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Following the 2008 financial crisis, mortgage credit tightened and banks lost significant mortgage market share to nonbank lenders, including to fintech firms recently. Have fintech firms expanded credit access, or are their customers similar to those of traditional lenders? Unlike in small business and unsecured consumers lending, fintech mortgage lenders do not have the same incentives or flexibility to use alternative data for credit decisions because of stringent mortgage origination requirements. Fintech loans are broadly similar to those made by traditional lenders, despite innovations in the marketing and the application process. However, nonbanks market to consumers with weaker credit scores than do banks, and fintech lenders have greater market shares in areas with lower credit scores and higher mortgage denial rates.

Keywords: fintech, mortgage lending, homeownership, online mortgages, credit access
JEL Classifications: G20, G21, G28, R20, R30

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I. Introduction

The U.S. mortgage market has changed dramatically since the 2008 financial crisis. Specifically, conventional lending plummeted while loans insured by the Federal Housing Administration (FHA) skyrocketed following the collapse of the private-label securities market. Nonbank mortgage lending also grew rapidly, especially after 2011. Banks dramatically decreased FHA lending, with nonbanks picking up the slack (Figure 1). Nonbanks originated as many conventional conforming-sized loans as banks in 2017, up from half as many for most of the previous 20 years.[1] One growing segment of nonbank mortgage originations is financial technology (fintech) lending, in which nonbank lenders use online platforms and advanced technology to process mortgage applications more quickly than traditional lenders. Following previous literature, we define *fintech lenders* as those that allow the borrower to apply for a mortgage online, such that the lender does a credit pull without the borrower needing to speak to anyone (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2018b).

Fintech lenders' presence in the U.S. mortgage market has grown dramatically in recent years. By 2017, about 1 in 10 mortgages were originated by fintech firms. How fintech and nonbank expansion affect credit pricing and credit availability for consumers is one of the central questions in the mortgage market today. On the one hand, new technology in mortgage applications and underwriting may unlock credit access for those borrowers who are not well served by traditional lenders. On the other hand, the technology could allow fintech firms to have a more complete picture of individual consumers' finances and skim the most creditworthy segment of the market for themselves.

We provide several pieces of evidence that fintech lenders are expanding credit access. Our analysis primarily focuses on comparing fintech lenders with other nonbanks, as these institutions are similar in dimensions apart from technology, as opposed to banks, which have a deposit base and different regulatory requirements. First, we show that fintech market share is larger in areas with greater mortgage denial rates and lower consumer credit scores. These results are robust

[1] The literature has identified a few reasons for nonbank growth, primarily related to an increased regulatory burden following the crisis. First, the U.S. Department of Justice enforcement of the False Claims Act (particularly for Federal Housing Administration (FHA) lending) may have led banks to leave this market (Goodman, 2017). Buchak et al. (2018) discuss how increased capital requirements under the Dodd–Frank Wall Street Reform and Consumer Protection Act and Basel III may have caused banks to lend less. The growth in nonbank lending provides reasons for concern regarding financial stability. Nonbanks do not hold capital, relying instead on short-term credit that may dry up in a stress environment (Kim, Laufer, Pence, Stanton, and Wallace, 2018).

across different types of mortgages and when comparing fintech lenders with banks or with traditional nonbanks.

Second, fintech lenders have attempted to reach (through advertisement and direct mail credit offers) borrowers in nonmetropolitan areas more than other nonbanks have. As we show, borrowers in nonmetropolitan areas have relied more on small bank lending and have articulated a stronger preference for nearby branches when choosing a lender. Fintech lenders may be well suited to provide credit in low-density (nonmetropolitan) areas through their online application and credit-decision process to reduce borrowers' travel costs to the nearest branch.[2]

Third, we also show that fintech market share is larger if the tract falls in the CRA assessment area of fewer than 10 banks, with the fintech share increasing further as the number of banks serving the tract declines. We use additional data on bank branches and lender concentration to better understand the mechanism driving this result. We provide evidence that fintech firms actively lend in areas with higher mortgage market concentration, rather than fintech lenders targeting areas with fewer bank branches.

On most dimensions, however, fintech loans are similar to loans being made by other nonbank and bank lenders. Like traditional nonbank lenders, fintech firms sell the majority of their conventional conforming-size loans to Fannie Mae or Freddie Mac, and nearly all of the rest of their mortgage lending is in the FHA or VA program. Origination standards for these loans are quite prescriptive and may leave little incentive for the type of innovative underwriting that fintech firms have been well known for in other consumer credit segments.

