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Which Lenders Are More Likely to Reach Out to Underserved Consumers: Banks versus Fintechs versus Other Nonbanks?

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Abstract

There has been a great deal of interest recently in understanding the potential role of fintech firms in expanding credit access to the underbanked and credit-constrained consumers. We explore the supply side of fintech credit, focusing on unsecured personal loans and mortgage loans. We investigate whether fintech firms are more likely than other lenders to reach out to "underserved consumers," such as minorities; those with low income, low credit scores, or thin credit histories; or those who have a history of being denied for credit. Using a rich data set of credit offers from Mintel, in conjunction with credit information from TransUnion and other consumer credit data from the FRBNY/Equifax Consumer Credit Panel, we compare similar credit offers that were made by banks, fintech firms, and other nonbank lenders. Fintech firms are more likely than banks to offer mortgage credit to consumers with lower income, lower-credit scores, and those who have been denied credit in the recent past. Fintechs are also more likely than banks to offer personal loans to consumers who had filed for bankruptcy (thus also more likely to receive credit card offers overall) and those who had recently been denied credit. For both personal loans and mortgage loans, fintech firms are more likely than other lenders to reach out and offer credit to nonprime consumers.

Keywords: fintech, P2P lending, consumer credit access, personal lending, credit cards, mortgage lending, online lending, credit offers

JEL Classifications: G21, G23, G28, G51

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I. Introduction

Fintech firms became a well-known and trusted supplier of a wide variety of financial services to consumers in the last decade, from payment services to personal loans and mortgage loans. By 2019, about 96 percent of global consumers became aware of at least one fintech money transfer and payment service, and over three-quarters had heard of a fintech in the consumer credit space.[1] Many fintech firms, such as LendingClub, SoFi, and Rocket Mortgage (owned by Quicken), have now become household names in the United States.

One of the biggest shares of fintech expansion has been in consumer credit, especially unsecured personal installment loans, which have been typically used for paying off credit card balances, debt consolidation, or large household purchases. Fintech firms have exploded into this small but growing product line, undoubtedly contributing to the increase in personal loan usage in recent years. The average year-over-year growth for personal loan market has been more than 15 percent for the last several years (Beiseitov, 2019). According to TransUnion (2019), 38 percent of personal loans outstanding as of December 2018 were originated by fintech firms, compared with only 5 percent in 2013, a dramatic increase over the span of six years.

This trend is borne out in credit mailing offers as well. Figure 1 presents the total volume of personal loan (offer) mailings sent to consumers, broken down by lender types (banks, traditional nonbanks, and fintech lenders). Starting from almost zero credit offers in 2010, fintech credit offers started growing rapidly — and surpassed credit offers by both banks and traditional nonbanks in 2014 to peak at about $1.2 billion in 2016. Recall that this is the volume of credit offers (not loan originations) by various lenders, based on a survey of credit offers received by random households (assuming these sampled households in the survey are good representations of the general consumer population). In addition to establishing footprints in the personal lending space, fintech firms have also established a significant presence in mortgage lending. We observe increasing mortgage credit offers by fintech firms in recent years. Indeed, one of the fintech mortgage lenders, Quicken, and its subsidiary Rocket Mortgage, have become the largest mortgage originator in the United States.

Along with the growth in fintech credit offers in recent years, the volume of fintech loan originations has also seen explosive growth, especially among personal loans and mortgage loans. Most of the literature posits two potential explanations. On the one hand, fintech firms may be reaching out to consumers with little access to formal financial markets — filling a gap in the credit market. On the other hand, fintech lenders may simply be attempting to poach the highest-quality

[1] See EY Global Financial Services (2019) Global Fintech Adoption Index. https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/banking-and-capital-markets/ey-global-fintech-adoption-index.pdf.

borrowers from traditional banks, wooing consumers with faster and superior service and potentially a price advantage over banks. This is what is often referred to as fintech firms "cream skimming" the best borrowers who may already have access to credit and are not underserved in the traditional sense.

The goal of this paper is to explore the role of fintech lenders in expanding credit access to underserved consumers in the personal lending and mortgage lending space. We focus on lenders' willingness to lend (as measured by their credit offers) to underserved consumers, using a unique data set containing consumer risk characteristics, the financial products offered, and the lenders' characteristics that allow us to examine details about the financial product offered to different types of consumers (with varying credit scores, income, etc.). Specifically, we ask these questions. First, are fintech lenders targeting underserved consumers in the personal loan and /or mortgage markets? Second, are consumers paying a higher or lower interest rate (measured in annual percentage rate (APR)) to fintech firms compared with banks and traditional nonbank lenders, controlling for consumers' risk characteristics and general economic factors?

Our study is unique in several ways. First, we focus solely on the supply side of credit (mortgages and personal loans) — to explore fintech lenders' willingness to offer credit to those who would not have been able to access credit otherwise. It would be then up to the consumers to choose whether to take up the offer from fintech lenders or traditional lenders. Most research studies so far have focused on loan origination, which is determined by both supply and demand. We fill the literature gap by providing additional insights into fintech firms' commitment and lending behavior. Second, we compare fintech lenders with both traditional banks and traditional nonbanks (also called other nonbank lenders) to also control for the regulatory environment to which lenders are subject. All lenders, whether banks or nonbanks, are subject to regulations, including fair lending, consumer protection, and other state regulations.[2] Banks, with access to deposit insurance, are subject to more stringent capital and liquidity regulations, and they are subject to periodic onsite examination by the banking regulators (the Federal Reserve, the Office of the Comptroller of the Currency, state banking regulators, and the Federal Deposit Insurance Corporation). Shadow banks are not subject to periodic onsite examination, and they operate in a more similar environment, regardless of whether they are fintech lenders or traditional nonbank lenders. The only difference is that fintech lenders use more data (including alternative data) and more complex artificial intelligence/machine learning (AI/ML) modeling in their risk evaluation and pricing and in their fully digitized credit-decisioning process. Lastly, we use a diverse and

[2] Some states, such as California, require greater transparency and more stringent interest rate ceilings, not only for consumer loans but also for small business loans.

extensive set of measures of access to credit at both the individual consumer level and the geographic (zip code) level to gain a robust understanding of the potential roles of fintech lenders in filling the credit gaps and enhancing consumer credit access overall.

The remainder of the paper proceeds as follows. Section II provides a brief review of the literature, highlighting recent research on fintech lending and focusing on mortgages and personal loans. Section III discusses the data used in this paper. The empirical approach is presented in Section IV. Section V presents our results for both the mortgages and personal loans. Section VI discusses limitations, and finally, Section VII provides implications and concludes.

II. Related Literature and Our Contribution

Along with the growth in fintech credit offers (as shown in Figure 1), the volume of fintech loan originations has also experienced explosive growth, especially among personal loans and mortgage loans. The current literature posits two potential explanations, with mixed empirical results. On the one hand, fintech firms may be reaching out to consumers with little access to formal financial markets, thus filling the credit gap. Specifically, fintech lenders may be able to identify good borrowers of the subprime pool, using more complex, proprietary algorithms, and alternative data. These "hidden prime" consumers may appear high risk using traditional metrics (such as credit scores) but who have a high likelihood of repayment, especially those with a short credit history whose credit score may not reflect their creditworthiness. On the contrary, as mentioned earlier, fintech firms may simply be "skimming the cream" and serving the same market segments as banks, wooing well-served consumers with faster service and potentially lower rates. Jagtiani and Lemieux (2018) find evidence supporting the hypothesis that fintech (personal loan) lenders penetrate areas that are underserved. In addition, Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) find similar evidence for fintech mortgage lenders; that is, mortgage loans are more likely to be a fintech loan in a zip code that experienced higher mortgage denial rates by traditional lenders.[3]

Several other previous studies explore the roles of fintech in expanding credit access and the price they offer, using different data sets and different methodologies, and they arrive at different results. Cornaggia et al. (2018) show that the expansion of fintech firms in the unsecured loan market leads to declining loan volumes for traditional banks, driven largely by declines in the higher-risk segment. This implies that fintech firms compete for bank customers (especially those higher-risk borrowers), probably because some of those borrowers being considered high risk by

[3] See Allen, Gu, and Jagtiani (2021) for an overview of fintech growth, potential disruption, literature review, and policy discussion. For more background on important factors that drive fintech lending growth and loan performance, see Jagtiani and Lemieux (2019); Goldstein, Jagtiani, and Klein (2019); Jagtiani and John (2018); and Croux, Korivi, Jagtiani, and Vulanovic (2020).

traditional banks could get lower-cost credit from fintech lenders. The authors also find that fintech firms offer lower interest rates than traditional banks for high-quality (less risky) borrowers (they only have data for this group of borrowers). The fact that riskier borrowers leave their banks for fintech lenders would imply that the lower interest rate may have been offered to higher-risk borrowers as well. Despite higher-funding cost at fintech firms, Cornaggia et al. (2018) conclude that fintech lenders are able to offer a lower rate of interest than banks because of their cost advantage driven by smaller overheads and other operational costs.

Similarly, Di Maggio and Yao (2019) ask whether fintech firms are expanding access to credit for the underserved or simply capturing the most creditworthy borrowers from banks. Using account-level consumer credit panel data, focusing on unsecured installment personal loans, they find that, in a longer term, fintech borrowers are more likely to be more indebted (overleveraged) than traditional bank customers. Based on this, they posit that fintech borrowers are likely to be consumers with a preference for immediate consumption who overborrow and use the loans to finance increased expenditure. In addition, they find that consumers who receive fintech personal loans tend to, on average, have a higher income, have a better credit history, live in more affluent neighborhoods, and have significantly more credit accounts, but they tend to have higher credit-utilization ratios than a matched sample of bank borrowers. These borrowers might have already maxed out their ability to get credit from traditional lenders, given their large credit lines and high utilization ratios.

In a similar vein, Tang (2019) examines whether fintech and traditional bank loans are substitutes or complements. The author notes that if they are complements, fintech lenders and banks would be serving different segments of customers, with fintech firms serving the lower-quality (lower-score) segment. Any negative exogenous change in bank credit supply would result in a higher quality of the fintech firms' borrower pool, as the least creditworthy bank consumers (but higher quality than the fintech segment assuming they are complements) would be denied loans by traditional banks and migrate to fintech lenders, thereby raising the average quality of the fintech pool.

On the contrary, using an exogenous constriction in bank credit supply resulting from a change in regulations, Tang (2019) finds that banks and fintech firms are most likely substitutes rather than complements. In other words, fintech firms and traditional banks serve the same borrower pool (based on credit scores), providing potential evidence against the claim that fintech lenders serve credit-constrained consumers. In this paper, we examine borrower characteristics (pool) at a more granular level, based not only on credit scores but also on income, delinquency status, and more. We find that fintech lenders target the subprime borrower pool more than banks do.

In examining whether fintech and bank loans serve the same pool of borrowers, De Roure, Pelizzon, and Tasca (2016), using data from the German peer-to-peer (P2P) lending market, find that these lenders tend to serve a riskier segment of the market that traditional banks are unwilling to serve. The P2P lenders charge a higher price to compensate for the extra risk that they assume. In this sense, fintech firms operate as a complement to traditional banks, expanding their access to consumers who would not be served by traditional credit markets.

Similarly, Jagtiani and Lemieux (2018) find that fintech firms provide access to credit to borrowers in areas that are underserved by traditional banks. The authors use account-level data from the LendingClub consumer lending platform, account-level data from Federal Reserve Y-14M stress test data (reported by large banks that are subject to CCAR stress testing), and other data sources to explore the relationship between fintech lending activity and various measures of credit gaps, such as banking market concentration, bank branches per capita, and local economic conditions. Their results indicate that the ratio of personal loans originated by LendingClub is proportionately larger in zip codes (or counties) with highly concentrated banking markets and in areas with fewer bank branches per capita, which is consistent with an argument that fintech lenders have a potential to expand credit access in areas that are underserved by traditional banks. Further, Jagtiani and Lemieux (2019) find that below-prime consumers could access funding at significantly lower cost through fintech lenders.

Studies of the mortgage sector paint a slightly different picture, with some evidence that fintech firms actually draw customers away from traditional banks, either through better or more convenient service. Fuster et al. (2018) find no evidence that fintech firms disproportionally target consumers in traditionally underserved demographic groups in the mortgage market. The main draw of fintechs appears to be the faster loan process, particularly for refinances. The authors find that fintech firms reduce processing time by about 10 days with an even larger effect for refinances. Similarly, Buchak et al. (2018) do not find dramatic differences between consumers who obtain mortgages from fintechs and those who obtain them from banks. They do find, however, that the average income of fintech borrowers is about $1,000 lower than traditional bank borrowers. They also find that fintech firms charge a premium of 14–16 basis points, concluding that the main driver of the fintech expansion is added convenience and changing consumer tastes, rather than cost savings or the expansion of credit to previously underserved consumers.

Conversely, Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021) find suggestive evidence that fintech firms are expanding credit access to those likely to be underserved by traditional lenders. For example, they show that mortgage loans are more likely to be fintech loans in zip codes that experience higher mortgage denial rate by traditional lenders (banks and nonbank lenders) in the previous period. In addition, they find a larger market share of fintech mortgage origination in areas with lower average credit scores. They also find that fintech firms tend to market more to borrowers in nonurban areas than other nonbanks. They also explain that interest rates charged by fintech mortgage lenders (relative to bank loans) vary by product types — studies that examine Federal Housing Administration (FHA) mortgages find different results than those that examine conventional mortgages. Conventional mortgage borrowers are not likely to be underserved by banks, but they may choose to go with fintech lenders and be willing to pay a premium rate in exchange for faster, better service.

Another potential benefit of fintech firms is reducing discrimination in credit markets. The limited face-to-face interaction allowed by online applications may limit a lender's ability to discriminate against minority borrowers. Bartlett et al. (2019) investigate discrimination in the mortgage market and find some evidence of discrimination for mortgage loans originated by fintech lenders. Interestingly, they find that the degree of discrimination is significantly reduced when the mortgages are originated by fintech lenders, although they do not eliminate discrimination completely. They find that fintech lenders charge African Americans 5.3 basis points more than other applicants on average, while traditional banks charge 7.9 points more. In our paper, we investigate whether fintech firms are more likely to reach out to areas with higher percentages of minorities to provide additional evidence on this question.[4]

Our paper builds on the previous literature and extends it in three main ways. First, we use fintech credit offers, rather than actual originations, which allows us to provide a detailed examination of the supply side of fintech loans. Second, we use a diverse and extensive set of measures of a consumer's credit access. This allows us to develop a more nuanced picture of the types of consumers receiving offers from fintech firms compared with traditional banks and traditional nonbank lenders. Lastly, we compare fintech firms not only with traditional banks but also other nonbank lenders to control for the regulatory environments in which they operate.

In our analysis, we define *underserved* consumers along two main dimensions: demographic characteristics and credit access. Certain populations, such as low-income consumers, minorities, and those living in low-income and minority areas, are known to face larger barriers to obtaining credit.[5] We examine the extent to which fintech firms reach out to these consumers, as compared with banks and traditional nonbanks. We also employ several direct measures of credit access, such as total balances on all accounts combined and total number of credit card offers that the customer

[4] Fair lending and consumer protection have been important topic of consideration among regulators and bank supervisors. For more information and discussion on the impact of fintech and AI/ML on future regulatory guidance and third-party vendor risk management, see Jagtiani, Vermilyea, and Wall (2018).

[5] See Federal Reserve Board (2007), Weller (2007), Desilver and Bialik (2017), and Fairlie, Rob, and Robinson (2016).

received, to identify whether a consumer is likely to be underserved and whether the areas may be underserved overall. In addition, we investigate credit offers to specific underserved consumers as well as specific underserved areas (zip codes) to further explore the potential expansion of credit access by fintech lenders; examples include credit offers targeted to subprime consumers who may happen to live in a zip code with relatively higher average income and higher average credit scores.

Interestingly, we find that fintech lenders play a somewhat different role in personal versus mortgage lending. Overall, when comparing fintech lenders with banks, fintech firms tend to reach out to subprime consumers more than banks do, and this is true for both personal loans and mortgage loans. In addition, fintech lenders attempt to reach those consumers who have experienced bankruptcy and/or get denied (at least once) for credit within the past six months. We also find that fintech lenders are more likely to send credit offers to consumers in zip codes that have higher ratios of minorities, although the effect here is quite small.

