination month fixed effects. Standard errors are clustered at state level. The regression is based on panel data for our random sample of personal loans.

Table 1

Summary Statistics

This table reports summary statistics of loan-level data (Panel A) based on our random sample of personal loans as well as a subset of loans originated in 2015 (Panel B). We randomly draw 25% of all personal loans originated by Fintech and by non-Fintech lenders, excluding loans with missing origination date, missing credit score, missing total balance, missing number of accounts, and invalid loan balance (negative or zero). In Panel A, we report statistics on consumer credit variables at the time of origination of personal loans. All the variables are from credit report data from one of the credit bureaus. Borrower DLQ indicator is defined as an indicator for the borrowers who have positive delinquent balance. We also report statistics on the loan-level and borrower-level demographic characteristics for the sample we analyze in the paper. All the variables are from credit trade data as well as demographic data from the credit bureau. High income indicator is defined as an indicator for the households whose income is more than $100,000. Professional indicator is defined as an indicator for the households whose heads work in the professional, technical and management occupations. Fintech and bank borrower indicator is defined as an indicator for borrowers who have borrowed from both Fintech and non-Fintech lenders during our sample period. We also report few county-level statistics from various sources. Home price and home price changes are from Zillow. Unemployment rate, fraction of college degree and median household income are from Census Bureau. Fraction of Fintech loans and average bank loan rate are computed based on all loans in our sample originated in the prior three months in a given county. High-speed internet coverage is from Census Bureau's American Community Survey (available from 2013 by county). In Panel B, we report statistics for the subset of loans originated in 2015.

Panel A

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Credit Score	3,384,786	658.234	84.809	441	598	658	721	840
Age of Credit History	3,384,710	186.755	100.729	0	120	168	239	1,012
No of Accounts	3,384,767	22.779	13.49	1	13	21	30	92
Rev. Utilization	2,736,130	0.49	0.308	0	0.22	0.495	0.759	1
Rev. Balance	2,842,338	10,343.19	16,021.47	0	1,228.00	4,896.00	12,422.00	101,294.30
DLQ Indicator	3,384,786	0.167	0.373	0	0	0	0	1
Transactor Indicator	3,376,573	0.067	0.251	0	0	0	0	1
Student Loan Indicator	3,384,786	0.283	0.451	0	0	0	1	1
Mortgage Indicator	3,384,786	0.54	0.498	0	0	1	1	1
No of Inquiries	3,384,767	1.258	1.609	0	0	1	2	74
Age	3,244,140	48.716	14.312	14	37	48	59	99
Male Indicator	3,384,786	0.515	0.5	0	0	1	1	1
Married Indicator	3,384,786	0.571	0.495	0	0	1	1	1
College Indicator	3,384,786	0.239	0.427	0	0	0	0	1
High Income Indicator	3,384,786	0.211	0.408	0	0	0	0	1
Professional Indicator	3,384,786	0.084	0.277	0	0	0	0	1
Credit Limit	3,384,786	8,256.06	8,531.97	1	1,575	5,300	11,600	40,000
Loan Terms	3,384,786	39.041	26.142	1	13	36	60	360
Loan Note Rate	1,981,958	13.024	9.674	0	7.05	11.549	18.637	36
Borrower DLQ	3,382,506	22.596	41.821	0	0	0	0	100
Loan DLQ	3,384,786	1.406	11.774	0	0	0	0	100
QoQ HP Change	3,384,767	0.013	0.017	-0.137	0.003	0.012	0.022	0.137
HP Level	3,377,336	202,183.70	130,777.20	39,900	118,000	159,000	233,400	981,500
Cum. HP Decline 2007-10	3,384,786	-0.182	0.185	-0.662	-0.314	-0.168	-0.042	0.731
UnEmployment Rate	2,119,619	6.519	2.043	2	5.1	6.2	7.6	31.2
Median HH Income	2,791,683	55,429.71	14,776.34	23,358	45,213	52,610	61,523	134,609
Fraction of College Degree	2,119,619	27.632	9.758	6.866	20.568	27.889	33.498	75.091
Fraction of Fintech Loans	3,335,398	0.137	0.109	0	0.037	0.117	0.223	0.774
Average Bank Rate	3,335,371	12.592	5.15	0	10.048	13.32	16.012	33.783
High-Speed Internet Coverage	2,940,013	0.747	0.077	0.298	0.71	0.754	0.794	0.937