The similarity of loan and borrower characteristics for loans originated through 2017 suggests that the main innovation of fintech firms in mortgages had been online applications, streamlined data collection, and automated, faster underwriting decisions. This builds on prior technological innovations in the mortgage industry, such as the advent of automated underwriting in the 1990s, which has been shown to have increased homeownership rates, especially among those who previously were excluded from the market because of high debt-to-income ratios (Foote, Loewenstein, and Willen, 2018). As we discuss in the conclusion, the GSEs have shown recent signs of willingness to accept alternative data, which may enable fintech firms to become greater disruptors in the mortgage market.

[2] Understanding the Home Mortgage Disclosure Act (HMDA) reporting requirements in nonmetropolitan areas is important for evaluating these results. We provide a discussion of these when discussing the results in Section IV.4.

II. Related Literature

In this section, we highlight three strands of literature that our paper complements. First, we discuss our findings in light of the relatively few studies that address fintech activity in the U.S. mortgage market. Then we discuss how our study fits into the broader literature of fintech lenders in other areas of consumer credit.

II.1 Fintech in the U.S. Mortgage Market

Although numerous studies have examined the impact of fintech firms in other consumer credit markets, few have focused on the role of fintech firms in the mortgage market. However, this relatively sparse literature about fintech lending in mortgages has established several stylized facts about fintech lenders in the U.S.

First, fintech mortgage loans are processed more quickly. Fuster et al. (2018b) find that the processing duration from application to origination is one week shorter for fintech loans compared with nonfintech loans. Relatedly, fintech firms appear to sell the mortgage faster on the secondary market after origination. Buchak et al. (2018) measure the time from mortgage origination to sale of the mortgage to Fannie Mae or Freddie Mac and find that fintech firms are about two weeks faster than banks and about a week faster than other nonbanks.

That fintech firms are able to process loans more quickly through technological innovation is intuitive, but selection questions make this causal story difficult to prove. A competing explanation introduced in Fuster et al. (2018b) is that fintech firms receive simpler applications as applicants endogenously match with a lender. The authors perform robustness tests to address this alternative explanation, but it is difficult to completely rule out. Fuster et al. (2018b) also find that among FHA loans, the default rate for fintech loans is lower after controlling for observable borrower risk factors, suggesting that the applicants, or at least the originated loans, differ in some unobservable way between lender types. Buchak et al. (2018) find that among conventional mortgages (rather than FHA), the default rates are not significantly different across lender types, conditional on controlling for observable borrower and loan characteristics.

Second, fintech lenders charge higher interest rates on conventional loans and lower interest rates on FHA loans (Buchak et al., 2018; Fuster et al., 2018b).[3] Taken together, these results are consistent with fintech firms charging consumers of conventional loans a premium for convenience while pricing lower for potentially more price-sensitive FHA borrowers. It remains to

[3] See Table A2 in the Appendix for the FHA estimates in Buchak et al. (2018). Fuster et al. (2018b) study the interest rate on FHA loans only but have data with more loan-level controls than Buchak et al. (2018).

be seen if this pricing pattern will persist as fintech lending matures and more competitors enter the market.[4]

Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2018a) show that mortgage credit could be more efficiently priced using machine learning, but they highlight concerns about such methods generating statistical discrimination. In particular, they discuss that even if lenders are not allowed to include race as a predictor, the new technology still may create winners and losers along racial lines (Fuster et al., 2018a). Bartlett, Morse, Stanton, and Wallace (2019) find that fintech lenders charge minority borrowers higher interest rates, but so do nonfintech lenders. In fact, they find that fintech lenders discriminate *less* than traditional, face-to-face lenders.

Last, Buchak et al. (2018) and Fuster et al. (2018b) provide evidence on how local lending conditions and credit accessibility impact fintech market share. More concentration in the local lending market, measured either by the Herfindahl Hirschman Index (HHI) of mortgage lending in a county or the number of lenders, is correlated with greater fintech market share (Buchak et al., 2018). Loans in tracts with lower average credit scores, indicative of areas with less credit access, are more likely to be fintech loans (Fuster et al., 2018b).