Within the subprime pool of consumers, our data suggest that those who are likely to get personal loan credit offers from fintech lenders tend to be borrowers with higher income and higher credit balances (on both revolving and nonrevolving accounts). This finding is partly consistent with Di Maggio and Yao (2019), although we find that this cream-skimming behavior of fintech lenders only holds among the *subprime* population, not for the general consumer population. Fintech lenders may be using more data and more complex modeling to identify low-risk borrowers from the subprime pool — this is consistent with Jagtiani and Lemieux (2019). Overall, our findings are consistent with an argument that fintech firms reach out to certain types of underserved consumers.

In addition to comparing fintech lenders with banks, we attempt to control for the regulatory environment faced by lenders by separately comparing fintech lenders with other nonbank lenders. We find that, for *personal loans*, fintech lenders are more likely to reach out to consumers who have experienced bankruptcy and those residing in rural (rather than urban) areas than other nonbanks do. We find that fintech firms are less likely to reach out to subprime consumers than other nonbanks, but they typically offer lower interest rates to this group.

We find a different impact when considering *mortgage* offers. Fintech mortgage lenders and other nonbank lenders actively reach out to low-income consumers with poor credit scores, compared with banks. In addition, fintech mortgage offers are more likely to reach areas with fewer bank branches and in zip codes with lower average credit scores, although these effects are very small. Again, there is evidence that fintech lenders make efforts to fill credit gaps in underserved areas.

III. The Data

III.1 Data on Credit Offers — Personal Loans and Mortgage Loans

The main data source used in this paper is the Mintel Comperemedia, Inc. Direct Mail Monitor Data and TransUnion LLC Match File (hereafter referred to as *Mintel-TransUnion*) data set, which is anonymized data from monthly surveys of credit offers that households receive. Mintel collects this data by sending a survey to a random sample of 8,000 households every month. The data set contains a wealth of information on each of the credit offers sent to consumers, including the type of financial product offered (mortgage offers, personal loan offers, credit card offers, etc.), name of the offering lender, characteristics of the consumer, and detailed information about the offer (e.g., loan amount and interest rates). Our analysis, using data from Mintel, automatically excludes consumers who were not included in the survey. Our conclusions on the characteristics of credit offers from different lender types are drawn from those consumers who receive credit offers only.[6] Of the overall 98,379 credit offers in the sample, 34.9 percent are from fintech lenders, 31.3 percent are from banks, and the remaining 33.8 percent are from traditional nonbank lenders.[7]

These data are then merged with TransUnion (TU) data on the consumers' credit characteristics, such as credit score (VantageScore 3.0), location, and number of credit accounts past due, and anonymized. This merged data set provides a detailed picture of the supply side of financial product offerings, allowing us to compare who gets offers from banks versus fintech versus other nonbank lenders,[8] controlling for a range of important characteristics of the offers and other relevant factors.

From the Mintel data set, we define the two main dependent variables of interest: 1) a binary indicator of whether an offer is from a fintech firm or traditional lenders, and 2) the interest

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[6] The Mintel data set contains information on consumers who received credit offers only — in other words, the surveyed consumers who did not receive any credit offers are not in the data set. In this study, our sample includes consumers who received not only personal loan offers but also broader types of credit offer (i.e., credit card offers) and mortgage offers.

[7] We note that the vast majority (about 80 percent) of solicitations are in the form of direct mail, rather than email or other methods. Banks did not traditionally use direct mail as a mean to execute customer acquisition strategy, although banks also started using more and more direct mail in recent years. Our sample incudes approximately equal shares of credit offer from each lender type.

[8] We have grouped the lenders in a few different ways to identify traditional nonbank lenders for the analysis. First, we started by including only classified shadow banks that we knew were traditional nonbank lenders (shadow banks that are not fintech lenders). Then, we decided to include all lenders that are not banks or fintechs as traditional nonbank lenders. We find that the results did not change much, depending on how we identified traditional nonbank lenders.

rates offered to consumers.[9] Mintel reports a range of interest rates for the loan in each mail offer: the lower bound interest rate and the upper bound interest rate mentioned in the mail piece. For the pricing analysis, we calculate two separate spread variables (*spread_low* using the lower-bound offer rate and the variable *spread_high* using the upper-bound offer rate), which is the difference between the rates offered and the Treasury bill rate (risk-free rate) of the same time to maturity from the same month and year. If the loan period is missing, which is often the case, we use the three-year Treasury rate. We perform the analysis separately for each set of the spreads, and the results of these analyses and their implications shed light on our understanding of the roles of fintech lenders in the current financial landscape.

III.2 Underserved Population Indicators

We are interested in understanding whether fintech firms are reaching out to consumers who have less access to credit or are typically underserved by traditional lenders. As such, we create several indicators that are intended to proxy for whether a consumer is being underserved, based on two different approaches: 1) demographic variables, and 2) measures that proxy consumers' ability to access credit.

Using Demographic Indicators to Proxy for Being "Underserved"

Previous studies have documented that minorities, low-income individuals, and those who live in low-income areas or areas with high-minority populations tend to have a harder time accessing credit (higher loan-denial rates) than more affluent and nonminority consumers, and this is true across a wide variety of financial products; see Federal Reserve Board (2007), Weller (2007), Desilver and Bialik (2017), and Fairlie, Rob, and Robinson (2016). In addition, there have also been concerns among policymakers about credit access in rural areas, given there are often fewer bank branches in these areas. We use these demographic data contained within the Mintel data set, along with data from the U.S. Census Bureau's American Community Survey, to examine whether fintech lenders are reaching out differentially to these groups of consumers, compared with banks and other nonbank lenders.

Household Annual Income: We use the household income variable in the Mintel data set to group consumers into four segments based on their household annual income: 1) less than $25,000,

[9] We use the firm name field in the Mintel data to categorize offers received by consumers as from banks, fintech lenders, other nonbank lenders. We started with a list of 50 fintech lenders to identify fintech lenders in our sample. For traditional lenders, we included the top 10 largest banks as well as any other firm that had the word *bank* in its name. Anything that did not fall into these two categories was placed in the nonbank lender category. We reviewed the list of nonbank lenders in the sample and performed Google searches when necessary to determine if a lender was indeed a nonbank lender.

2) $25,000 to $49,999, 3) $50,000 to $74,999, and 4) more than $75,000. We consider consumers with incomes of less than $25,000 to be low income and those with incomes between $25,000 and $50,000 to be moderate income. The other groups are considered higher income.

Rural versus Urban: We also create a rural indicator to identify consumers in rural areas, based on the rural–urban continuum codes developed by the U.S. Department of Agriculture's Economic Research Service. Each county is assigned a code ranging from 1 to 9, with 1 being the most urbanized (counties in metro areas of 1 million or more) and 9 being the most rural (nonmetro, completely rural, or less than 2,500 in urban population, not adjacent to a metro area). From these codes, we create a dummy for whether a county is in the two most rural categories, both of which are classified as *nonmetro rural*.

Minorities: We use Census Bureau data to calculate the ratio of zip code's population that is minority and the zip code's median income as geographic measures of areas that typically have more limited access to mainstream finance.

Other Measures of a Consumer's Ability to Credit Access (to Proxy for Potentially Being Underserved)

We construct six different measures to proxy consumer's ability to access credit. Two of these are at the geographic (zip code) level: 1) bank branches per capital at zip code level, and 2) average credit scores of consumers in the zip code. And four of which are at the individual consumer level: 3) credit score, 4) number of credit offers received, 5) number of credit accounts and total loan amount, and 6) total number of recent credit requests that were denied.

Proximity to Bank Branches: We use the number of bank branches per 100,000 population (at the zip code level) to proxy for amount of banking/financial services in the local area. We collect bank branch data from the FDIC and population data from the American Community Survey (ACS) to calculate the number of bank branches per 100,000 people in each zip code. This serves as an indicator of credit access in a geographic sense; consumers who live in an area with more banks may find it easier to go to the bank to get a loan and may obtain lower rates because of increased competition. Fintechs' online nature may give them an advantage in reaching out to consumers in areas with fewer bank branches, which we investigate directly with this measure.

Average Credit Scores at Zip-Code Level and Credit Scores at Consumer Level: We calculate the average Equifax Risk Score of consumers who live in the zip code as one of the variables that proxy for consumer's credit access. This variable allows us to observe the impact of an individual consumer's credit score versus the consumer neighborhood's average credit score on the probability of getting credit offers from fintech and other lenders. In attempting to reach low-score consumers through direct mail offers, some lenders might have chosen to use the bulk-style mailing (e.g., doing indiscriminate dumps) to reach out to underserved consumers. Different lenders might have different ways to identify these targeted borrowers, both individually and/or by zip codes.[10] In other words, we examine consumer risk scores in two ways: 1) credit scores for each individual consumer; and 2) relative credit score for each individual consumer relative to other consumers in the same neighborhood (i.e., relative to average credit score for the zip code). This approach has allowed us to isolate lenders approaching individual low-score consumers (regardless of their location) versus those lenders approaching good borrowers in low-score neighborhoods.

The consumer-level variables on credit score and other credit access are collected from the Mintel-TransUnion merged data, which contains not only the Mintel mailing information but also many variables related to a consumer's creditworthiness. The average Equifax Risk Score of the zip code is calculated based on consumers in the zip code, using a separate data set from the FRBNY Consumer Credit Panel/Equifax Data.

Total Number of Credit Offers Received: We calculate the number of credit offers that each consumer receives each month, using Mintel data. This is used as a proxy for the consumer's ability to access unsecured credit. We perform a similar calculation to derive average total number of credit offers that consumers in each zip code received. This allows us again to explore potential differences at the geographic zip-code level versus individual consumer level.

Total Number of Credit Accounts and Total $ Loan Amount: We use the merged Mintel/TransUnion data set to create two additional measures of credit access at the consumer level: the number of all financial accounts (bankcard and non-bankcard accounts) and the log of the dollar amount of account balances (revolving and nonrevolving balances). The number of accounts and the balance amount variables are direct measures of each consumer's credit access, at least for the recent past; consumers with better access to credit are likely to have more financial accounts, and they tend to receive offers with larger loan amount (or credit limits).[11]

Total Number of Credit Requests Being Denied: This is a categorical variable for how many loan denials a consumer has had in the last six months. This variable is calculated by subtracting the number of accounts opened in the last six months from the number of credit inquiries in the last six months. We convert this into a categorical variable with the following categories: 1) consumers who have had no denials, 2) consumers with one denial, 3) consumers with two to five denials, and 4) consumers with more than five denials. We also estimated separate models using a dummy

[10] In general, direct mailing is used for consumers who have lower scores and are considered *less sophisticated* because more sophisticated consumers tend to do their own comparison and shop around, rather than relying on credit offers in the mail.

[11] Note that this measure does, however, ignore the demand side of the equation. In equilibrium, some consumers may not accept the credit offers they received in the mail; thus, they have smaller number of financial accounts and smaller loan amounts than others who receive less credit offers but accept all the credit offers they received. Some may have low balances and few accounts simply because they do not need or want to borrow, regardless of their ability to access credit.

variable for whether a consumer had any denials and using a continuous variable for the number of denials. The results are robust across these additional model specifications.

Our sample contains monthly credit offers data during the period 2015–2018. We do not include data from earlier years because fintech firms did not become prominent in the financial landscape until around 2014–2015. Our data sample does not include credit unions. In addition, consumers with extremely low credit scores (below a 450 VantageScore) are excluded because these very low-score consumers tend to behave significantly differently than other subprime consumers. Tables 1 and 2 provide summary statistics for our final samples for the analysis of personal loans and mortgage loans, respectively.[12]

IV. Preliminary Analysis

Before delving into the statistical analysis, we perform a graphical analysis to establish an intuitive understanding of the types of consumers to whom fintech lenders attempt to reach through their mail offers. Mintel creates an estimate of nationwide mail volume from its sample of consumers, which we use to analyze personal loan and mortgage mail volume, segmented by consumer groups (such as income brackets) and lender type (banks, fintech, or other nonbank lenders).

Personal Loan Sample: Figures 2–4 picture mail volume trends — by the various consumer characteristics. Three key facts emerge from this analysis. First, Figure 2 shows that fintech firms are clearly reaching out to nonprime consumers (those with VantageScore 3.0 less than or equal to 660) more so than banks, and this is true for all income categories. Then, Figure 3 shows that most of the credit offers are mailed to consumers who are not in the low- and moderate-income (LMI) areas, and this holds for all lenders (banks, fintech firms, and other nonbank lenders). Fintech firms do not seem to be targeting LMI areas more than banks, probably because banks tend to receive Community Reinvestment Act (CRA) credits for making loans in LMI neighborhoods. Interestingly, although most of the fintech mails are sent to zip codes with average Equifax Risk Scores that are in the prime range (scores above 660), the majority (about 60 percent) of these mail offers are sent to *nonprime* consumers in the prime zip codes. Note that banks and other nonbank lenders also send

[12] One potential issue with this type of research is that fintech firms' business and marketing strategies have been changing and would continue to adapt to the newly available technology and the new regulatory landscape. This makes it difficult to pin down exactly who fintech firms are targeting because they are constantly adjusting their business models and their AI/ML analysis to offer new products and services to new groups of customers and in different markets. According to TransUnion, only about 25 percent of new unsecured personal loans from fintech firms went to households with below-prime credit scores in 2019, compared with around 60 percent for similar loans issued up through 2018 (American Banker, 2019). For this reason, we restrict our sample to a relatively stable middle period of fintech expansion — after the dramatic initial boom in fintech lending in the early 2010s and before the significant tightening in 2019 and later.

most of their offers to prime zip codes and that only about 27 percent of these mail offers by banks are sent to nonprime consumers (see Figure 4).

Mortgage Loan Sample: Figures 5–7 show a similar analysis for the mortgage offers, although the story is less clear cut, probably because of the nature of mortgage products which are more regulated for government-sponsored enterprise (GSE) approvals. From Figure 5, we see less of an emphasis on nonprime consumers, which makes sense given that there is typically a minimum credit score required to qualify for a mortgage. Even so, fintech firms still have a clear focus on nonprime consumers relative to traditional banks. Figure 6 pictures mail volume to LMI and non-LMI areas, by consumer income segments. Fintech firms seem to have a larger focus on LMI areas than banks, and even within non-LMI areas, over one-quarter of fintech mail still goes to lower-income (<$50K) individuals. Traditional nonbank lenders reach out more extensively to LMI consumers than both fintechs and banks. Looking at mail volume by average zip code's risk score, Figure 7 shows that the vast majority of the mail goes to prime zip codes. Despite this, fintech firms appear to be reaching out to nonprime consumers in these prime zip codes more than banks (but less than traditional nonbank lenders), similar to what we saw in the personal loan sector; however, the difference is not as large as in the mortgage sector (22 percent for fintech compared with 17 percent for banks).

Figure 8 presents interest rate spreads among offers by banks, fintechs, and nonbank lenders — for personal loan offers (on the left panel) and mortgage offers (on the right panel).

V. The Empirical Methodology

V.1 Are Fintech Lenders Targeting Underserved Consumers/Communities?

Our first analysis in this study addresses the question of what types of consumers fintech firms target, relative to banks and other nonbank lenders. To investigate this question, we estimate a simple logistic regression model that relates a series of consumer characteristics to the probability of a receive offer being sent by a fintech firm — relative to banks and relative to traditional nonbank lenders in separate analysis. We estimate an equation of the following form:

$$P(Fintech\ Offer\ |\boldsymbol{x}) = G(\beta_0 + \ + \boldsymbol{\beta} * Underserved\_ind\ + \boldsymbol{x\beta}), \qquad (1)$$

where the dependent variable is a dummy variable, $Fintech\ Offer$, indicating whether or not an offer is from a fintech firm — it takes a value of 1 if the offer is made by a fintech lender and zero otherwise. The variable $\boldsymbol{x}$ represents a set of control factors, which includes measures of creditworthiness, such as dummies for credit score range (VantageScore 3.0), number of accounts past due, and a dummy for whether a consumer has experience bankruptcy, as well as other consumer characteristics, such as age. The control variable $\boldsymbol{x}$ also includes month-year dummies to absorb cyclical variations in credit offers and other time-varying factors that do not vary across panelists.