Panel B

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Credit Score	673,672	658.818	83.778	441	600	659	720	838
Age of Credit History	673,655	190.03	100.593	0	123	172	242	812
No of Accounts	673,667	23.082	13.543	1	13	21	31	92
Rev. Utilization	553,942	0.491	0.304	0	0.229	0.498	0.754	1
Rev. Balance	573,405	10,498.56	16,080.38	0	1,348.00	5,052.00	12,570.00	101,294.30
DLQ Indicator	673,672	0.162	0.368	0	0	0	0	1
Transactor Indicator	673,104	0.069	0.254	0	0	0	0	1
Student Loan Indicator	673,672	0.286	0.452	0	0	0	1	1
Mortgage Indicator	673,672	0.546	0.498	0	0	1	1	1
No of Inquiries	673,667	1.249	1.621	0	0	1	2	74
Age	646,609	49.142	14.211	17	38	49	59	99
Male Indicator	673,672	0.515	0.5	0	0	1	1	1
Married Indicator	673,672	0.57	0.495	0	0	1	1	1
College Indicator	673,672	0.244	0.429	0	0	0	0	1
High Income Indicator	673,672	0.215	0.411	0	0	0	0	1
Professional Indicator	673,672	0.085	0.279	0	0	0	0	1
Credit Limit	673,672	8,598.89	8,441.46	1	1,788	6,000	12,000	40,000
Loan Terms	673,672	39.615	25.292	1	15	36	60	240
Loan Note Rate	370,487	12.344	9.555	0	6.495	10.942	17.696	36
Borrower DLQ	673,672	23.019	42.095	0	0	0	0	100
Loan DLQ	673,672	1.598	12.539	0	0	0	0	100
QoQ HP Change	673,672	0.014	0.015	-0.113	0.005	0.013	0.021	0.129
HP Level	672,258	204,305.10	130,915.60	40,000	120,000	160,200	234,200	968,800
Cum. HP Decline 2007-10	673,672	-0.186	0.185	-0.662	-0.317	-0.169	-0.051	0.731
UnEmployment Rate	673,672	5.342	1.506	2	4.4	5.2	6.1	27
Median HH Income	673,672	57,017.85	14,729.81	27,711	46,696	53,994	63,589	125,900
Fraction of College Degree	673,672	28.418	9.79	6.866	20.877	28.691	34.502	75.091
Fraction of Fintech Loans	673,672	0.163	0.1	0	0.076	0.156	0.241	0.611
Average Bank Rate	673,672	11.886	4.795	0	9.37	12.754	15.435	30.281
High-Speed Internet Coverage	587,185	0.748	0.077	0.298	0.71	0.754	0.794	0.937

Table 2

Geographic Characteristics

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

	Dependent variable: FinTech Loan Indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
QoQ HP Change	0.008***								
	(0.000)								
HP Level		0.031***							
		(0.001)							
Cum. HP Decline 2007-10			-0.022***						
			(0.001)						
UnEmployment Rate				-0.015***					
				(0.001)					
Median HH Income					0.025***				
					(0.001)				
Fraction of College Degree						0.023***			
						(0.001)			
Fraction of Fintech Loans							0.110***		
							(0.001)		
Average Bank Rate								0.024***	
								(0.001)	
High-Speed Internet Coverage									0.018***
									(0.001)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384,767	3,377,336	3,384,786	2,119,619	2,791,683	2,119,619	3,335,398	3,335,371	2,940,013
R^2	0.075	0.078	0.076	0.083	0.08	0.086	0.099	0.075	0.07