We, too, find that fintech lenders are relatively more active in areas with higher lender concentration as measured by HHI and a new measure: the number of CRA assessment areas in which a tract is located. Consistent with the literature, we find greater fintech mortgage lending activity in Census tracts with lower consumer credit scores. In addition, we offer an alternative measure of credit access: the percentage of non-fintech mortgage applications that were denied in the previous calendar year in each zip code, which is positively correlated with fintech use.

II.2 Other Areas of Fintech Research

A substantial literature studies fintech lenders in other areas of consumer and small business lending. In the U.S. mortgage market, Fannie Mae, Freddie Mac, and Ginnie Mae provide most of the liquidity to mortgage lenders. The government-sponsored enterprises (GSEs) have prescriptive underwriting rules that reduce the incentive for creative underwriting. As a result, the experience of fintech in other credit markets may be less relevant to the current mortgage market. However, if conditions change and more private capital is again invested in mortgages, those results may have stronger applications to the mortgage market.

[4] From 2010 through 2015, the time period of study in Buchak et al. (2018), Quicken Loans dominated the fintech market (Figure 2). In fact, when Quicken is excluded, conventional fintech loans have no greater interest rates than non-fintech loans (Table A.8.2 of the online Appendix, Buchak et al., 2018).

Several studies have used the emergence of fintech platforms in peer-to-peer (P2P) consumer lending to study whether fintech lenders have expanded credit access. So far, the results have been mixed. Freedman and Jin (2011) find that, after initially expanding credit to riskier borrowers, improved screening over time has meant that fintech lenders have increasingly targeted customers who are already well served by traditional lenders. In contrast, Jagtiani and Lemieux (2018) find that fintech lending in P2P markets has penetrated more in areas with poor credit accessibility, specifically counties with highly concentrated credit card lending, few bank branches per person, and a distressed local economy. Similarly, Ahmed, Beck, McDaniel, and Schropp (2016) find greater fintech P2P small business lending in areas with a larger decline in the number of bank branches.

Another literature has emerged to test whether fintech lenders provide a better product by using advanced technology. In addition to Fuster et al. (2018a), which focuses on the potential and pitfalls of machine learning algorithms in mortgage lending, several studies focus on how alternative data and more advanced analytics could improve credit risk measures and underwriting to enable lenders to extend credit to the unbanked and underbanked (Carroll and Rehmani, 2017; Crosman, 2016; and Consumer Financial Protection Bureau, 2017). In P2P lending, Jagtiani and Lemieux (2019) find that personal loans originated through fintech platforms could generate significant savings to borrowers when compared with similar traditional loans, in part because of a more accurate evaluation of risk.[5]

III. Data

Our empirical analysis is based on two main sources of data: the Mintel Comperemedia, Inc. Direct Mail Monitor Data and TransUnion LLC Match File (Mintel-TransUnion) and Home Mortgage Disclosure Act (HMDA) data at the application/loan level. We combine these data sets with neighborhood demographics from the Census, bank CRA assessment area data from the Federal Financial Institutions Examination Council (FFIEC), Census tract consumer credit characteristics, and house price indices.

Mintel-TransUnion Data

The Mintel-TransUnion data set contains direct mail mortgage offers made to a random sample of 8,000 households sampled monthly. The data set is matched by TransUnion with data

[5] For more details about the impact of alternative data and the use of artificial intelligence and machine learning algorithms in the new lending landscapes, see Jagtiani, Wall, and Vermilyea (2018).

from each consumer's credit report. The Mintel-TransUnion data reflect mostly the supply side of the mortgage lending market, since it includes solicitations for applications but no information on whether the credit offer actually results in a loan origination. The Mintel-TransUnion data include lender name, year of solicitation, and consumer demographic and credit characteristics, including the consumer's VantageScore 3.0 credit score at the time of the mailing.

HMDA

HMDA data contain information about the lenders, the borrowers, and the location of the collateral property for most mortgage applications and originations in the United States. Unless otherwise noted, our loan-level HMDA analysis focuses on first-lien, owner-occupied loans secured by one- to four-family properties or manufactured homes and originated in 2016–2017. Both purchase and refinance mortgages are included for conventional, FHA, VA, and Rural Housing Service mortgages, but we omit jumbo mortgages.