The independent variable $Underserved\_ind$ is a vector of the various underserved indicators (discussed earlier) to proxy for whether a consumer is being underserved by traditional lenders. Again, the underserved variables include household annual income, rural or urban residence, minorities, number of bank branches per capita in the local area, individual credit scores (VantageScore 3.0), average credit scores at zip code level (Equifax Risk Score), total number of credit card offers that the consumer receives, number of open credit accounts, total amount of loans, and total number of credit inquiries that were recently denied.

We run the regression analysis separately — one with banks as the base group (results in Tables 3 and 4) and another with traditional nonbanks as the base group (results in Tables 5 and 6), because these institutions have very distinct business models, and they are subject to different regulations and target different types of consumers relative to fintech lenders. We weight observations using the *weight* variable included in the Mintel data set, which is used to balance the panel to be representative of the United States' general population, based on income, age, home ownership, and census region. We also assume that each mailing is an independent event, even though some consumers receive offers from a combination of different types of firms. However, we cluster the standard errors at the consumer level to account for multiple offers.

We estimate an almost identical regression for the mortgage sample — one with traditional banks as the base group (results in Tables 7 and 8) and another with traditional nonbanks as the base group (results in Tables 9 and 10) — with some slight differences with the credit access variables. For the accounts and balances variables, we use total number of accounts and total loan balances, rather than separating the revolving and nonrevolving accounts, when we analyze mortgage offers. For a similar reason, we calculate the total number of credit denials for the previous six months for each consumer, rather than focusing on only personal finance inquiries and accounts. In addition, we also include dummy variables for whether a mortgage is part of a government-sponsored program (FHA or VA) and whether the offer is for a refinance loan or new purchase.

If fintech lenders play a role in expanding credit access to the underserved consumers, we would expect the coefficients to reflect that fintech firms reach out to lower credit-score consumers and those with difficulty accessing credit from traditional lenders. In other words, we anticipate that offers to lower-income consumers, those in lower-income areas, and offers to areas with more minorities would be more likely to be fintech offers, as these consumers often have more difficulty accessing credit from banks and may have incentives to switch to fintech firms.

V.2 Robustness Testing

We perform three additional analyses that provide further evidence to support our main findings from the previous section. These robustness results are presented in the Appendix.

First, we recognize *credit card offers* (by banks) as a potential substitute for personal loan offers. We run a multinomial logistic regression for the personal loan offers, using the full sample of both credit cards and personal loans. We do this to account for the fact that credit cards and personal loans are highly substitutable. So, ignoring credit cards in our earlier specification may not paint the full picture of who fintech firms are targeting to relative to traditional banks, particularly since the majority of traditional banks' mail are in the form of credit card offers (rather than personal loan offers). In this extended analysis, we use credit cards as the base group and compare both traditional and fintech personal loan offers with the base group and to each other.

Second, we differentiate between mortgage offers for *refinance* versus for home *purchase*. We rerun our initial specification for the mortgage offers but restrict the sample to only purchase offers (excluding refinance offers). We do this because consumers who receive refinance offers already own a home, and they are therefore likely to systematically differ from consumers who receive purchase offers in a number of respects. Most notably, homeowners typically already have relatively easy access to credit, so including this group in our original regressions may cause bias in the estimates of the credit access variables.

Third, we apply *more complex algorithms* to reevaluate the main findings. We run machine learning algorithms, specifically random forest and decision tree models, using the same variables we included in our logistic regression models (presented in Tables 3–10) to better understand the factors that are most important for predicting whether a credit offer is from a fintech or a traditional lenders. We then perform a feature importance calculation for each variable to determine the importance of each variable based on its contribution in predicting the outcome (whether a credit offer is from a fintech or traditional firms).

VI. The Empirical Results: Personal Loan Offers

VI.1 Main Results on Personal Loan Offers — Logistic Regressions

We first compare fintech firms with traditional banks. The sample observations only include credit offers made by banks or fintech lenders during the period 2015–2018. Nonbank offers are excluded in this section of the analysis. The results will help us understand the potential for fintech to fill the credit gaps in the banking sector. However, banks and fintech firms are not subject to the same regulatory requirements (e.g., banks are required to maintain adequate capital and liquidity to ensure safety and soundness due to their federally insured deposits). To compare lending incentives among similar lenders, we also compare fintech lenders with other nonbank lenders in a separate analysis.

Personal Loan Offers — Fintechs versus Banks

In comparing credit offers by fintech lenders versus banks, we find that, overall, fintech firms target subprime consumers more than banks do. We also find some evidence that fintech lenders reach out to the underserved, such as those who have experienced a bankruptcy and those whose credit applications have been denied (in the last six months) by traditional lenders, more than banks do. However, we also find that fintech firms target consumers with higher balances on both revolving and nonrevolving accounts and those with more credit card offers, two indications of consumers being adequately served by banks. The full sets of results are shown in Tables 3 and 4. Table 3 shows the results from the logistic regressions that estimate the probability that a personal loan offer is a fintech offer, rather than a bank offer. Table 4 presents the marginal impact probabilities calculated from the logistic results presented in Table 3.

Consumer Credit Scores: In column 1 of Table 3, the coefficient of dummy indicators for being near prime, prime, and super prime (with subprime being the base case) are significantly negative, and they are in rank order with coefficients, getting more negative from near prime (-0.49), prime (-01.45), and super prime (-2.53). The marginal impact of these variables, from Table 4, are -0.09 for near prime, -0.282 for prime, and -0.475 for super prime. The results indicate that credit offers to subprime consumers are almost 30 percentage points (50 percentage points) more likely to be from a fintech firm, rather than a bank, compared with offers to prime (super prime) consumers. The coefficients and the marginal impacts remain significantly negative and in rank order even when additional risk characteristics and control factors are also included in the models, as presented in columns 2–6 of Tables 3 and 4. These results are consistent with an argument that fintech lenders attempt to reach out to subprime borrowers and those consumers are underserved by banks.

Household Income: The effect of income is much more muted. The marginal impacts of income, as shown in column 6 of Table 4, are relatively small and only significant for the higher-income brackets. The medium-income borrowers ($50K–$75K income) are around 2 points more likely to receive a fintech offer, while the higher-income bracket is 3 points more likely to receive fintech offers. These results indicate that the higher-income groups are more likely to receive an offer from a fintech firm, but there is no difference among lower-income groups. Consistent with this finding, the results on the marginal impact (in the full model in column 6 of Table 4) indicate that there is no significant difference between fintech offers and bank offers with regard to the zip code's median income of consumers.

Underserved Consumers: Aside from credit score, there are other indications that fintech firms are specifically reaching out to consumers with significant credit issues. The coefficients of *bankruptcy* indicators and *credit denial* indicators are consistently positive and significant in Tables 3 and 4. From column 6 of Table 4, in the full model where all the risk and control factors are included, the results indicate that credit offers made to consumers who had experienced bankruptcy are 27 percentage point more likely to be from a fintech firm, rather than from a bank. And credit offers made to consumers whose credit applications have been denied at least once in the past six months are 3.8 percentage points more likely to be from a fintech firm, rather than from a bank, suggesting once again that fintech lenders attempt to reach out to consumers who are credit constrained or have trouble obtaining credit through the traditional channels.

Despite this, our other indicators of being underserved seem to paint a slightly different picture. Consumers with more credit accounts and those with higher loan balances — two indicators of having adequate access to credit — are more likely to receive offers from fintech firms, and the effect is rather large. In our full specification, a 10 percent increase in a consumer's nonrevolving balance is associated with a 11 percent increase in the probability of an offer being from a fintech firm, and a similar increase in revolving balances leads to a 13 point increase. Since both the revolving and nonrevolving balance variables are positive, it indicates that fintech firms are more likely to reach out to consumers with high balances (on all accounts combined), not just their revolving (credit card) accounts. The *number of credit card offers* variable and the *number of accounts* variable are in the same direction but have a much smaller magnitude. Contrary to our other results, these findings present evidence that fintech firms also reach out to consumers who may already have good access to credit, at least from a historical perspective (since balances may be carried over from earlier periods). Taken together, we find that, in addition to subprime and underserved consumers, fintech firms also reach out to consumers who have had adequate access to credit in the past but who may have recently seen their credit scores drop and are now credit constrained.

Lastly, the coefficients of ratio of *minorities* in the zip code are also consistently positive and significant, as shown in columns 1–6 of Tables 3 and 4. The marginal impacts reported in Table 4 indicate that a credit offer is more likely to be an offer from a fintech lender, rather than from a bank, when the offer is sent consumers who live in a zip code with higher ratio of minorities, although the effect is rather small.

Personal Loan Offers — Fintechs versus Other Nonbanks

Both fintech and other nonbank lenders are not subject to the regulatory requirements that banks are subject to. In comparing fintech lenders with other nonbank lenders, we control for the regulatory landscape in this section. The results are in line with what we have observed earlier from raw data in Figures 2–5. The full results of our analysis comparing fintech and other nonbanks are presented in Tables 5 (logistic regression coefficients) and 6 (the associated marginal probabilities based on the coefficients presented in Table 5).

Consumer Credit Scores: In column 1 of Table 5, where we only include demographic variables without the indicators of credit access, the coefficient of dummy indicators for being near prime, prime, and super prime (with subprime being the base case) are significantly positive, but they are not in rank order — with coefficients for near prime (0.989), to prime (1.158), and super prime (0.710). The marginal impact of these variables, from Table 6, are 0.203 for near prime, 0.238 for prime, and 0.142 for super prime. The results indicate that credit offers to subprime consumers are about 24 percentage points (14 percentage points) less likely to be from a fintech firm, rather than other nonbanks, compared with offers to prime (super prime) consumers. The coefficients and the marginal impacts remain significantly positive when additional risk characteristics and control factors are also included in the models, as presented in columns 2–6 of Tables 5 and 6. These results are opposite to those discussed earlier when comparing fintech lenders with banks. Both fintech and other nonbank lenders are more likely to reach out to less creditworthy (subprime) consumers than banks do, although other nonbank lenders seem to be more aggressive in doing so than fintech lenders.

Household Income: Similarly, in column 1 of Table 5, we find the coefficients of income to be all significantly positive; that is, 0.325 for the low-income consumers (with household incomes $25K–$50K), 0.637 for the next income bracket ($50K–$75K), and 0.748 for the highest income brackets (more than $75K). However, the coefficients are muted when additional risk characteristics and other control factors are also included, as shown in column 6 of Tables 5 — with much smaller coefficients of 0.112 (for $25K–$50K), 0.234 (for $50K–$75K), and 0.256 (for more than $75K). The marginal impacts of income, as shown in the full model in column 6 of Table 6, are 0.021 (for $25K–$50K), 0.045 (for $50K–$75K), and 0.050 (for more than $75K), suggesting that credit offers to the lowest-income consumers (with household income below $25K) is about 5 percentage points less likely to be a fintech offer, rather than an offer from other nonbanks, compared with offers to consumers in the highest-income bracket of more than $75K. Overall, we have observed so far that there is only a small marginal difference across lender types with regard to consumer household income, which are quite the opposite results from the credit score story.

Underserved Consumers: The results are somewhat mixed. On the one hand, we find that fintech lenders are more committed to serve some groups of underserved consumers than other nonbank lenders. The coefficients on the *bankruptcy* indicator are consistently positive and significant in Tables 5 and 6. From column 6 of Table 6, in the full model where all the risk and control factors are included, the results indicate that credit offers made to consumers who had experienced bankruptcy are about 12 percentage points more likely to be from a fintech firm, rather than from other nonbanks. We also observed earlier the same impact when comparing fintech with banks — overall, the results on bankruptcy are consistent with a statement that fintech firms are making a significant effort to serve this group of consumers, above and beyond what other lenders are willing to do.

However, on the *credit denial* factor, we find that credit offers made to consumers whose credit applications have been denied at least once in the past six months are 4.8 percentage points *less* likely to be from a fintech firm, rather than from other nonbanks. In addition, consumers with larger balances (i.e., those who have had good access to credit in the past are more likely to get a fintech offer).

Unlike when we compare fintech with banks, we find that the coefficients of the ratio of *minorities* in the zip code are consistently insignificantly different from zero, as shown in columns 1–6 of Tables 5 and 6. The marginal impacts reported in Table 6 indicate that a credit offer is equally likely to be an offer from a fintech lender or other nonbanks, regardless of the ratio of minorities in the zip code where consumers reside. There is, however, a significant marginal impact when considering rural versus urban consumers. The full model (column 6 of Table 6) indicates that credit offers made to consumers in rural areas (which tend to be less likely to have good access to traditional financial services) are about 6 percentage points more likely to be a fintech offer, rather than one from other nonbanks.

Overall, the results on bankruptcy and rural indicators are consistent with an argument that fintech lenders attempt to reach underserved consumers and penetrate underserved areas, even when comparing with other nonbank lenders. These findings are consistent with Jagtiani and Lemieux (2018), which explore the roles and fintech lenders using the actual loan *origination* (data from LendingClub's personal lending platform), rather than credit *offers*. They find that LendingClub personal lending activities penetrate areas that are likely to be underserved by traditional banks. Despite this, other indicators of being underserved point in the opposite direction. Consumers who have recently experienced a credit denial are less likely to receive a fintech offer (rather than a nonbank offer), and those with larger revolving balances are also more likely to receive a fintech offer rather than a nonbank offer.

VI.2 Robustness Testing on Personal Loan Offers

Multinomial Logistic Regression Model

In this section, we consider an additional financial product, which is relatively substitutable to personal loan offers: credit card offers. It has been documented that more than 80 percent of personal installment loans have been used by consumers to pay off their credit card balance. We include credit card offers in the sample, using a multinomial logistic regression to compare the characteristics of offers across the three groups: fintech personal loans, bank personal loans, and bank credit cards. The marginal probabilities for an offer being from a fintech firm are shown in Table A1 in the Appendix.

The results confirm our main results reported in the previous section; that is, we find that credit offers to *subprime* consumers are 24 percentage points more likely to be from fintech firms than from banks. In addition, the results hold even when we compare fintech loan offers with the overall credit offers from banks (including both bank personal loan and credit card offers). Specifically, credit offers to subprime consumers are 11 percentage points more likely to be from fintech firms than from banks when considering all credit offers from banks. Similarly, the results on the *bankruptcy* indicator remain robust, although the magnitude is somewhat smaller when including credit cards. In addition, we find that credit offers to consumers in *rural areas* are 5 percentage points more likely to be from fintech firms than from banks, although the effect of being located in a rural area was not significant in the main results. The percent minority and zip code median income effects are still either very small or insignificant. The effect of credit *denials* is now somewhat more muted, with offers to consumers with credit denials in the last six months around 2 percentage points more likely to be from fintech firms than from banks.

These findings provide additional evidence of fintech firms' marketing efforts in the personal loan sector and echo our main results. Overall, we find that fintech firms are significantly more likely to reach out to subprime consumers and those who have recently been denied credit, compared with traditional banks.

Machine Learning Algorithm

We rerun Models 5 and 6 from Table 3, using machine learning (ML) algorithms, specifically random forest and decision tree algorithms, to examine the most important factors that determine whether an offer is from fintech firms or from nonfintech lenders. Figure A1 shows the 10 most important factors in the model, in terms of their ability to correctly classify observations as being either fintech offers or bank offers.

In Model 5, which includes the number of credit card offers received (at the zip code and consumer level) as a measure of credit access, the ML algorithms find that the dummy variables for *credit score* bins have the most impact, which is in line with our logistic regression estimates. Interestingly, when *credit utilization* and *balances* are included in the model (Model 6), credit utilization becomes the single-most important variable in predicting whether an offer is from a fintech lender, although the coefficient on credit utilization was significant but quite small in size in the logistic analysis.[13] The *bankruptcy* indicator was another one of the most important variables in the ML models, typically the second-most important. This confirms the results of our logistic model, which showed a very strong positive effect of bankruptcy on determining whether an offer is from a fintech lender. Some variables were determined to be somewhat stronger predictors of an offer being from a fintech offer when using ML models, despite having very small coefficients (although still statistically significant) in the logistic models. The variables are the percentage of *minorities* in the zip code, the median income of the zip code, and the number of bank branches per 100,000 people in the county.