Table 3

Borrowers' Characteristics

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

Panel A

	Dependent variable: FinTech Loan Indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit Score	-0.021***								-0.045***
	(0.0005)								(0.001)
Age of Credit History		-0.006***							-0.003***
		(0.0003)							(0.0003)
No of Accounts			0.018***						0.015***
			(0.0003)						(0.0004)
Rev. Utilization				0.030***					0.010***
				(0.0004)					(0.0003)
DLQ Indicator					-0.031***				-0.093***
					(0.001)				(0.001)
Transactor Indicator						-0.045***			-0.027***
						(0.001)			(0.001)
Student Loan Indicator							0.061***		0.053***
							(0.001)		(0.001)
Mortgage Indicator								0.0002	0.007***
								(0.001)	(0.001)
Zip-YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384,786	3,384,710	3,384,767	2,736,130	3,384,786	3,376,573	3,384,786	3,384,786	2,729,983
R^2	0.28	0.278	0.28	0.288	0.279	0.279	0.283	0.278	0.301

Panel B

	Dependent variable: FinTech Loan Indicator	
	High FICO	Low FICO
	(1)	(2)
Credit Score	-0.105***	0.027***
	(0.002)	(0.001)
Age of Credit History	-0.007***	0.006***
	(0.001)	(0.001)
No of Accounts	0.019***	0.014***
	(0.001)	(0.0005)
Rev. Utilization	0.011***	0.001*
	(0.001)	(0.0004)
DLQ Indicator	-0.049***	-0.034***
	(0.012)	(0.001)
Transactor Indicator	-0.017***	0.002
	(0.001)	(0.002)
Student Loan Indicator	0.041***	0.056***
	(0.001)	(0.001)
Mortgage Indicator	0.008***	0.002**
	(0.001)	(0.001)
Zip-YearMonth FE	Yes	Yes
Observations	1,061,040	1,668,943
R^2	0.445	0.428

Panel C

	Dependent variable: FinTech Loan Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Male Indicator	0.007***					0.006***
	(0.0005)					(0.0005)
Married Indicator		-0.012***				-0.017***
		(0.0005)				(0.0005)
College Indicator			0.018***			0.014***
			(0.001)			(0.001)
High Income Indicator				0.027***		0.028***
				(0.001)		(0.001)
Professional Indicator					0.011***	0.007***
					(0.001)	(0.001)
Zip-YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384,786	3,384,786	3,384,786	3,384,786	3,384,786	3,384,786
R^2	0.278	0.278	0.278	0.278	0.278	0.279

Table 4

Loan Terms

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

	Credit Limit	Loan Term	Note Rate	Credit Limit	Loan Term	Note Rate
	Borrowers that have Fintech or Bank Loans			Borrowers that have FinTech and Bank Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Loan Indicator	3,847.157***	-0.872***	3.629***	2,665.209***	-2.022***	0.307***
	(27.692)	(0.094)	(0.044)	(37.233)	(0.103)	(0.068)
Credit Attributes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Limit and Loan Terms			Yes			Yes
Zip-YearMonth FE	Yes	Yes	Yes			
Borrower FE				Yes	Yes	Yes
YearMonth FE				Yes	Yes	Yes
Observations	3,244,071	3,244,071	1,898,127	179,503	179,503	110,896
R^2	0.439	0.478	0.55	0.703	0.566	0.746