We identify nine companies as fintech lenders, relying on a combination of the lists of fintech mortgage lenders from Fuster et al. (2018b) and Buchak et al. (2018).[6] These papers distinguish fintech lenders as those that offer the ability to receive a mortgage preapproval or even full approval online without the borrower needing to communicate directly with a loan officer or broker. The included fintech lenders are: AmeriSave, Better Mortgage, CashCall, Everett Financial (Supreme), Guaranteed Rate, loanDepot, Movement Mortgage, Quicken (Rocket Mortgage loans and those originated through other channels), and SoFi. All other mortgage lenders — both banks (depository institutions) and nonbanks — are referred to as "traditional" lenders.[7]

In Figure 2, we present the volume of mortgage originations by fintech lenders between 2012 and 2017, as captured in HMDA. The majority of fintech mortgage loans have been originated by Quicken in each year, followed by loanDepot, the second largest originator in 2016–2017. In

[6] If a lender is classified by either paper as fintech, we consider it a fintech lender. The list from Fuster et al. (2018b) is very similar to that of Buchak et al. (2018), although Buchak et al. (2018) also includes AmeriSave and CashCall as fintech lenders. In contrast, the Buchak et al. (2018) list of fintech firms excludes loanDepot and Everett Financial (Supreme).

[7] See Table A1 in the Appendix for more details about the list of fintech mortgage lenders and sample periods in Fuster et al. (2018b), Buchak et al. (2018), and our paper. Two fintech lenders began reporting HMDA data in 2016: Better Mortgage and SoFi. Since the Fuster et al. and Buchak et al. papers were focused on earlier time periods and larger lenders, they were excluded from their analysis. However, we have added them because they have significant and growing volume, and they have been named among the "Best Online Mortgage Lenders." See https://www.nerdwallet.com/blog/mortgages/online-mortgage-lenders/?trk=nw_gn1_4.0.

2016, the number of fintech lenders reporting HMDA data also grew significantly from six to 10 lenders; thus, we focus our analysis on 2016 and 2017 originations.

Figures 3 and 4 plot the share of conventional conforming-size loans and FHA mortgage loans, respectively, that were originated by fintech lenders at the county level during 2016–2017. The top panel shows the percentage of all conventional mortgages that were provided by traditional nonbanks, and the bottom panel displays the percentage of loans originated by fintech firms. Interestingly, both Figures 3 and 4 show higher shares of fintech mortgages in less densely populated areas of the Midwest and the southeastern U.S. for both mortgage products.

We link data at the U.S. Census tract level to identify the percentage of residents in the loan's Census tract that are nonwhite or Hispanic, the tract median income, and the area median income. A loan counts toward a bank's CRA activity if it is in a lender's assessment area and is made to a low- and moderate-income (LMI) Census tract or to an LMI borrower. A Census tract is defined as being LMI if its median family income is less than 80% of the area median family income (AMI). Some additional tracts are also CRA-eligible because they have received designation as distressed or underserved, owing to population loss, persistent poverty, or other challenges. A loan is considered to have been made to an LMI borrower if the borrower's HMDA-reported income is less than 80% of AMI.

We also use the HMDA data to calculate the denial rate of mortgage loan applications made to nonfintech lenders in each 5-digit zip code, and we lag the value by one year.[8] This is an indicator of a potential credit gap in the local market, where demand for mortgage loans has not been met by traditional lenders.

We also calculate the HHI for nonfintech mortgage lenders at the county level. We compute the measure by taking the sum of lenders' squared market shares within each county each year, excluding fintech lenders. We expect fintech lenders' entrance to more highly concentrated markets to help expand credit access and lower the cost of credit in those markets. We lag the HHI by one year in the regression analysis.

Avery HMDA Lender File

We use a data set developed by Robert Avery of the Federal Housing Finance Agency (FHFA), which is a match of HMDA data to FFIEC National Information Center data and Call Report

[8] We use crosswalk tables from the U.S. Department of Housing and Urban Development to match each Census tract in the HMDA data to the zip code where the plurality of housing units is located. Zip codes are used because Census tracts more often have too few mortgage applications to provide a reasonably stable estimate.

data. The data set includes each institution's asset size as of December 31 of the HMDA reporting year. This field allows us to segment banks by size: large banks (> $50 billion in assets), regional banks ($10 billion–$50 billion), and community banks (< $10 billion). We also use the Avery data set to classify lenders as banks (including commercial banks and thrifts), credit unions, and nonbanks.[9]

Federal Reserve Bank of New York/Equifax Consumer Credit Panel

We use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) to calculate the mean Equifax Risk Score (a proprietary credit score) in each Census tract. We restrict the calculation to include records between 2014 Q2 and 2017 Q4 for consumers with at least one credit inquiry recorded on their credit report in the prior 30 days to capture the typical Equifax Risk Score credit score of a consumer seeking mortgage credit. We further restrict our sample to the CCP's subset of "primary consumers," who are a random 5% sample of U.S. adults with credit reports, sampled based on the last digits of their Social Security numbers, as described by Lee and van der Klaauw (2010).