Interest Rates Offered by Fintech versus Banks versus Other Nonbanks

Now that we understand the types of consumers that fintech firms are targeting in the personal loan sector, we perform a basic comparison of the rates offered by different types of lenders, controlling for consumer credit risk as proxied by VantageScore 3.0 ranges. As mentioned earlier, interest rates are generally offered as a range, such as 15 percent (Lowest rate) to 24 percent (Highest rate).[14]

Figure 8 (left panel) compares the rates offered by different lender types for personal loans graphically. Fintech firms offer the least expensive rate when considering the Lowest rate — generally between 75 and 400 basis points lower than the rate offered by traditional lenders. The interest rates offered by traditional nonbank lenders are a great deal higher than that of fintechs and banks — typically many times higher, especially for subprime and near-prime consumers. The potentially lower rates offered by fintech firms, particularly to subprime consumers, indicate that fintech lenders are more willing to serve certain subprime consumers than banks — the so-called hidden prime, who have a high likelihood of repayment despite their low credit scores.

When considering the Highest rate offered, we find that the maximum rate offered by fintech lenders tends to be much higher than banks' rates. Once again, traditional nonbank lenders offer rates that are much higher than either banks or fintech lenders. It is interesting to observe that fintech firms tend to offer a rate range that is wider than that of traditional firms. This potentially indicates that fintech firms are able to provide loans at a lower cost than traditional firm to consumers they deem as the most creditworthy but may also be reaching out to very risky borrowers that traditional banks do not serve, compensating for this risk with higher interest rates.

[13] These differences could result from credit utilization having a nonlinear or interactive effect on the probability of an offer being from a fintech firm, something that our logistic model would not detect.

[14] However, some mailings include only one rate, so the sample size will differ slightly for the lowest rate and highest rate calculations. Note that we only include personal loans in these calculations, so credit cards are excluded.

VII. The Empirical Results on Mortgage Loan Offers

VII.1 Main Results — Logistic Regressions

A mortgage is a very different product than a personal loan, which is unsecured and generally much smaller in loan size and with a much shorter term to maturity. In addition, most mortgages qualify for federal guarantee through the government-sponsored enterprises (GSEs). As documented in Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021), fintech lenders have been part of the recent growth in mortgage origination in the nonbank sector. In fact, more than 80 percent of all FHA mortgages originated in 2018 were originated by nonbank (including fintech) lenders. We explore whether fintech lenders attempt to reach out to underserved consumers (to fill the credit gap) more than other types of lenders, based on their credit offers (which may or may not result in the actual mortgage origination). We first compare fintech lenders with banks, and then compare fintech lenders with other nonbank lenders.

Mortgage Loan Offers — Fintechs versus Banks

We use monthly data on mortgage credit offers during the period 2015–2018, excluding offers by traditional nonbank lenders in this analysis. The logistic regression results are presented in Table 7, and the marginal impacts are reported in Table 8.

Consumer Credit Scores: In columns 1–4 of Table 7, the coefficients of dummy indicators for being prime and super prime (with subprime being the base case) are significantly negative across all models from column 1–4. The coefficients for super prime are more negative than the coefficients for prime, while the coefficients for near prime are insignificantly different from subprime (base case). The marginal impact of these variables, from column 1 of Table 8, are -0.028 for near prime, -0.08 for prime, and -0.15 for super prime. These results indicate that mortgage credit offers to subprime consumers are about 15 percentage points and 8 percentage points more likely to be from a fintech firm, rather than a bank, compared with offers to super prime and prime consumers, respectively. The coefficients and the marginal impacts remain significantly negative and in ranking order even when additional risk characteristics and control factors are also included in the models, as presented in columns 2–4 of Tables 7 and 8. While the effect of a credit score is smaller for mortgage offers than for personal loan offers, our findings overall indicate that mortgage fintech lenders attempt to reach out to subprime borrowers and those being underserved by banks.

Household Income: The effect of household income is also strong. From columns 1–4 of Table 7, the coefficients for those with income in the $25K–$50K and $50K–$75K brackets are significantly positive, but the coefficients for those with the highest income bracket is insignificant.

Mortgage offers to the low- to moderate-income population are more likely to be from fintech lenders than from a bank. The marginal probability impacts of income, as shown in Table 8, are 0.056, 0.056, 0.055, and 0.054 in columns 1, 2, 3, and 4, respectively, for the lowest income bracket of \$25K–\$50K. While mortgage credit offers to consumers in higher household income brackets are equally likely to be from fintech or banks, those offers sent to the low- to moderate-income bracket (\$25K–\$50K) are about 5 percentage points more likely to be from a fintech firm than from a bank, compared with offers to the lowest income bracket (<\$25K).

Underserved Consumers: In comparing mortgage offers from fintech versus banks, we find evidence that fintech lenders reach out to consumers in areas where there is less *access to banking services*. From Table 7, the coefficients of bank branch density (number of bank branches per 100K people in the zip code) are consistently significantly negative. In addition, we find that *credit inquiries* and credit *denial* factors are also important. The coefficients of number of credit inquiries (in the past six months) and the coefficient for the dummy indicator for being denied credit at least once (in the past six months) are all significantly positive. Using the marginal impact estimated in Table 8, we find that mortgage offers to those who have been denied credit are 6 percentage points more likely to be from fintech firms than from banks. These results are consistent with Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021), who find that mortgage loans are more likely to be originated by fintech lenders in zip codes where mortgage denial rates are higher in the previous period.

In addition, the coefficients for *FHA mortgages* are consistently positive and significant, indicating that mortgage offers associated an FHA purchase (generally a smaller loan amount and for lower-score borrowers) are more likely to be fintech offers, rather than bank offers. Mortgage credit offers associated with an FHA purchase are 40 percentage points more likely to be from a fintech lender rather than from a bank.[15] *Refinancing* is another significant factor for mortgage offers, and it is controlled for in our models. Fintech lenders are likely to send offers to those who already have a mortgage to refinance at a better rate. We find that mortgage offers associated with refinancing are almost 48 percentage points more likely to be from a fintech firm than from a bank.[16]

Recipients of fintech mortgage offers are generally lower-income, subprime, have more need to access more credit (through number of inquiries), have been denied credit recently, and

[15] Note that the volume of FHA mortgage offers for both groups is quite small, so this result should not be overemphasized. However, it has been documented in the literature that banks have been originating less than half of FHA mortgages since 2012; see Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021).

[16] The process for obtaining a refinance is easier and less bureaucratic, so this gives fintechs more of an advantage over traditional banks.

tend to live in areas with fewer bank branches. Fintech firms appear to be stepping in to fill this credit gap, potentially providing significant benefits to underserved consumers.

Mortgage Loan Offers — Fintechs versus Other Nonbanks

Fintech lenders appear to target a lower-income population, relative to banks and other nonbank lenders. Mortgage offers to consumers with high incomes (greater than $75,000) are 4 percentage points less likely to be from a fintech firm than from other nonbank lenders. The full results of the analysis comparing mortgage mailing offers of fintechs and traditional nonbanks are shown in Tables 9 and 10.

The results from Model 1 indicate that credit offers to low- to moderate-income consumers are around 4 percentage points more likely to be from a fintech lenders than from other nonbank lenders. Despite their efforts to reach low-income population, fintech firms are slightly less likely (3 percentage points) to target subprime consumers than other nonbanks do, compared with prime consumers. The focus of traditional nonbank lenders on subprime consumers does not come without cost, however. As we will see, they offer consistently higher interest rates to subprime consumers than fintech lenders do, highlighting that traditional nonbank lenders charge a premium relative to both banks and fintech firms.

We also find that credit offers from fintech firms are more likely to be for a refinance (rather than purchase), a finding that mirrors our results in the fintech versus bank sample. When considering loan type (conforming, FHA, VA mortgages), we find that fintech firms are much less likely than traditional nonbanks to send offers for VA loans as the traditional nonbank lenders seem to have a very significant presence in this market. Regarding credit access, fintech firms appear to be targeting consumers with limited access to credit, as evidenced by the negative coefficients on the number of accounts and total loan balances variables. Despite this, offers to consumers who have experienced credit denial are less likely to come from fintech firms rather than traditional nonbank lenders, although the effect is small.

VII.2 Robustness Testing — Mortgage Loan Offers (Excluding Refi)

For robustness, we further test our main findings reported earlier in Tables 7–8 (fintech versus banks) and Tables 9–10 (fintech versus traditional nonbanks). Given that the majority of mortgage mail offers are for refinances rather than purchases and that consumers who already have a mortgage tend to be relatively more creditworthy (assuming they are not delinquent on their mortgage), it could be argued that the results from our main analysis are not generalizable to less creditworthy populations, the very group we are interested in studying. To remedy this, we rerun our main analysis but exclude refinance offers — to focus on new purchase offers only. This allows us to isolate offers to potentially credit-constrained consumers to better understand who fintech firms are targeting within this group, as compared with banks and traditional nonbanks. The findings are shown in the Appendix Tables A2 (for fintechs versus banks) and Table A3 (for fintech versus traditional nonbank lenders).

From Table A2, some of our earlier findings no longer hold in this reduced-sample regression, at least in a statistically significant sense. The point estimates for our highlight findings are in the same direction as our main analysis, but few results remain significant, probably because of the much smaller sample size. The coefficient on the \$25K–\$50K income group dummy is still positive, but the value is small and not statistically significant. The credit score dummies also remain in the same direction, but only the super prime dummy is significant, with offers to super prime consumers around 8 points less likely to be from fintech firms. The bank branches concentration variable (branches per 100,000 people) is also in the same direction as our main analysis but no longer significant.

The finding that fintech firms target consumers who have experienced a credit denial is still strong and significant, with offers to these consumers 8 percentage points more likely to come from fintech firms. The finding that FHA offers are much more likely to be from fintech firms, compared with traditional banks, also remains significant and strong. These results suggest that fintech has allowed the underserved consumers to access mortgage credit and potentially has a role to play in promoting homeownership for purchase transactions by first-time homebuyers.

The results comparing fintechs to traditional nonbank lenders (in Table A3) are qualitatively similar to the main analysis, although few of the coefficients remain significant. The VA offers are still significantly less likely to be from fintech firms as well as offers to low-balance consumers. Since the point estimates for the coefficients from this additional set of regressions are in the same direction as in the main analysis, this provides some indication of the robustness of our main results, but one should be cautious when generalizing our mortgage offer results to the wider population of credit-constrained consumers.

Additional Analysis: Machine Learning Algorithms

Again, we rerun the previous analysis (Models 1 and 4 from Table 7) using ML algorithms, specifically the random forest and the decision tree algorithms, to determine the best predictors for whether a mortgage offer is fintech or nonfintech. Figure A2 show the 10 most important variables in the model, in terms of their ability to correctly classify observations as being either fintech or traditional.

The results from both the logistic and the ML models indicate that loan type indicators (refinance loan, VA, or FHA loan) are the most important determinants for whether a mortgage offer is a fintech offer. Both models also place a relatively high importance on consumer credit scores (the credit score bracket dummy variables) and bank branch concentration (bank branches per 100,000 people in zip code). This gives us confidence that our logistic models accurately represent the most important factors affecting mortgage fintech mailings.

There are some notable differences between the models. Although a zip code's median income is generally not significant in the logistic regression analysis, this variable is in the top five for importance in the decision tree and random forest models for both specifications. Similarly, zip code average Equifax Risk Score and percent minority per Census Bureau data are deemed somewhat important indicators of fintech status by the ML algorithms, but the coefficients on these variables are either small or insignificant in the logistic regression. Again, these differing results could be due to nonlinear relationships between zip code risk score and percent minority and the probability of a mortgage offer being from a fintech firm.

Comparison of Mortgage Interest Rates Offered

Figure 8 (right panel) compares the average interest rates spreads offered by lender types. It is interesting to note that the range of mortgage rates offered by fintechs is much narrower on average than in the unsecured personal loan sector — typically within 50 basis points of each other and within 25 basis points comparing fintech versus traditional nonbanks. This may mean that fintech firms have less of an efficiency advantage in the highly complex and bureaucratic mortgage market.

Unlike in the personal loan sector, fintechs offer universally higher rates to subprime consumers than banks do in the mortgage sector but offer lower rates to near-prime consumers. Fintech firms appear to have less of a price advantage over banks for subprime consumers in the mortgage market, where both the Lowest and Highest rates are higher for fintechs among this group of consumers. In contrast, fintech firms maintain a strong advantage among near-prime consumers, with both Lowest and Highest rates being lower than banks for this group.

Comparing fintechs with traditional nonbanks, it appears that traditional nonbank lenders offer the lowest rates among all lender types (lower rates than both fintechs and traditional banks) to super prime consumers. This cost advantage, however, erodes for the less-prime consumers. In fact, traditional nonbank lenders offer the highest mortgage rates to subprime consumers among the three lender types, and they also send the most offers to subprime consumers. Subprime consumers seem to be a profitable segment for traditional nonbank lenders.

VIII: Conclusions

Our goal in this paper is to explore whether fintech firms have been reaching out to underserved consumers to expand credit access and to fill the credit gaps. We focus on a few financial products: unsecured personal loans, mortgage loans, and credit cards. We identify the underserved consumers or underserved communities based on their demographic characteristics and geographic locations. For example, consumers who are minorities, with low credit scores and low income, and those who have filed for bankruptcy may have been sidelined from mainstream finance. In addition, those who reside in a low- to moderate-income neighborhood, in rural areas, or in areas where there are few bank branches may also have limited access to credit, thus potentially being underserved.[17]

This is an important question, given the growing prominence of fintech firms in the financial landscape and their potential to improve credit access for the underserved. Our paper is among the first to examine the supply side of fintech credit and compare fintechs with both traditional banks and nonbank lenders.[18] We find suggestive evidence that fintechs do reach out to certain groups of underserved consumers more than banks, particularly subprime consumers, and this is true for both the unsecured personal lending and mortgage lending. Subprime consumers usually apply for smaller loans, which are expensive for traditional lenders to originate, thus, making it much more likely that their loan applications will be denied. Unlike traditional lenders, fintech firms do not face significant origination cost for small loans because their end-to-end loan origination system is fully digitized.

For mortgage lending, we find evidence that fintech firms reach out to marginalized consumers more than traditional banks do. Among all mortgage products, FHA loans are more likely to be used by lower-income and lower-credit score consumers. We find that FHA loan offers are much more likely to be offered by fintech firms than banks. In a similar vein, offers to low- to moderate-income consumers ($25K–$50K annual household income) are also more likely to come

[17] Our definition of underserved consumers includes those with low-credit scores. Some might question whether lower-score consumers are actually underserved (as they might be too risky for lenders to extend credit to). We argue that low-score consumers are much more likely to be underserved by traditional lenders because they usually need small loans, and they would generally apply for smaller loans than the high-score consumers. For traditional lenders, it is expensive to originate small loans than large loans; therefore, small loans from low-score consumers are often denied because it is not worthwhile for lenders to pursue. This is where fintech lenders could make a difference, as they can originate small loans at minimal cost, and it makes no difference to fintech lenders in terms of origination cost whether the loans are large or small. For this reason, low-score consumers who may be underserved by traditional lenders are more likely to receive credit from fintech lenders. Jagtiani and Lemieux (2019) find that some low-score borrowers are charged less than what they would have had to pay for loans from traditional nonbank lenders.

[18] Our analysis, using data from Mintel, automatically excludes consumers who were not included in the survey. Our conclusions on the characteristics of credit offers from different lender types are drawn from those consumers who receive credit offers only.

from fintech lenders, as opposed to banks. Furthermore, fintech firms are more likely to target consumers who have been denied credit in the recent past and marginally more likely to target consumers in areas with fewer bank branches. Comparing fintechs with other nonbank lenders in the mortgage space, we find that fintech firms seem to target a more credit-constrained group, specifically lower-balance and lower-income consumers. Taken together, our results demonstrate that fintech firms help to expand access to credit for marginalized and underbanked consumers within the mortgage market. And the results in general hold even when we only consider mortgage loans for purchase transactions, excluding those for refinancing.

For unsecured personal lending, we find that fintech firms target lower-score consumers, compared with banks, particularly those who have experienced a bankruptcy and those with a recent credit denial. We also find that some consumers who might not be underserved —as proxied by their higher existing loan balances, higher incomes, more credit accounts, and receiving more credit card offers — are also likely to receive personal loan offers from fintech firms. These relatively well-served consumers might have had adequate credit access in the past but may have overextended themselves, missing a few payments or otherwise blighting their credit history, saw their credit score drop significantly, and are looking for ways to refinance their earlier debt.