Table 5

Loan and Borrower Delinquency

These tables report the regression results of borrower and loan performance based on loan-level data. In Panel A the dependent variable is delinquent loan indicator, which identifies whether the personal loan has a positive delinquent balance since the origination year-month through December 2017. In Panel B, the dependent variable is delinquent loan indicator for the columns (1)-(3) and delinquent borrower indicator, which identifies whether borrower has any delinquent account in the columns (4)-(6). In Panel B, columns (2) and (5) restrict attention to borrowers with credit score above 700 at origination, while columns (3) and (6) restrict attention to borrowers with credit score less than or equal to 700. FICO refers to the Vantage risk score that has a distribution from 350 to 850. In Panel A, we control for borrowers' age, credit score, age of credit history, and loans' credit limit and loan term. In Panel B, we control for borrowers' credit score and delinquency status at loan origination, and loans' credit limit and loan term. Additionally, fixed effects for borrower, month, origination month, month relative to origination are used in Panel B. Standard errors are double clustered at Zip Code and origination year-month levels in Panel A and at county and origination year-month levels in Panel B. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	Dependent variable: Loan DLQ Indicator			
	(1)	(2)	(3)	(4)
Fintech Loan Indicator	2.413***	2.343***	1.250***	2.784***
	(0.047)	(0.053)	(0.081)	(0.053)
x Fraction of Fintech Loans				-0.649***
				(0.042)
Fraction of Fintech Loans				0.593***
				(0.013)
Credit Characteristics	Yes	Yes	Yes	Yes
Loan Features	Yes	Yes	Yes	Yes
County FE	Yes			Yes
YearMonth FE	Yes			Yes
Zip-YearMonth FE		Yes		
Borrower FE			Yes	
Observations	3,244,071	3,244,071	3,244,071	3,196,728
R^2	0.02	0.193	0.741	0.018

Panel B

	Dependent variable: Loan DLQ Indicator			Dependent variable: Borrower DLQ Indicator		
	All FICO	High FICO	Low FICO	All FICO	High FICO	Low FICO
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Loan Indicator						
x 1-3 Months Before	-0.219***	-0.015*	-0.153***	-0.896***	-0.053*	-0.942***
	(0.017)	(0.009)	(0.023)	(0.046)	(0.029)	(0.064)
x 1 Month After	-0.251***	-0.028***	-0.206***	-0.795***	-0.077**	-0.802***
	(0.016)	(0.009)	(0.022)	(0.047)	(0.034)	(0.065)
x 2 Month After	-0.263***	-0.033***	-0.231***	-0.757***	-0.016	-0.818***
	(0.016)	(0.009)	(0.022)	(0.049)	(0.038)	(0.069)
x 3-7 Months After	0.002	-0.046***	0.085***	-0.211***	0.045	-0.313***
	(0.019)	(0.010)	(0.028)	(0.049)	(0.035)	(0.070)
x 8-12 Months After	1.351***	0.078***	1.835***	0.640***	0.294***	0.528***
	(0.034)	(0.017)	(0.047)	(0.06)	(0.047)	(0.083)
x 12-15 Months After	2.704***	0.250***	3.553***	1.559***	0.622***	1.506***
	(0.046)	(0.026)	(0.062)	(0.071)	(0.063)	(0.097)
Credit Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Loan Features	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Relative YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,017,514	16,843,463	36,174,051	53,017,514	16,843,463	36,174,051
R^2	0.321	0.272	0.328	0.58	0.298	0.552

Table 6

Evidences on the Mechanism

These tables report results from regressions of consumer credit outcomes based on loan-month panel data (in Panel A), and regressions of loan performance (in Panel B and C). Dependent variables are total amount of debt in Columns (1) and (2), and indicator for car purchases in Columns (3) and (4) in Panel A; loan DLQ in Columns (1) and (2), and borrower DLQ in Columns (3) and (4) and in Panel B and C. The indicator for car purchases is equal to one whenever a borrower opened a new auto tradeline, or their existing auto balance changes by more than $5,000. In Panel B, odd Columns restrict attention to the subsample of borrowers whose personal loan is from a lender that is not the borrower's largest personal loan creditor while even Columns restrict attention to borrowers whose personal loan is from a lender that is the borrower's largest personal loan creditor. In Panel C, odd Columns restrict attention to the subsample of borrowers who have been classified as *revolvers* by the credit bureau, while even Columns restrict attention to borrowers who have been classified as *transactors*. We control for borrowers' credit score and delinquency status at loan origination, and loans' credit limit and loan term. Also, fixed effects for month and month relative to origination are included. Columns (1) and (3) of Panel A include Fintech fixed effects while all the other columns include borrower fixed effects. Standard errors are double clustered at county and origination year-month levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	Dependent variable: Total Debt		*Dependent variable: New Car*	
	(1)	(2)	(3)	(4)
Fintech Loan Indicator				
x 1-3 Months Before	-269.541***	-526.643***	-0.172***	-0.316***
	(27.226)	(50.606)	(0.03)	(0.02)
x 1 Month After	-4,065.560***	-4,712.215***	-0.281***	-0.422***
	(37.425)	(62.596)	(0.04)	(0.033)
x 2 Month After	-2,640.109***	-3,386.416***	0.549***	0.404***
	(48.691)	(66.156)	(0.04)	(0.033)
x 3-7 Months After	3,762.933***	2,835.282***	0.468***	0.310***
	(53.652)	(54.866)	(0.029)	(0.019)
x 8-12 Months After	4,564.295***	3,604.349***	0.210***	0.036*
	(71.766)	(58.778)	(0.029)	(0.019)
x 12-15 Months After	4,698.685***	3,797.957***	0.139***	-0.032
	(85.361)	(62.53)	(0.032)	(0.023)
YearMonth FE	Yes	Yes	Yes	Yes
Relative Month FE	Yes	Yes	Yes	Yes
FinTech FE	Yes		Yes	
Individual FE		Yes		Yes
Observations	55,603,894	55,603,894	56,244,456	56,244,456
R^2	0.143	0.896	0.001	0.053