CRA Assessment Area Data

We use data from the FFIEC on the 2016 and 2017 assessment areas of depository institutions that are required to submit CRA reports annually (i.e., banks with more than about $1.2 billion in assets as of 2016 and 2017).[10] Each bank is required to delineate its own assessment areas and to "include the geographies in which its main office, branches, and deposit-taking ATMs are located as well as the surrounding geographies in which it has originated or purchased a substantial portion of its loans," (Federal Financial Institutions Examination Council, 2015, p. 7). Data are available at the Census tract level for each CRA respondent. We sum the number of lenders that report any given tract as in its assessment area to gain a measure of lending activity by CRA-regulated institutions.

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[9] RSSD item number 9346, Entity Type, is used for this classification. See https://www.federalreserve.gov/apps/mdrm/data-dictionary/search/item?keyword=9346&show_short_title=False&show_conf=False&rep_status=All&rep_state=Opened&rep_period=Before&date_start=99991231&date_end=99991231. This field is generally consistent with the information contained in the "agency code" field in HMDA, but it adds consistency over time and some more granular distinctions.

[10] The data are available at https://www.ffiec.gov/cra/craflatfiles.htm. For more information on how CRA assessment areas are delineated, see Benton and Harris (2014).

The FDIC's Summary of Deposits and Bank Structure Data

We use data from the FDIC's Summary of Deposits data set on banking (deposit) activities and the number of bank branches in each local market. We calculate the number of bank branches per square mile in each 3-digit zip code. We use these variables to proxy the deficiency of banking services in the local areas where there may be a role for fintech lenders to come in and fill the credit gaps. The final regression analysis includes this field with a one-year lag.

CoreLogic Solutions House Price Indices

Finally, we use repeat-sales home price indices provided by CoreLogic Solutions.[11] For loans in which the zip code-level index is available, we assign that index. Where it is not available, we apply the county-level index. Finally, for the 4% of loans that were originated in counties lacking an index value, we apply the state-level index. We then use this coalesced house price index (HPI) measure to calculate one-year house price appreciation (HPA), from June to June. Again, in the regression analysis, we lag this measure by one year. So, for example, a loan originated in 2016 would receive the HPA in its local area between June 2014 and June 2015.[12]

IV. Empirical Approach and Results

We first compare the offers fintech firms make to those made by traditional lenders using the Mintel/TransUnion data. We then use the HMDA data to determine which borrower, loan, and community traits are associated with more fintech originations. Last, we employ a regression discontinuity design to test whether fintech lenders and other lenders respond to the CRA incentive to lend in tracts with median income below 80%of the area median income.

IV.1 Mortgage Credit Offers

Fintech mortgage lenders are relatively new and tend to be specialized, not offering wide arrays of services for consumers. They do not take deposits, for example, and usually offer either just mortgages or a narrow menu of retail credit products. As a result, fintech lenders do not "cross sell" the way that banks do. Traditional nonbanks tend to be monoline financial institutions.

[11] Repeat sales house price indices are based on observed changes in prices of the same properties within the same geographic areas.

[12] Our interest in the effect of home price appreciation (HPA) comes from two sources. Fuster et al. (2018b) suggest that fintech lenders may be more desirable to borrowers in hot housing market areas because of their faster processing times, perhaps giving a competitive edge to borrowers making an offer on a property with multiple offers; however, they find no evidence of this effect. Additionally, Ramcharan and Crowe (2013) find evidence that local home prices may be a good proxy for consumer credit access via home equity.

Evidence from the Mintel-TransUnion data, which includes offers sent in 2016 and 2017, confirms anecdotal reports that fintech and other nonbank lenders advertise heavily through direct mail advertisements tailored to individual consumers.

For conventional loans, the majority of offers were sent by fintech lenders (48% over the sample period) and other nonbanks (35%), with the rest being made by banks. Among FHA loans, fintech lenders were even more dominant in advertising, sending 73% of all offers. Banks issued only a tiny number of FHA offers in our sample, which is in keeping with the general retreat of banks from the FHA space, following regulatory compliance concerns (Collins, 2014). Over 90% of the conventional and FHA mortgage offers from fintech firms explicitly mention refinancing. This is intuitive, since targeting refinance loans to existing homeowners is likely to have a higher yield than advertising purchase loans.