Our results find strong evidence of fintech's roles in making mortgage credit and personal unsecured credit more accessible to consumers who are below prime, low income, and have experienced credit denial or bankruptcy. We also find some evidence that paint a nuanced picture of the types of consumers that fintech firms market to with their direct mail. Much of our evidence points to fintechs driving credit expansion for particular groups of credit-constrained consumers — low-income, low-score, and recent credit denials for mortgage credit — and low-score, large debt carried over from the past, and bankruptcy for personal loans.

Overall, we find that the rapid entry and expansion of fintech firms into the personal lending and mortgage lending space have delivered potential benefits to subprime and other credit-constrained consumers, allowing them more credit options through fintech (direct mail) credit offers. As pointed out earlier, fintechs and other nonbank lenders compete with banks in offering personal and mortgage loans without being subject to the same regulatory constraints.[19] Mester (2020) points out that existing regulatory and supervisory structures need to adapt to keep pace with the new financial landscape — with new high-tech players delivering financial products and services. Financial regulators have contemplated *activity-based* regulations, rather than entity-

[19] Nonbank lenders are not subject to onsite examinations by the Fed, the OCC, and the FDIC. However, all lenders, whether they are banks or nonbank lenders, are subject to state regulations and the Consumer Financial Protection Bureau (CFPB) oversights. For example, the CFPB issued a no-action letter to a fintech lender, Upstart, to ensure that the use of its AI models and alternative data would not result in unfair credit decisions.

based regulations. Following the activity-based principle, "If it walks like a duck and quacks like a duck, it should be treated like a duck."

At the same time, financial regulators have contemplated other ways to facilitate successful integration of fintech into the traditional banks, especially the small community banks; see Bowman (2020a, 2020b, and 2021). Fintech partnerships could expedite digitization in banking and help banks to offer new products and services, expand customer base, digital customer onboarding, increase portfolio diversification through a greater geographic footprint, improve operational efficiency, and enhance customer satisfaction overall. Bowman (2020b) points out that "AI is becoming more prevalent in customer service and ML can offer real opportunities to assess risk and find new customers." Our results suggest that with access to technology and better data through fintech partnerships, small banks would be in a position to compete with high-tech challenger banks and more likely to identify good borrowers from the subprime pools. As a result, we would likely see more direct mail credit offers from banks to subprime consumers as well.

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Table 1: Summary Statistics — Personal Loan Offers
Data Period: 2015–2018

Panel A: Credit Offers by Fintech and Traditional Banks

	Mean	St. Dev.	Min	Max	Count
Num. accounts >=60 DPD	0.0449	0.3716	0	19	51814
Age <=35	0.1672	0.3731	0	1	51814
Age 35-55	0.4671	0.4989	0	1	51814
Age >55	0.3658	0.4817	0	1	51814
Bankruptcy_d	0.0892	0.2851	0	1	51814
Banks per 100K	27.66	28.76	0	1198	51814
Num. card offers (consumer)	2.213	2.789	0	38	51814
Card offers per 100K	19.05	39.51	0	1751	51814
Income <$25K	0.1033	0.3044	0	1	51814
Income $25K-$50K	0.2481	0.4319	0	1	51814
Income $50K-$75K	0.2466	0.431	0	1	51814
Income >$75K	0.402	0.4903	0	1	51814
Lender_d	0.5984	0.4902	0	1	51814
Ln(Total Bal)	10.88	1.759	0	14.77	51814
Ln(Non-Revolving Bal)	9.939	3.224	0	14.77	51814
Ln(Revolving Bal)	8.618	2.22	0	14	51814
Loan period (years)	3.866	1.101	.75	7	2521
Median income of zip code ($1,000s)	72.96	24.92	17.78	238.8	51814
Num. credit denials	0.7579	1.63	0	22	51814
Consumer: total # of accounts	23.7	13.15	1	142	51814
Consumer: # bankcards	3.813	2.838	0	44	51814
Consumer: # non-bankcard accounts	19.89	12.09	0	142	51814
Credit util. on all revolving a/c	41.62	27.25	0	760.3	51349
Percent minority in zip code	28.58	22.45	0	99.14	51814
High spread	25.91	9.77	-1.56	196.5	45770
Low spread	4.778	3.344	-1.56	96.48	47024
Subprime_d	0.1417	0.3487	0	1	51814
Near prime_d	0.2987	0.4577	0	1	51814
Prime_d	0.4064	0.4912	0	1	51814
Super prime_d	0.1532	0.3602	0	1	51814
Metro area	0.8873	0.3162	0	1	51814
Nonmetro area	0.1045	0.3059	0	1	51814
Rural area	0.0082	0.0902	0	1	51814
Mean Equifax Risk Score of zip code	703.5	51.51	370	834	51814
yr2015	0.1817	0.3856	0	1	51814
yr2016	0.2398	0.427	0	1	51814
yr2017	0.25	0.433	0	1	51814
yr2018	0.3285	0.4697	0	1	51814

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 1: Summary Statistics — Personal Loan Offers (Continued)
Data Period: 2015–2018

Panel B: Credit Offers by Fintech and Other Nonbank Lenders

	Mean	St. Dev.	Min	Max	Count
Num. accounts >=60 DPD	0.1882	0.8668	0	24	57029
Age <=35	0.1573	0.3641	0	1	57029
Age 35-55	0.4867	0.4998	0	1	57029
Age >55	0.356	0.4788	0	1	57029
Bankruptcy_d	0.1254	0.3311	0	1	57029
Banks per 100K	27.18	26.1	0	1198	57029
Num. card offers (consumer)	1.922	2.76	0	38	57029
Card offers per 100K	16.54	37.74	0	1756	57029
Income <$25K	0.1485	0.3556	0	1	57029
Income $25K-$50K	0.2815	0.4497	0	1	57029
Income $50K-$75K	0.236	0.4246	0	1	57029
Income >$75K	0.334	0.4716	0	1	57029
Lender_d	0.5437	0.4981	0	1	57029
Ln(Total Bal)	10.51	2.119	0	14.77	57029
Ln(Non-Revolving Bal)	9.692	3.218	0	14.77	57029
Ln(Revolving Bal)	7.928	2.973	0	13.24	57029
Loan period (years)	2.828	1.16	0.08333	10	3713
Median inc. of zip code ($1,000s)	69.04	23.5	12.47	238.8	57029
Num. credit denials	1.178	2.45	0	48	57029
Consumer: total # of accounts	23.09	14.03	1	110	57029
Consumer: # bankcard accounts	3.638	3.074	0	44	57029
Consumer: # non-bankcard accounts	19.45	12.82	0	107	57029
Credit util. on all revolving a/c	51.05	28.99	0	999.9	54837
Percent minority in zip code	30.93	23.48	0	99.14	57029
High spread	36.83	62.13	-2.97	897.5	33374
Low spread	11.86	42.94	-2.97	719.2	34440
Subprime_d	0.3165	0.4651	0	1	57029
Near prime_d	0.3318	0.4709	0	1	57029
Prime_d	0.2854	0.4516	0	1	57029
Super prime_d	0.0663	0.2488	0	1	57029
Metro area	0.8745	0.3313	0	1	57029
Nonmetro area	0.118	0.3226	0	1	57029
Rural area	0.0075	0.0863	0	1	57029
Mean Equifax Risk Score of zip code	697.9	51.61	362	833	57029
yr2015	0.183	0.3867	0	1	57029
yr2016	0.2817	0.4498	0	1	57029
yr2017	0.2479	0.4318	0	1	57029
yr2018	0.2874	0.4525	0	1	57029

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 2: Summary Statistics — Mortgage Loan Offers
Data Period: 2015–2018

Panel A: Credit Offers by Fintech and Traditional Banks

	Mean	**St. Dev.**	**Min**	**Max**	**Count**
Num. accounts >=60 DPD	0.0883	0.5601	0	16	11007
Age <=35	0.1055	0.3072	0	1	11007
Age 35-55	0.4843	0.4998	0	1	11007
Age >55	0.4102	0.4919	0	1	11007
Bankruptcy_d	0.0451	0.2075	0	1	11007
Banks per 100K	27.88	20.15	0	377	11007
Num. credit inqs.	0.5765	1.205	0	16	11007
Income <$25K	0.05615	0.2302	0	1	11007
Income $25K-$50K	0.2035	0.4026	0	1	11007
Income $50K-$75K	0.2351	0.4241	0	1	11007
Income >$75K	0.5052	0.5	0	1	11007
FHA_d	0.014	0.1175	0	1	11007
VA_d	0.1049	0.3065	0	1	11007
Refinance_d	0.6101	0.4878	0	1	11007
Lender_d	0.5251	0.4994	0	1	11007
Ln(Total Bal)	11.41	1.93	0	14.74	11007
Loan period (years)	22.23	7.968	4.75	84.5	6049
Median inc. of zip code ($1,000s)	79.32	27.5	19.32	238.2	11007
Consumer: total # of accounts	21.17	12.36	1	142	11007
Num. credit denials	0.6669	1.698	0	29	11007
Credit_denials_d	0.2823	0.4501	0	1	11007
Percent minority in zip code	28.17	21.04	0.2736	99.14	11007
High spread	1.521	1.19	-.73	18.09	6212
Low spread	1.433	0.5265	-.95	7.12	7015
Subprime_d	0.0667	0.25	0	1	11007
Near prime_d	0.122	0.3273	0	1	11007
Prime_d	0.3201	0.4665	0	1	11007
Super prime_d	0.491	0.4999	0	1	11007
Metro area	0.9311	0.2532	0	1	11007
Nonmetro area	0.0652	0.2469	0	1	11007
Rural area	0.0036	0.0602	0	1	11007
Mean Equifax Risk Score of zip code	708.5	50.09	370	833	11007
yr2015	0.2325	0.4224	0	1	11007
yr2016	0.3012	0.4588	0	1	11007
yr2017	0.2587	0.4379	0	1	11007
yr2018	0.2077	0.4057	0	1	11007

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 2: Summary Statistics — Mortgage Loan Offers (Continued)
Data Period: 2015–2018

Panel B: Credit Offers by Fintech and Other Nonbank Lenders

	Mean	St. Dev.	Min	Max	Count
Num. accounts >=60 DPD	0.1294	0.6435	0	16	19509
Age <=35	0.1096	0.3125	0	1	19509
Age 35-55	0.4941	0.5	0	1	19509
Age >55	0.3962	0.4891	0	1	19509
Bankruptcy_d	0.0623	0.2417	0	1	19509
Banks per 100K	25.96	19.36	0	307.7	19509
Num. credit inquiries	0.7278	1.378	0	16	19509
Income <$25K	0.053	0.224	0	1	19509
Income $25K-$50K	0.1925	0.3943	0	1	19509
Income $50K-$75K	0.2438	0.4294	0	1	19509
Income >$75K	0.5107	0.4999	0	1	19509
FHA_d	0.0402	0.1965	0	1	19509
VA_d	0.2915	0.4545	0	1	19509
Refinance_d	0.6002	0.4899	0	1	19509
Lender_d_shad (1=fintech)	0.2963	0.4566	0	1	19509
Ln(Total Bal)	11.64	1.881	0	14.74	19509
Loan period (years)	25.45	7.004	2	84.5	8927
Median inc. of zip code ($1,000s)	78.01	25.05	19.32	238.2	19509
Consumer: total # of accounts	23.11	14.04	1	142	19509
Num. credit denials	0.88	1.936	0	29	19509
Credit_denials_d	0.3566	0.479	0	1	19509
Percent minority in zip code	29.46	20.59	0	99.14	19509
High spread	1.915	36.48	-.84	3867	11229
Low spread	1.405	0.6816	-1.11	22.93	12253
Subprime_d	0.1023	0.303	0	1	19509
Near prime_d	0.1621	0.3686	0	1	19509
Prime_d	0.3851	0.4866	0	1	19509
Super prime_d	0.3505	0.4771	0	1	19509
Metro area	0.9331	0.2498	0	1	19509
Nonmetro area	0.0614	0.24	0	1	19509
Rural area	0.0055	0.0742	0	1	19509
Mean Equifax Risk Score of zip code	705.7	47.03	373	833	19509
yr2015	0.1998	0.3999	0	1	19509
yr2016	0.3353	0.4721	0	1	19509
yr2017	0.2651	0.4414	0	1	19509
yr2018	0.1999	0.3999	0	1	19509