Panel B

	Dependent variable: Loan DLQ		*Dependent variable: Borrower DLQ*	
	Revolvers	Transactors	Revolvers	Transactors
	(1)	(2)	(3)	(4)
Fintech Loan Indicator				
x 1-3 Months Before	-0.220***	-0.115***	-1.114***	-0.511***
	(0.017)	(0.041)	(0.048)	(0.139)
x 1 Month After	-0.257***	-0.132***	-1.226***	-0.697***
	(0.016)	(0.041)	(0.05)	(0.149)
x 2 Month After	-0.268***	-0.148***	-1.186***	-0.660***
	(0.016)	(0.041)	(0.052)	(0.158)
x 3-7 Months After	0.004	0.006	-0.621***	-0.451***
	(0.02)	(0.049)	(0.053)	(0.151)
x 8-12 Months After	1.399***	0.593***	0.267***	-0.151
	(0.036)	(0.073)	(0.064)	(0.176)
x 12-15 Months After	2.797***	1.276***	1.204***	0.700***
	(0.048)	(0.099)	(0.076)	(0.213)
YearMonth FE	Yes	Yes	Yes	Yes
Relative Month FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	52,412,988	3,739,019	52,412,988	3,739,019
R^2	0.305	0.265	0.567	0.573

Panel C

	Dependent variable: Loan DLQ		*Dependent variable:Borrower DLQ*	
	Non-Main Lenders	Main Lenders	Non-Main Lenders	Main Lenders
	(1)	(2)	(3)	(4)
Fintech Loan Indicator				
x 1-3 Months Before	-0.703***	0.001	0.019	0.007***
	(0.074)	(0.040)	(0.021)	(0.002)
x 1 Month After	-0.972***	0.008	-0.041**	-0.008***
	(0.079)	(0.041)	(0.021)	(0.001)
x 2 Month After	-1.109***	0.198***	-0.075***	0.003
	(0.083)	(0.049)	(0.021)	(0.006)
x 3-7 Months After	-1.087***	1.084***	-0.056**	0.430***
	(0.081)	(0.058)	(0.025)	(0.029)
x 8-12 Months After	-0.890***	2.454***	0.984***	1.947***
	(0.098)	(0.078)	(0.042)	(0.053)
x 12-15 Months After	-0.007	3.463***	2.188***	3.359***
	(0.119)	(0.094)	(0.062)	(0.067)
YearMonth FE	Yes	Yes	Yes	Yes
Relative Month FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Observations	26,026,137	30,262,037	26,026,137	30,262,037
R^2	0.561	0.62	0.246	0.406

Table 7

Loan Origination Volume

These tables report the regression results of loan origination volume based on loans originated in 2015. The dependent variable is log origination volume, which is aggregated at Zip Code by Month level. Panel A restricts attention to Fintech loans while Panel B focuses on non-Fintech loans. In both Panels, column (2) restricts attention to loans originated to borrowers with credit score less than or equal to 700 at origination while column (3) restricts attention to loans originated to borrowers with credit score above 700. FICO refers to the Vantage risk score that has a distribution from 350 to 850. The "NY/CT" dummy equals one if the Zip Code of aggregated volume is at New York or Connecticut and the "Post" dummy equals one if the month of aggregated volume is on or later than May 2015. We include county fixed effects and origination year-month fixed effects in the regression. Standard errors are clustered at state levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	Dependent variable: log Origination		
	Fintech & All FICO	*Fintech & Low FICO*	*Fintech & High FICO*
	(1)	(2)	(3)
NY/CT × Post	-0.099	-0.176***	0.047
	(0.069)	(0.052)	(0.065)
County FE	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes
Observations	101,637	101,637	101,637
R^2	0.134	0.097	0.076

Panel B

	Dependent variable: log Origination Volume		
	Non-Fintech & All FICO	*Non-Fintech & Low FICO*	*Non-Fintech & High FICO*
	(1)	(2)	(3)
NY/CT × Post	0.012	-0.075	-0.063
	(0.025)	(0.104)	(0.04)
County FE	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes
Observations	101,637	101,637	101,637
R^2	0.11	0.172	0.108

Table 8

Loan Rate

This table reports the regression results of loan rate based on Fintech loans originated in 2015. The dependent variable is average loan rate, which is aggregated at Zip Code by Month level. Odd columns use equal weights while even columns use volume weights in computing the averages. Columns (3) and (4) restrict attention to loans originated to borrowers with credit score less than or equal to 700 at origination, while columns (5) and (6) restrict attention to loans originated to borrowers with credit score above 700. FICO refers to the Vantage risk score that has a distribution from 350 to 850. The "NY/CT" dummy equals one if the Zip Code of aggregated loan rate is at New York or Connecticut and the "Post" dummy equals one if the month of aggregated loan rate is on or later than May 2015. We include county fixed effects and origination year-month fixed effects in the regression. Standard errors are clustered at state levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Dependent variable: Loan Rate					
	All FICO (1)	All FICO (2)	Low FICO (3)	Low FICO (4)	High FICO (5)	High FICO (6)
NY/CT × Post	-1.375**	-1.449**	-1.860**	-1.858**	-0.063	-0.13
	(0.551)	(0.58)	(0.914)	(0.888)	(0.282)	(0.291)
Weighting	equal weighted	volume weighted	equal weighted	volume weighted	equal weighted	volume weighted
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,206	38,206	25,980	25,980	19,379	19,379
R^2	0.062	0.058	0.077	0.074	0.077	0.076

Table 9

Loan Delinquency

These tables report the regression results of loan delinquency based on loans originated in 2015. The dependent variable is the number of delinquent loans, which is aggregated at Zip Code by Month level, in Panel A and B, and loan DLQ indicator at the individual level in Panel C. In Panel A, odd columns restrict attention to Fintech loans while even columns restrict attention to non-Fintech loans; columns (1) and (2) restrict attention to loans originated to borrowers with credit score less than or equal to 700 at origination while columns (3) and (4) restrict attention to loans originated to borrowers with credit score above 700. FICO refers to the Vantage risk score that has a distribution from 350 to 850. In Panel B, columns (1) and (2) restrict attention to Fintech loans while columns (3) and (4) restrict attention to non-Fintech loans; odd columns restrict attention to the subsample of borrowers who have been classified as *revolvers* by the credit bureau, while even columns restrict attention to borrowers who have been classified as *transactors*. Panel C provides panel-level analysis on loan DLQ where columns (1) and (2) restrict attention to Fintech loans while columns (3) and (4) restrict attention to non-Fintech loans. In Panel A and B, the "NY/CT" dummy equals one if the Zip Code of aggregated loan DLQ is at New York or Connecticut and the "Post" dummy equals one if the month of aggregated loan DLQ is on or later than May 2015. In Panel C, the "NY/CT" dummy equals one if the Zip Code of the loan is at New York or Connecticut; the "OrigPost" dummy equals one if the loan was originated on or later than May 2015; the "Post" dummy equals one if the panel observation is after the loan was originated. In Panel A and B, we include county fixed effects and origination year-month fixed effects in the regression. In Panel C, we control for FICO at origination, credit limit, loan terms, and fixed effects for origination month, month relative to origination, and county. For even columns in Panel C, borrower fixed effects are also included. Standard errors are clustered at state levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A