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 3: Logistic Regression Results
Probability That a Personal Loan Offer Is from a Fintech Lender
Fintech Lenders versus Banks (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Age 35-55	0.130***	0.137***	0.0611*	0.0300	0.134***	0.0290
	(0.0345)	(0.0346)	(0.0346)	(0.0353)	(0.0347)	(0.0354)
Age >55	-0.0954***	-0.0839**	-0.183***	-0.128***	-0.0672*	-0.119***
	(0.0359)	(0.0361)	(0.0364)	(0.0366)	(0.0362)	(0.0367)
Income $25K-$50K	0.140***	0.146***	0.0669	-0.0051	0.134***	-0.0071
	(0.0484)	(0.0484)	(0.0483)	(0.0510)	(0.0485)	(0.0509)
Income $50K-$75K	0.346***	0.350***	0.215***	0.0905*	0.343***	0.0939*
	(0.0498)	(0.0499)	(0.0501)	(0.0531)	(0.0499)	(0.0531)
Income >$75K	0.461***	0.468***	0.294***	0.167***	0.452***	0.166***
	(0.0494)	(0.0497)	(0.0503)	(0.0534)	(0.0497)	(0.0535)
Near prime_d	-0.490***	-0.513***	-0.457***	-0.421***	-0.510***	-0.415***
	(0.0439)	(0.0443)	(0.0446)	(0.0474)	(0.0445)	(0.0475)
Prime_d	-1.499***	-1.524***	-1.436***	-1.284***	-1.518***	-1.272***
	(0.0419)	(0.0426)	(0.0438)	(0.0510)	(0.0428)	(0.0510)
Super prime_d	-2.527***	-2.535***	-2.451***	-2.060***	-2.510***	-2.031***
	(0.0539)	(0.0540)	(0.0550)	(0.0668)	(0.0542)	(0.0669)
# accounts >=60 DPD	-0.224***	-0.220***	-0.210***	-0.153***	-0.231***	-0.159***
	(0.0369)	(0.0369)	(0.0361)	(0.0368)	(0.0382)	(0.0377)
Bankruptcy_d	1.490***	1.508***	1.602***	1.735***	1.503***	1.730***
	(0.0621)	(0.0623)	(0.0630)	(0.0676)	(0.0627)	(0.0678)
Rural area_d	-0.0146	0.0463	0.130	-0.0479	0.0385	-0.0537
	(0.131)	(0.136)	(0.132)	(0.130)	(0.135)	(0.130)
% minority in zip code	0.0040***	0.0037***	0.0038***	0.0038***	0.0039***	0.004***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Med. income zip ($1,000)	0.0015***	0.0014**	0.0011*	0.0007	0.0018***	0.001
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Mean Equifax Risk Score zip	0.0007***	0.0007***	0.0007***	0.0007**	0.0007**	0.0006**
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Banks per 100k		-0.0001	0.0001	0.0002	-0.0001	0.0002
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
% card offers (consumer)		0.0249***	0.0203***	0.0156**	0.0253***	0.0161***
		(0.0064)	(0.0062)	(0.0062)	(0.0064)	(0.0061)
Card offers per 100K (zip)		-0.0006*	-0.0007*	-0.001**	-0.0007*	-0.0009**
		(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Ln(Non-Revolving Bal)				0.0642***		0.0590***
				(0.0046)		(0.0047)
Ln(Revolving Bal)				0.0707***		0.0720***
				(0.007)		(0.0070)
Utilization revolving a/c				0.0079***		0.0079***
				(0.0007)		(0.0007)
# bankcard accounts			0.0668***			
			(0.0052)			
# non-bankcard accounts			0.0137***			
			(0.0011)			
Credit_denials_d					0.270***	0.207***
					(0.0266)	(0.0271)
Observations	51,814	51,814	51,814	51,349	51,814	51,349
Month-Year Dummies	YES	YES	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 4: Logistic Regression Results
Marginal Probability Impact on Personal Loan Offer Being from a Fintech Lender
Fintech Lenders versus Banks (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Age 35-55	0.0249***	0.0263***	0.0115*	0.0056	0.0257***	0.0054
	(0.0066)	(0.0066)	(0.0065)	(0.0066)	(0.0066)	(0.0066)
Age >55	-0.0183***	-0.0161**	-0.0345***	-0.0239***	-0.0128*	-0.0222***
	(0.0068)	(0.0069)	(0.0068)	(0.0069)	(0.0069)	(0.0069)
Income $25K-$50K	0.0267***	0.0277***	0.0126	-0.0009	0.0255***	-0.0013
	(0.0092)	(0.0091)	(0.0091)	(0.0095)	(0.0091)	(0.0094)
Income $50K-$75K	0.0652***	0.0660***	0.0402***	0.0167*	0.0644***	0.0173*
	(0.0092)	(0.0092)	(0.0093)	(0.0098)	(0.0092)	(0.0098)
Income >$75K	0.0866***	0.0878***	0.0549***	0.0308***	0.0847***	0.0306***
	(0.0090)	(0.0090)	(0.0092)	(0.0098)	(0.0090)	(0.0098)
Near prime_d	-0.0906***	-0.0946***	-0.0835***	-0.0759***	-0.0938***	-0.0747***
	(0.0077)	(0.0078)	(0.0078)	(0.0083)	(0.0078)	(0.0083)
Prime_d	-0.282***	-0.286***	-0.268***	-0.238***	-0.284***	-0.236***
	(0.0069)	(0.0070)	(0.0073)	(0.0088)	(0.0070)	(0.0088)
Super prime_d	-0.475***	-0.476***	-0.460***	-0.398***	-0.472***	-0.393***
	(0.0072)	(0.0071)	(0.0076)	(0.0108)	(0.0072)	(0.0109)
# accounts >=60 DPD	-0.0428***	-0.0421***	-0.0397***	-0.0284***	-0.0441***	-0.0294***
	(0.0070)	(0.0070)	(0.0068)	(0.0068)	(0.0073)	(0.0070)
Bankruptcy_d	0.249***	0.251***	0.261***	0.272***	0.250***	0.271***
	(0.0080)	(0.0079)	(0.0077)	(0.0076)	(0.0080)	(0.0077)
Rural area_d	-0.0028	0.0088	0.0243	-0.00892	0.00732	-0.00998
	(0.0252)	(0.0258)	(0.0245)	(0.0243)	(0.0257)	(0.0243)
% minority in zip code	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Med. income zip ($1,000)	0.0002***	0.0002**	0.0002*	0.0001	0.0003***	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean Equifax Risk Score zip	0.0001***	0.0001***	0.0001***	0.0001**	0.0001**	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K			0.0000	0.0000	-0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
# card offers (consumer)		0.0047***	0.0038***	0.0029**	0.0048***	0.003***
		(0.0012)	(0.0011)	(0.0011)	(0.0012)	(0.0011)
Card offers per 100K (zip)		-0.0001*	-0.0001*	-0.0002**	-0.0001*	-0.0001**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ln(Non-Revolving Bal)				0.0119***		0.0109***
				(0.0009)		(0.0009)
Ln(Revolving Bal)				0.0131***		0.0133***
				(0.0013)		(0.0013)
Utilization revolving a/c				0.0015***		0.0015***
				(0.0001)		(0.0001)
# bankcard accounts			0.0126***			
			(0.0009)			
# non-bankcard accounts			0.0025***			
			(0.0002)			
Credit_denials_d					0.0514***	0.0382***
					(0.0050)	(0.005)
Observations	51,814	51,814	51,814	51,349	51,814	51,349
Month-Year Dummies	YES	YES	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); US Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 5: Logistic Regression Results
Probability That a Personal Loan Offer Is from a Fintech Lender
Fintech Lenders versus Other Nonbank Lenders (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Age 35-55	-0.0886**	-0.0668*	-0.194***	-0.171***	-0.0599*	-0.164***
	(0.0357)	(0.0355)	(0.0357)	(0.0364)	(0.0353)	(0.0363)
Age >55	-0.198***	-0.169***	-0.347***	-0.281***	-0.185***	-0.291***
	(0.0377)	(0.0376)	(0.0377)	(0.0383)	(0.0374)	(0.0383)
Income $25K-$50K	0.325***	0.335***	0.239***	0.119***	0.338***	0.112***
	(0.0426)	(0.0426)	(0.0424)	(0.0431)	(0.0424)	(0.0429)
Income $50K-$75K	0.637***	0.646***	0.471***	0.242***	0.648***	0.234***
	(0.0442)	(0.0442)	(0.0449)	(0.0455)	(0.0441)	(0.0453)
Income >$75K	0.748***	0.767***	0.530***	0.267***	0.770***	0.256***
	(0.0424)	(0.0425)	(0.0437)	(0.0449)	(0.0424)	(0.0447)
Near prime_d	0.989***	0.913***	1.072***	0.882***	0.898***	0.868***
	(0.0330)	(0.0335)	(0.0344)	(0.0355)	(0.0333)	(0.0354)
Prime_d	1.158***	1.061***	1.318***	1.000***	1.042***	0.979***
	(0.0336)	(0.0347)	(0.0362)	(0.0429)	(0.0346)	(0.0428)
Super prime_d	0.710***	0.674***	1.037***	0.758***	0.629***	0.711***
	(0.0519)	(0.0523)	(0.0544)	(0.0661)	(0.0522)	(0.0657)
# accounts >=60 DPD	-0.624***	-0.603***	-0.461***	-0.440***	-0.591***	-0.431***
	(0.0440)	(0.0432)	(0.0400)	(0.0388)	(0.0428)	(0.0384)
Bankruptcy_d	0.280***	0.343***	0.551***	0.606***	0.356***	0.620***
	(0.0395)	(0.0396)	(0.0406)	(0.0416)	(0.0394)	(0.0415)
Rural area_d	0.152	0.142	0.278*	0.290*	0.148	0.295*
	(0.139)	(0.144)	(0.146)	(0.157)	(0.144)	(0.156)
% minority in zip code	-0.0003	-0.0002	-0.0005	-0.0008	-0.0003	-0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Med. income zip ($1,000)	0.0067***	0.0067***	0.0058***	0.0041***	0.0065***	0.0039***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)
Mean Equifax Risk Score zip	0.0013***	0.0013***	0.0011***	0.0012***	0.0014***	0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Banks per 100K		-0.0005	-0.0001	-0.0003	-0.0004	-0.0003
		(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
# card offers (consumer)		0.0747***	0.0736***	0.0550***	0.0741***	0.0543***
		(0.0079)	(0.0080)	(0.007)	(0.0080)	(0.0073)
Card offers per 100K (zip)		0.000575	0.000599	0.000324	0.000621	0.0004
		(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Ln(Non-Revolving Bal)				0.0241***		0.0312***
				(0.0043)		(0.0044)
Ln(Revolving Bal)				0.261***		0.257***
				(0.0074)		(0.0074)
Utilization revolving a/c				-0.00357***		-0.0035***
				(0.0006)		(0.0006)
# bankcard accounts			0.144***			
			(0.0060)			
# non-bankcard accounts			-0.0006			
			(0.0012)			
Credit_denials_d					-0.244***	-0.244***
					(0.0256)	(0.0264)
Observations	57,029	57,029	57,029	54,837	57,029	54,837
Month-Year Dummies	YES	YES	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 6: Logistic Regression Results
Marginal Probability Impact — on Personal Loan Offer Being from a Fintech Lender
Fintech Lenders versus Other Nonbank Lenders (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Age 35-55	-0.0186**	-0.0139*	-0.0390***	-0.0333***	-0.0124*	-0.0318***
	(0.0075)	(0.0074)	(0.0071)	(0.0071)	(0.0073)	(0.0070)
Age >55	-0.0418***	-0.0354***	-0.0702***	-0.0554***	-0.0386***	-0.0571***
	(0.0078)	(0.0079)	(0.0076)	(0.0076)	(0.0078)	(0.0075)
Income $25K-$50K	0.0668***	0.0684***	0.0477***	0.0231***	0.0687***	0.0217***
	(0.0085)	(0.0085)	(0.0083)	(0.0083)	(0.0084)	(0.0083)
Income $50K-$75K	0.130***	0.131***	0.0938***	0.0469***	0.131***	0.0453***
	(0.0086)	(0.0090)	(0.0087)	(0.0087)	(0.0085)	(0.0087)
Income >$75K	0.157***	0.160***	0.108***	0.0525***	0.160***	0.0501***
	(0.0086)	(0.0086)	(0.0088)	(0.0088)	(0.0085)	(0.0088)
Near prime_d	0.203***	0.187***	0.210***	0.170***	0.184***	0.167***
	(0.0063)	(0.0065)	(0.0062)	(0.0066)	(0.0064)	(0.0065)
Prime_d	0.238***	0.218***	0.258***	0.193***	0.214***	0.188***
	(0.0063)	(0.0067)	(0.0064)	(0.0078)	(0.0067)	(0.0078)
Super prime_d	0.142***	0.135***	0.194***	0.139***	0.126***	0.131***
	(0.0097)	(0.0098)	(0.0090)	(0.0112)	(0.0099)	(0.0112)
# accounts >=60 DPD	-0.131***	-0.126***	-0.0928***	-0.0859***	-0.123***	-0.0840***
	(0.0091)	(0.0089)	(0.0080)	(0.0075)	(0.0088)	(0.0074)
Bankruptcy_d	0.0582***	0.0706***	0.108***	0.114***	0.0730***	0.116***
	(0.0081)	(0.0080)	(0.0077)	(0.0074)	(0.0079)	(0.0074)
Rural area_d	0.0318	0.0293	0.0551*	0.0555*	0.0305	0.0563*
	(0.0286)	(0.0295)	(0.0286)	(0.0294)	(0.0294)	(0.0290)
% minority in zip code	-0.0001	-0.0001	-0.0001	-0.0002	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Med. income zip ($1,000)	0.0014***	0.0014***	0.0012***	0.0008***	0.0014***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean Equifax Risk Score zip	0.0003***	0.0003***	0.0002***	0.0002***	0.0003***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K		-0.0001	-0.0000	-0.0000	-0.0000	-0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
# card offers (consumer)		0.0156***	0.0148***	0.0108***	0.0154***	0.0106***
		(0.0016)	(0.0016)	(0.0014)	(0.0016)	(0.0014)
Card offers per 100K (zip)		0.0001	0.0001	0.0001	0.0001	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Ln(Non-Revolving Bal)				0.0047***		0.0061***
				(0.0008)		(0.0009)
Ln(Revolving Bal)				0.0510***		0.0501***
				(0.0013)		(0.0013)
Utilization_revolving a/c				-0.0007***		-0.0007***
				(0.0001)		(0.0001)
# bankcard trades			0.0290***			
			(0.0012)			
# non-bankcard trades			-0.0001			
			(0.00024)			
Credit_denials_d					-0.0511***	-0.0480***
					(0.0054)	(0.0052)
Observations	57,029	57,029	57,029	54,837	57,029	54,837
Month-Year Dummies	YES	YES	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); US Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 7: Logistic Regression Results
Probability That a Mortgage Loan Offer Is from a Fintech Lender
Fintech Lenders versus Banks (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.357***	0.357***	0.357***	0.359***
	(0.0910)	(0.0911)	(0.0910)	(0.0906)
Age >55	0.239**	0.239**	0.241***	0.243***
	(0.0934)	(0.0936)	(0.0936)	(0.0932)
Income $25K-$50K	0.336***	0.336***	0.333***	0.327***
	(0.123)	(0.123)	(0.123)	(0.124)
Income $50K-$75K	0.213*	0.213*	0.208*	0.213*
	(0.121)	(0.122)	(0.122)	(0.123)
Income >$75K	-0.0209	-0.0219	-0.0282	-0.0211
	(0.118)	(0.119)	(0.120)	(0.120)
Near prime_d	-0.169	-0.169	-0.171	-0.185
	(0.135)	(0.135)	(0.135)	(0.134)
Prime_d	-0.453***	-0.452***	-0.457***	-0.456***
	(0.123)	(0.123)	(0.123)	(0.123)
Super prime_d	-0.892***	-0.892***	-0.897***	-0.887***
	(0.123)	(0.123)	(0.124)	(0.124)
Num. accounts >=60 DPD	0.0450	0.0449	0.0444	0.0344
	(0.0483)	(0.0484)	(0.0484)	(0.0486)
Bankruptcy_d	-0.0210	-0.0206	-0.0123	-0.0195
	(0.136)	(0.135)	(0.136)	(0.138)
Num. credit inqs.	0.0604**	0.0602**	0.0596**	-0.0028
	(0.0255)	(0.0261)	(0.0256)	(0.0284)
FHA Purchase_d	3.015***	3.015***	3.017***	3.005***
	(0.248)	(0.248)	(0.249)	(0.249)
VA Purchase_d	-1.210***	-1.210***	-1.212***	-1.231***
	(0.180)	(0.180)	(0.180)	(0.179)
Refinance_d	2.361***	2.361***	2.360***	2.369***
	(0.0586)	(0.0587)	(0.0588)	(0.0586)
Rural area	-0.0850	-0.0852	-0.0865	-0.144
	(0.443)	(0.442)	(0.443)	(0.441)
Percent minority in zip code	-0.0040***	-0.0040***	-0.0041***	-0.0039***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Med. income zip ($1,000)	-0.00147	-0.0015	-0.0015	-0.0015
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Mean Equifax Risk Score zip	-0.0009	-0.0009	-0.0009	-0.0009
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Banks per 100k	-0.00319**	-0.0032**	-0.00319**	-0.0030**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
# total accounts		0.0001		
		(0.0023)		
Ln(Total Bal)			0.00526	0.0014
			(0.0146)	(0.0146)
Credit_denials_d				0.337***
				(0.0687)
Observations	11,007	11,007	11,007	11,007
Year Dummies	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 8: Logistic Regression Results
Marginal Probability Impact — on Mortgage Offer Being from a Fintech Lender
Fintech Lenders versus Banks (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.0601***	0.0600***	0.0600***	0.0602***
	(0.0152)	(0.0153)	(0.0152)	(0.0151)
Age >55	0.0399***	0.0399**	0.0402***	0.0403***
	(0.0155)	(0.0155)	(0.0155)	(0.0154)
Income $25K-$50K	0.0558***	0.0557***	0.0552***	0.0542***
	(0.0201)	(0.0202)	(0.0202)	(0.0203)
Income $50K-$75K	0.0356*	0.0355*	0.0347*	0.0355*
	(0.0201)	(0.0202)	(0.0203)	(0.0204)
Income >$75K	-0.00350	-0.00367	-0.00472	-0.00353
	(0.0197)	(0.0200)	(0.0201)	(0.0201)
Near prime_d	-0.0284	-0.0283	-0.0288	-0.0310
	(0.0228)	(0.0228)	(0.0228)	(0.0226)
Prime_d	-0.0756***	-0.0756***	-0.0763***	-0.0760***
	(0.0203)	(0.0203)	(0.0204)	(0.0202)
Super prime_d	-0.151***	-0.151***	-0.152***	-0.150***
	(0.0208)	(0.0208)	(0.0209)	(0.0207)
Num. accounts >=60 DPD	0.0076	0.0075	0.0075	0.0059
	(0.0081)	(0.0081)	(0.0081)	(0.0081)
Bankruptcy_d	-0.0035	-0.0035	-0.0021	-0.0033
	(0.0227)	(0.0227)	(0.0229)	(0.0231)
Num. credit inqs.	0.0101**	0.0101**	0.001**	-0.0005
	(0.0043)	(0.0044)	(0.0043)	(0.0048)
FHA Purchase_d	0.385***	0.385***	0.385***	0.383***
	(0.0184)	(0.0184)	(0.0184)	(0.0186)
VA Purchase_d	-0.209***	-0.210***	-0.210***	-0.212***
	(0.0302)	(0.0302)	(0.0302)	(0.0298)
Refinance_d	0.476***	0.476***	0.476***	0.476***
	(0.0099)	(0.0099)	(0.0099)	(0.0098)
Rural area	-0.0143	-0.0143	-0.0146	-0.0241
	(0.0747)	(0.0747)	(0.0748)	(0.0746)
Percent minority in zip code	-0.0007***	-0.0007***	-0.0007***	-0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Med. income zip ($1,000)	-0.0002	-0.0002	-0.0002	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean Equifax Risk Score zip	-0.0001	-0.0001	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K	-0.0005**	-0.0005**	-0.0005**	-0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
# total accounts		0.0000		
		(0.0004)		
Ln(Total Bal)			0.0009	0.0002
			(0.0024)	(0.0024)
Credit_denials_d				0.0560***
				(0.0113)
Observations	11,007	11,007	11,007	11,007
Year Dummies	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); US Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Table 9: Logistic Regression Results
Probability That a Mortgage Offer Is from a Fintech Lender
Fintech Lenders versus Other Nonbank Lenders (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.350***	0.365***	0.355***	0.353***
	(0.0703)	(0.0704)	(0.0703)	(0.0705)
Age >55	0.315***	0.338***	0.279***	0.278***
	(0.0727)	(0.0726)	(0.0727)	(0.0728)
Income $25K-$50K	0.105	0.147	0.161*	0.158
	(0.0958)	(0.0962)	(0.0970)	(0.0970)
Income $50K-$75K	-0.180*	-0.107	-0.0621	-0.0596
	(0.0933)	(0.0940)	(0.0949)	(0.0948)
Income >$75K	-0.396***	-0.284***	-0.239**	-0.242***
	(0.0910)	(0.0929)	(0.0932)	(0.0931)
Near prime_d	0.142	0.121	0.229**	0.231**
	(0.0889)	(0.0901)	(0.0915)	(0.0915)
Prime_d	0.0861	0.0497	0.203**	0.200**
	(0.0821)	(0.0840)	(0.0850)	(0.0850)
Super prime_d	0.534***	0.484***	0.646***	0.635***
	(0.0846)	(0.0869)	(0.0872)	(0.0873)
Num. accounts >=60 DPD	0.00113	-0.00442	0.0160	0.0191
	(0.0351)	(0.0363)	(0.0350)	(0.0346)
Bankruptcy_d	-0.271***	-0.306***	-0.438***	-0.429***
	(0.0872)	(0.0875)	(0.0915)	(0.0915)
Num. credit inqs.	-0.0437***	-0.0237	-0.0299*	-0.0017
	(0.0168)	(0.0169)	(0.0169)	(0.0187)
FHA Purchase_d	0.0213	-0.00314	0.0252	0.0284
	(0.118)	(0.118)	(0.118)	(0.118)
VA Purchase_d	-2.669***	-2.644***	-2.617***	-2.621***
	(0.159)	(0.159)	(0.160)	(0.160)
Refinance_d	1.176***	1.179***	1.222***	1.218***
	(0.0522)	(0.0522)	(0.0531)	(0.0531)
Rural area	-0.651*	-0.679**	-0.613*	-0.597*
	(0.342)	(0.341)	(0.338)	(0.334)
Percent minority in zip code	-0.0031***	-0.0032***	-0.0029**	-0.0030***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Med. income zip ($1,000)	-0.0035***	-0.0034***	-0.0030***	-0.0031***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Mean Equifax Risk Score zip	-0.0001	-0.0002	-0.0001	-0.0001
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Banks per 100K	0.0040***	0.0039***	0.0040***	0.0039***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
# total accounts		-0.0104***		
		(0.0017)		
Ln(Total Bal)			-0.113***	-0.110***
			(0.0119)	(0.0119)
Credit_denials_d				-0.169***
				(0.0493)
Constant	-1.993***	-1.754***	-0.934**	-0.918**
	(0.403)	(0.404)	(0.414)	(0.414)
Observations	19,509	19,509	19,509	19,509
Year Dummies	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