	Dependent variable: Number of Loan DLQ			
	Fintech & Low FICO	*Non-Fintech & Low FICO*	*Fintech & High FICO*	*Non-Fintech & High FICO*
	(1)	(2)	(3)	(4)
NY/CT × Post	-0.015***	0.00002	-0.002***	0.004***
	(0.004)	(0.007)	(0.0003)	(0.001)
County FE	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes
Observations	107,328	107,328	107,328	107,328
R^2	0.034	0.073	0.012	0.016

Panel B

	Dependent variable: Number of Loan DLQ			
	Fintech & Revolver	*Fintech & Transactor*	*Non-Fintech & Revolver*	*Non-Fintech & Transactor*
	(1)	(2)	(3)	(4)
NY/CT × Post	-0.016***	-0.001***	0.004	-0.0002
	(0.004)	(0.0003)	(0.006)	(0.0004)
County FE	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes
Observations	107,328	107,328	107,328	107,328
R^2	0.035	0.01	0.072	0.015

Panel C

	Dependent variable: Loan DLQ			
	Fintech	*Fintech*	*Non Fintech*	*Non Fintech*
	(1)	(2)	(3)	(4)
NY/CT × Post × OrigPost	-0.676***	-0.676***	0.048**	0.048**
	(0.227)	(0.232)	(0.02)	(0.02)
NY/CT × OrigPost	0.207*	-0.262	-0.036***	0.078
	(0.122)	(0.248)	(0.007)	(0.053)
NY/CT × Post	-0.753***	-0.753***	0.191***	0.191***
	(0.251)	(0.257)	(0.062)	(0.064)
OrigPost × Post	0.319	0.32	0.140***	0.140***
	(0.218)	(0.224)	(0.016)	(0.017)
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes
Relative Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Borrower FE		Yes		Yes
Observations	2,086,645	2,086,645	10,712,879	10,712,879
R^2	0.042	0.381	0.01	0.319

Table 10

Borrower Debt

This table reports results from regression of loan performance. Dependent variable is total debt where we restrict attention to Fintech loans in columns (1) and (2) and to non-Fintech loans in columns (3) and (4). The "NY/CT" dummy equals one if the Zip Code of the loan is at New York or Connecticut; the "OrigPost" dummy equals one if the loan was originated on or later than May 2015; the "Post" dummy equals one if the panel observation is after the loan was originated. We control for credit score at origination, credit limit, loan terms, and fixed effects for origination month, month relative to origination, and county. For even columns (2) and (4), borrower fixed effects are also included. Standard errors are clustered at state levels. The regression is based on loan-level data for our random sample of personal loans. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Dependent variable: Total Debt			
	Fintech	*Fintech*	*Non Fintech*	*Non Fintech*
	(1)	(2)	(3)	(4)
NY/CT × Post × OrigPost	-398.224**	-365.742**	102.679	106.31
	(160.617)	(158.770)	(109.067)	(103.3)
NY/CT × OrigPost	15.317	-325.245	359.224	1,347.464***
	(1750.322)	(577.833)	(420.18)	(199.115)
NY/CT × Post	437.894	379.589	1,274.195***	1,246.419***
	(362.837)	(354.507)	(444.392)	(453.257)
OrigPost × Post	1,791.602***	1,772.519***	410.373***	433.198***
	(123.936)	(116.731)	(97.24)	(100.976)
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes
Origination YearMonth FE	Yes	Yes	Yes	Yes
Relative Month FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Borrower FE		Yes		Yes
Observations	2,082,314	2,082,314	10,575,382	10,575,382
R^2	0.15	0.931	0.139	0.913