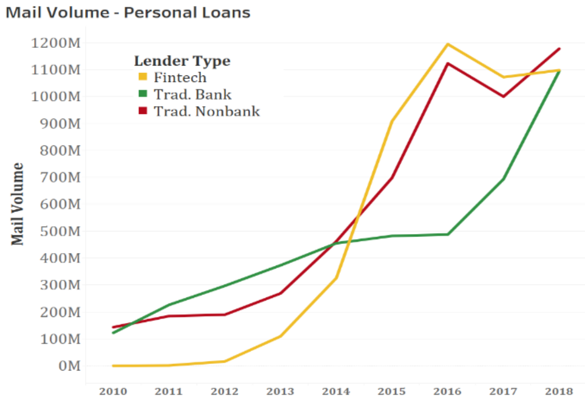
Table 10: Logistic Regression Results
Marginal Probability Impact — on Mortgage Offer Being from a Fintech Lender
Fintech Lenders versus Other Nonbank Lenders (Data Period: 2015–2018)

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.0608***	0.0630***	0.0611***	0.0607***
	(0.0120)	(0.0120)	(0.0119)	(0.0119)
Age >55	0.0556***	0.0594***	0.0487***	0.0486***
	(0.0128)	(0.0128)	(0.0127)	(0.0127)
Income $25K-$50K	0.0186	0.0259	0.0282	0.0278
	(0.0170)	(0.0172)	(0.0173)	(0.0172)
Income $50K-$75K	-0.0310*	-0.0185	-0.0107	-0.0103
	(0.0158)	(0.0161)	(0.0163)	(0.0163)
Income >$75K	-0.0694***	-0.0496***	-0.0416**	-0.0419***
	(0.0158)	(0.0162)	(0.0162)	(0.0162)
Near prime_d	0.0252	0.0212	0.0403**	0.0406**
	(0.0158)	(0.0160)	(0.0163)	(0.0163)
Prime_d	0.0150	0.00866	0.0352**	0.0346**
	(0.0143)	(0.0146)	(0.0147)	(0.0147)
Super prime_d	0.0954***	0.0860***	0.114***	0.112***
	(0.0152)	(0.0156)	(0.0155)	(0.0155)
Num. accounts >=60 DPD	0.0002	-0.0008	0.0028	0.0033
	(0.00614)	(0.00633)	(0.00605)	(0.00599)
Bankruptcy_d	-0.0457***	-0.0513***	-0.0716***	-0.0701***
	(0.0142)	(0.0140)	(0.0140)	(0.0140)
Num. credit inqs.	-0.0076***	-0.0041	-0.0052*	-0.0003
	(0.0029)	(0.0030)	(0.0029)	(0.0032)
FHA Purchase_d	0.00374	-0.000547	0.00438	0.00493
	(0.0208)	(0.0205)	(0.0205)	(0.0206)
VA Purchase_d	-0.281***	-0.280***	-0.278***	-0.278***
	(0.0070)	(0.0071)	(0.0073)	(0.0073)
Refinance_d	0.195***	0.195***	0.200***	0.200***
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
Rural area	-0.102**	-0.106**	-0.0962**	-0.0940**
	(0.0471)	(0.0461)	(0.0471)	(0.0468)
Percent minority in zip code	-0.0005***	-0.0005***	-0.0005**	-0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Med. income zip ($1,000)	-0.0006***	-0.0006***	-0.0005***	-0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean Equifax Risk Score zip	-0.0000	-0.0000	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
# total accounts		-0.0018***		
		(0.0003)		
Ln(Total Bal)			-0.0196***	-0.0191***
			(0.0020)	(0.0020)
Credit_denials_d				-0.0291***
				(0.0084)
Observations	19,509	19,509	19,509	19,509
Year Dummies	YES	YES	YES	YES

Note: Robust standard errors are in parentheses.
*** indicate p<0.01; ** indicates p<0.05; and * indicates p<0.1

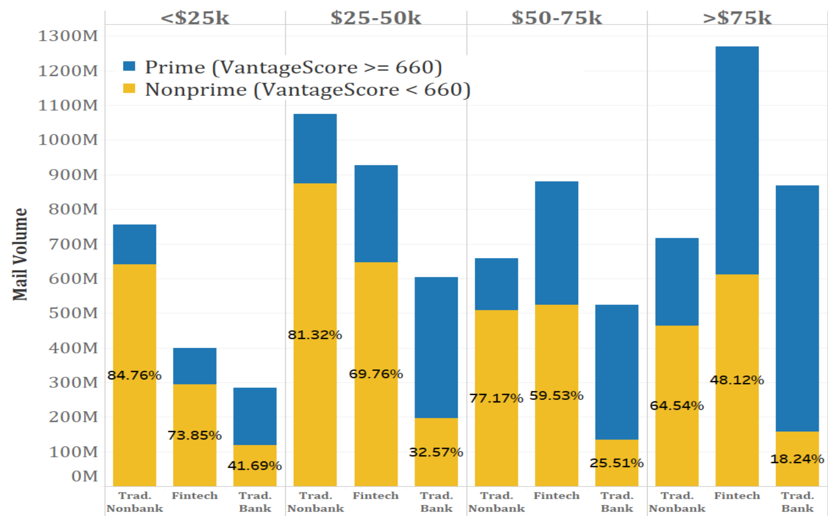
Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Figure 1: Trends in Personal Loan Mail Volume by Lender Type



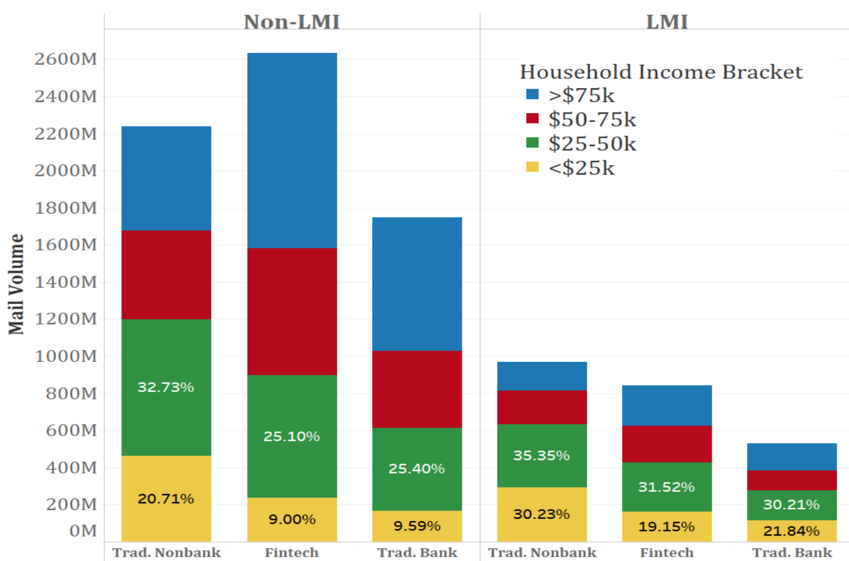
Source: Mintel Comperemedia, Inc. Direct Mail Monitor Data and TransUnion LLC Match File (2018)

Figure 2: Personal Loan Mail Volume by Income Bracket and Prime/Nonprime Status



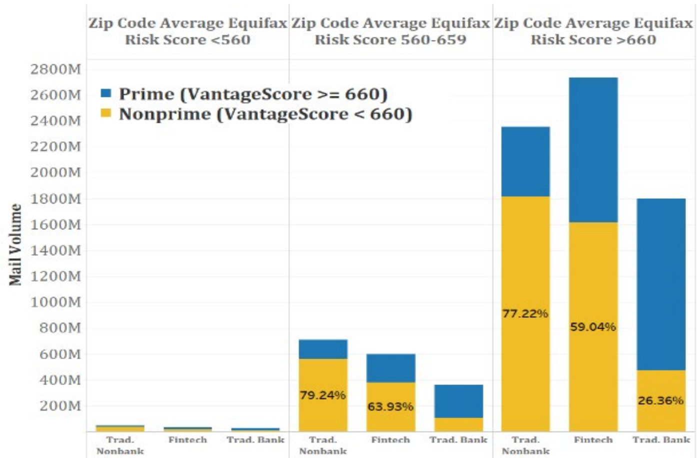
Source: Mintel-TransUnion (2018)

Figure 3: Personal Loan Mail Volume by LMI Status (Zip Code) and Household Income



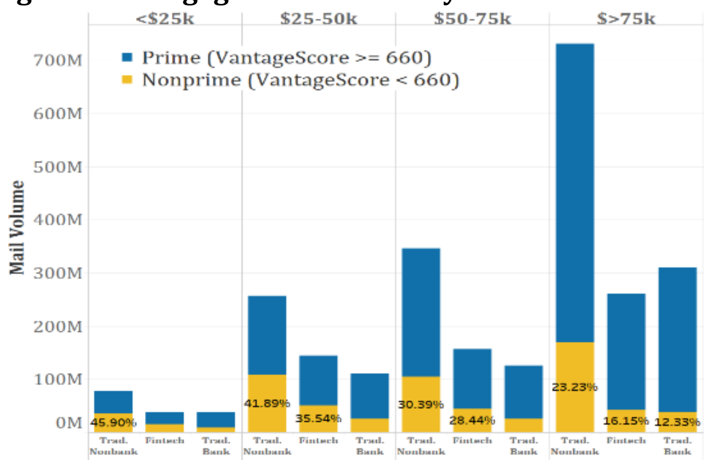
Source: Mintel-TransUnion (2018) and U.S. Census Bureau's American Community Survey (2017)

Figure 4: Personal Loan Mail Volume by Average Equifax Risk Score (Zip Code) and Prime/Nonprime Status



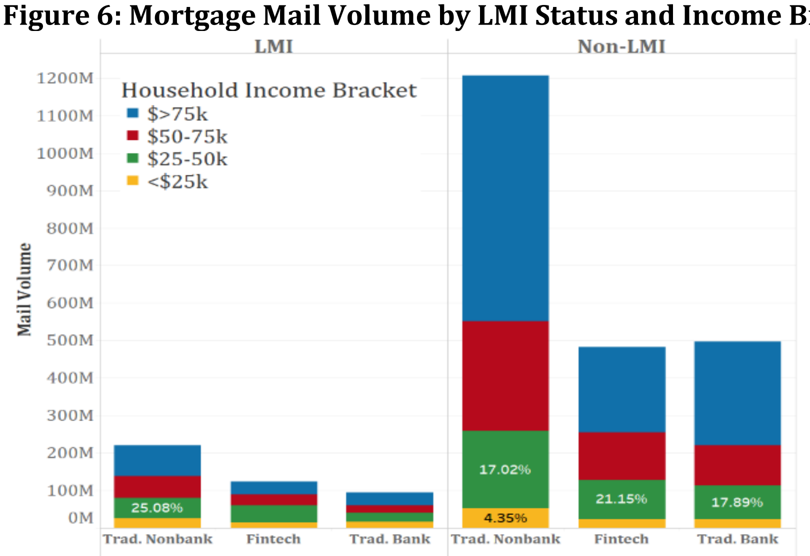
Source: Mintel-TransUnion (2018) and FRBNY Consumer Credit Panel/Equifax Data (2018)

Figure 5: Mortgage Mail Volume by Income Bracket and Prime/Nonprime Status



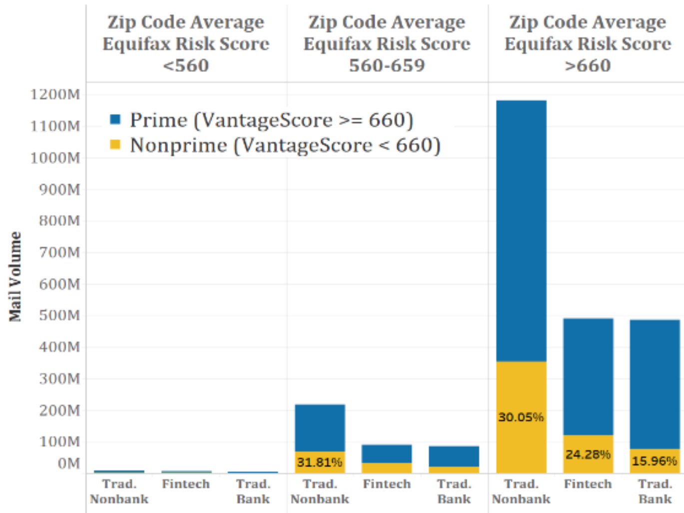
Source: Mintel-TransUnion (2018)

Figure 6: Mortgage Mail Volume by LMI Status and Income Bracket



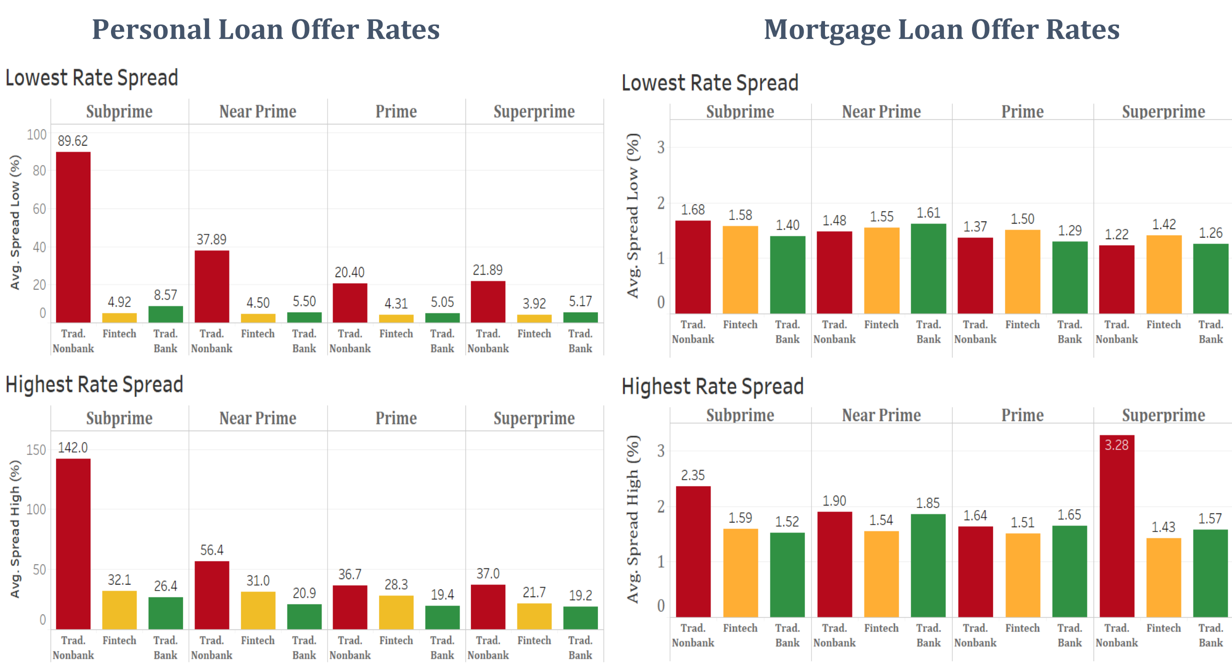
Source: Mintel-TransUnion (2018)

Figure 7: Mortgage Mail Volume by Average Equifax Risk Score (Zip Code) and Prime/Nonprime Status



Source: Mintel-TransUnion (2018) and FRBNY Consumer Credit Panel/Equifax Data (2018)

Figure 8: Interest Rate Spreads (Using Lowest Rate and Highest Rate) Offered by Different Lender Types (Banks, Fintechs, Other Nonbanks) Controlling for Consumer Credit Scores — for Personal Loans (Left) versus Mortgage Loans (Right)



Source: Mintel-TransUnion (2018)

Appendix 1: Robustness Test on Personal Loan Offers
Additional Regression Results — Fintech versus Banks
(Including Credit Card Offers)

Table A1: Personal Loan Offers — Multinomial Regression Results
Marginal Probability of Offer Being Fintech (Includes Credit Card Offers) Rather Than Banks

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.0603***	0.0259***	0.0250***	0.0247***
	(0.0035)	(0.0031)	(0.0031)	(0.0031)
Age >55	0.0374***	0.000206	0.0126***	0.0133***
	(0.0037)	(0.0032)	(0.0033)	(0.0033)
Income $25K-$50K	0.0466***	0.0240***	0.00976**	0.00979**
	(0.0049)	(0.0042)	(0.0043)	(0.0043)
Income $50K-$75K	0.0811***	0.0381***	0.0151***	0.0153***
	(0.0053)	(0.0045)	(0.0045)	(0.0045)
Income >$75K	0.0921***	0.0414***	0.0201***	0.0201***
	(0.0048)	(0.0043)	(0.0044)	(0.0044)
Near prime_d	-0.0224***	-0.0111***	-0.0245***	-0.0235***
	(0.0036)	(0.0032)	(0.0034)	(0.0034)
Prime_d	-0.121***	-0.0985***	-0.112***	-0.110***
	(0.0037)	(0.0033)	(0.0041)	(0.0041)
Super prime_d	-0.199***	-0.183***	-0.177***	-0.175***
	(0.0028)	(0.0025)	(0.0033)	(0.0033)
Num. accounts >=60 DPD	-0.0660***	-0.0456***	-0.0397***	-0.0401***
	(0.0049)	(0.0040)	(0.0040)	(0.0040)
Bankruptcy_d	0.0947***	0.122***	0.158***	0.156***
	(0.0058)	(0.0054)	(0.0059)	(0.0058)
Rural area	-0.0219*	0.0613***	0.0499***	0.0480***
	(0.0121)	(0.0161)	(0.0160)	(0.0161)
Percent minority in zip code	0.0003***	-0.0001*	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Med. income zip ($1,000)	0.0000	-0.0002***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Mean Equifax Risk Score zip	0.0001**	0.0000	0.0001**	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Card offers per 100K		-0.0009***	-0.0010***	-0.0010***
		(0.0001)	(0.0001)	(0.0001)
Ln(Revolving Bal)			0.0261***	0.0263***
			(0.0007)	(0.0007)
Ln(Non-Revolving Bal)			0.0101***	0.0096***
			(0.0004)	(0.0004)
Utilization revolving a/c			0.0006***	0.0006***
			(0.0001)	(0.0001)
# bankcard accounts		0.0208***		
		(0.0005)		
# non-bankcard accounts		0.00237***		
		(0.0001)		
Cred_denials_d				0.0202***
				(0.0024)
Observations	193,984	193,984	186,486	186,486
Month-Year Dummies	YES	YES	YES	YES

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Appendix 2: Robustness Test on Mortgage Loan Offers
Additional Regression Results — Fintech versus Banks (Exclude Refi Offers)

Table A2: Mortgage Loan Offers (Regression Excluding Refinance Offers)
Multinomial Regression Results: Marginal Probability of Offer Being Fintech (Rather Than Banks)

VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	0.0109	0.0101	0.0107	0.00891
	(0.0204)	(0.0204)	(0.0204)	(0.0202)
Age >55	0.00443	0.00179	0.00400	0.00283
	(0.0214)	(0.0215)	(0.0214)	(0.0211)
Income \$25K-\$50K	0.0152	0.0125	0.0161	0.0135
	(0.0278)	(0.0278)	(0.0282)	(0.0279)
Income \$50K-\$75K	-0.0170	-0.0232	-0.0158	-0.0165
	(0.0267)	(0.0265)	(0.0273)	(0.0271)
Income >\$75K	-0.0307	-0.0415	-0.0291	-0.0305
	(0.0268)	(0.0274)	(0.0278)	(0.0276)
Near prime_d	0.0145	0.0183	0.0148	0.0108
	(0.0298)	(0.0302)	(0.0298)	(0.0288)
Prime_d	-0.0322	-0.0312	-0.0316	-0.0302
	(0.0258)	(0.0259)	(0.0259)	(0.0255)
Super prime_d	-0.0836***	-0.0815***	-0.0825***	-0.0779***
	(0.0285)	(0.0285)	(0.0288)	(0.0283)
Num. accounts >=60 DPD	-0.00622	-0.00737	-0.00612	-0.00916
	(0.0121)	(0.0119)	(0.0121)	(0.0127)
Bankruptcy_d	0.00131	0.00283	-6.42e-05	0.00375
	(0.0267)	(0.0269)	(0.0270)	(0.0274)
Num. credit inqs.	0.0187***	0.0165***	0.0189***	0.00527
	(0.00474)	(0.00472)	(0.00476)	(0.00536)
FHA Purchase_d	0.569***	0.573***	0.568***	0.564***
	(0.0418)	(0.0415)	(0.0419)	(0.0425)
VA Purchase_d	-0.130***	-0.132***	-0.130***	-0.133***
	(0.0160)	(0.0158)	(0.0161)	(0.0156)
Rural area	0.0331	0.0284	0.0325	0.0202
	(0.0970)	(0.0937)	(0.0970)	(0.0939)
Percent minority in zip code	-0.0000	0.0000	-0.0000	0.0000
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Med. income zip (\$1,000)	0.000200	0.000219	0.000201	0.000206
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Mean Equifax Risk Score zip	-0.0003*	-0.0002*	-0.0003*	-0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K	-0.0005	-0.0005	-0.0005	-0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
# total accounts		0.00134***		
		(0.0005)		
Ln(Total Bal)			-0.000908	-0.00166
			(0.0034)	(0.0034)
Credit_denials_d				0.0841***
				(0.0175)
Observations	4,292	4,292	4,292	4,292
Year Dummies	YES	YES	YES	YES

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Appendix 3: Robustness Test on Mortgage Loan Offers
Additional Regression Results — Fintech versus Other Nonbanks
(Exclude Refi Offers)

Table A3: Mortgage Loan Offers (Regression Excluding Refinance Offers)
Multinomial Regression Results: Marginal Probability of Offer Being Fintech (Rather Than Traditional Nonbank Lenders)

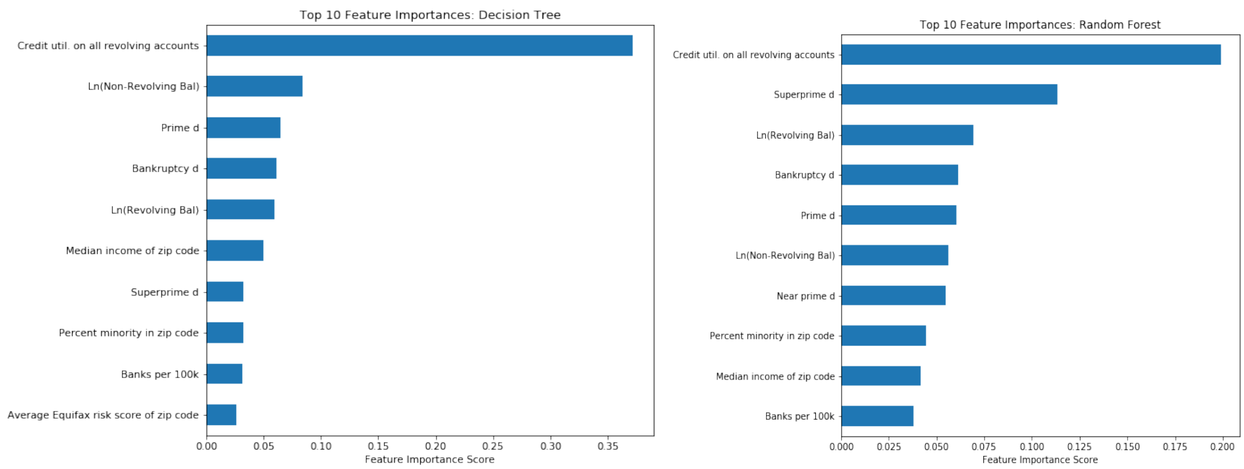
VARIABLES	(1)	(2)	(3)	(4)
Age 35-55	-0.0133	-0.0132	-0.0121	-0.0118
	(0.0126)	(0.0126)	(0.0125)	(0.0125)
Age >55	-0.00591	-0.00567	-0.00953	-0.00940
	(0.0132)	(0.0132)	(0.0131)	(0.0131)
Income $25K-$50K	0.0140	0.0159	0.0214	0.0216
	(0.0172)	(0.0174)	(0.0180)	(0.0180)
Income $50K-$75K	-0.0296**	-0.0270*	-0.0174	-0.0175
	(0.0151)	(0.0153)	(0.0162)	(0.0162)
Income >$75K	-0.0366**	-0.0322*	-0.0199	-0.0197
	(0.0160)	(0.0165)	(0.0166)	(0.0166)
Near prime_d	0.00429	0.00348	0.0109	0.0108
	(0.0165)	(0.0165)	(0.0172)	(0.0172)
Prime_d	-0.0102	-0.0113	-0.000157	1.70e-05
	(0.0153)	(0.0154)	(0.0158)	(0.0159)
Super prime_d	0.0166	0.0151	0.0267	0.0273
	(0.0167)	(0.0168)	(0.0173)	(0.0174)
Num. accounts >=60 DPD	-0.0048	-0.0050	-0.0036	-0.0039
	(0.0087)	(0.0088)	(0.0084)	(0.0085)
Bankruptcy_d	0.00137	0.00103	-0.0126	-0.0126
	(0.0152)	(0.0151)	(0.0150)	(0.0150)
Num. credit inqs.	0.0049**	0.0055**	0.0059**	0.0048*
	(0.0024)	(0.0024)	(0.0024)	(0.0027)
FHA Purchase_d	-0.0063	-0.0072	-0.0063	-0.0065
	(0.0108)	(0.0108)	(0.0107)	(0.0107)
VA Purchase_d	-0.158***	-0.157***	-0.155***	-0.155***
	(0.0068)	(0.0068)	(0.0068)	(0.0068)
Rural area	-0.0630**	-0.0638**	-0.0612*	-0.0613*
	(0.0312)	(0.0309)	(0.0313)	(0.0313)
Percent minority in zip code	-0.0003	-0.0003	-0.0003	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Med. income zip ($1,000)	0.0001	0.0001	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Mean Equifax Risk Score zip	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Banks per 100K	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
# total accounts		-0.0004		
		(0.0003)		
Ln(Total Bal)			-0.0084***	-0.0085***
			(0.0017)	(0.0017)
Credit_denials_d				0.0082
				(0.0091)
Observations	7,799	7,799	7,799	7,799
Year Dummies	YES	YES	YES	YES

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Appendix 4: Machine Learning Algorithm Results — Personal Loan Offers

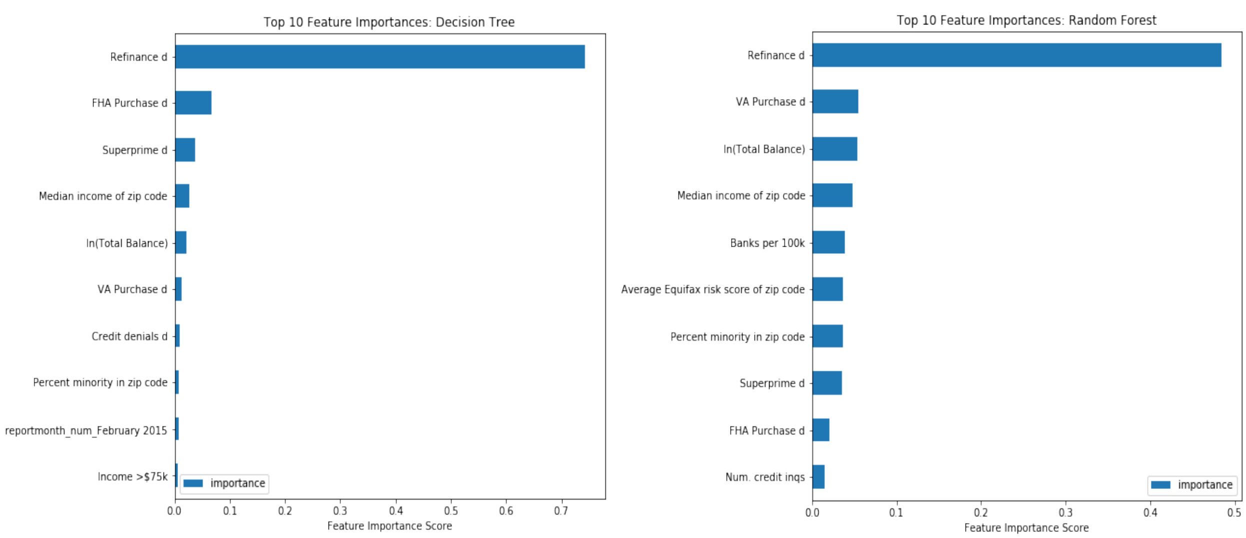
Figure A1: Top 10 Important Variables for Personal Loan Offers to Be Fintech Offers (Based on Model 6 of Table 3) — Using Decision Tree (left) and Random Forest (right)



Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)

Appendix 5: Machine Learning Algorithm Results — Mortgage Loan Offers

Figure A2: Top 10 Important Variables for Mortgage Loan Offers to Be Fintech Offers (Based on Model 4 of Table 7) — Using Decision Tree (left) and Random Forest (right)



Data sources: Mintel-TransUnion (2018); U.S. Census Bureau's American Community Survey (2017); FRBNY Consumer Credit Panel/Equifax Data (2018); and FDIC Summary of Deposits (2018)