We note two significant differences in offer behavior with banks, fintech lenders, and traditional nonbanks. First, for conventional mortgages, banks target consumers with higher credit scores (specifically, VantageScore 3.0 scores) than do fintech firms, which in turn target consumers with higher credit scores than traditional nonbank lenders (see Figure 5). For FHA, fintech and traditional nonbanks send offers to similar groups. Second, as shown in Figure 6, fintech lenders send a greater share of their solicitations to consumers in nonmetropolitan areas. A fintech offer is nearly three times as likely as a bank offer to go to nonmetro consumers and about 1.3 times as likely as a nonbank offer.

In the next sections, we use HMDA data to assess whether fintech originations differ from other nonbank originations.

IV.2 Who Ultimately Receives Fintech Loans?

We test two main hypotheses about the roles of fintech mortgage lenders relative to non-fintech lenders:

Hypothesis 1: Fintech lenders have expanded access to mortgage credit in communities with less access to credit, as measured by credit scores and lagged mortgage denial rates.

Hypothesis 2: Enabled by their digital platforms, fintech lenders more readily extend credit to nonmetropolitan areas and to communities outside the assessment areas of CRA-regulated institutions than do traditional nonbanks.

First, we summarize the loans in our data and draw attention to the differences — and similarities — between fintech loans and those originated by other lender types. Tables 1–3 provide descriptive statistics.

FHA Lending. Although fintech lenders and traditional nonbanks originate most of their loans as conventional mortgages, they are also very active in the FHA and VA space. Fintech lenders originated 31% of their loans as FHA/VA, with nonbanks originating 39% of their loans in these two government-sponsored programs. In the current lending environment, FHA offers the most opportunity for borrowers with blemished credit and little money to use for a down payment (Van Order and Yezer 2014; Quercia and Park 2013). FHA and VA loans make up 18% of bank loans and 10% of credit union loans (Table 1).

Areas with higher denial rates and lower median credit scores. Fintech lenders and other nonbanks lend in zip codes with higher average (one-year lagged) mortgage denial rates and Census tracts with lower mean Equifax Risk Scores, but differences between fintech and nonbank are not large (Table 1). One possible confounding factor in these comparisons is the much larger proportion of refinances that make up fintech loans. In Table 2, we compare fintech lenders to other nonbanks within loan purpose (refinance or purchase) and loan type (FHA, VA, or conventional) bins. Fintech loans consistently have (modestly) lower mean credit scores and higher mean zip code denial rates than other nonbanks across all bins. In the next section, we describe our regression analysis; our results provide evidence that these differences are statistically and economically meaningful after controlling for other community and loan characteristics.

Loans to LMI borrowers and communities. Interestingly, across lender types, similar shares of loans are made to LMI or distressed and underserved tracts or to LMI borrowers (noted as "CRA loan" in Table 1). The distribution of tract median family income and borrower income, shown in Table 3, is also similar across lender types, with fintech lenders falling between bank and other nonbank lenders in most categories. The racial and ethnic composition of borrowers across lender type is also similar, in cases in which the race and ethnicity of the borrower are known.

HMDA rules require lenders to ask applicants to report their race and ethnicity. If an application is taken in person and the applicant fails to answer the question, the lender must impute the values for these fields based on the applicant's surname and "visual observation" of the borrower's appearance. The lender is not required to impute the applicant's race or ethnicity, if the application is taken online, over the phone, or through the mail. Table 3 shows that loans originated by fintech lenders are much less likely to have data on race and ethnicity. If online applications and automated data collection become more prevalent, it may be difficult for these staple fields of HMDA to remain useful.

Nonmetropolitan lending. Fintech lenders originate 9% of their loans in nonmetro counties, versus 7% for other nonbanks. However, banks and credit unions originate 13% and 11% of their loans in nonmetro counties, respectively.[13] These data should be considered with HMDA

[13] See Figure A1 in the Appendix for a map of nonmetropolitan counties in our data set.

reporting requirements for nonmetro institutions in mind, which we discuss in detail in the next section, but probably result in bank and credit union nonmetro shares being underestimated. Fintech lenders and nonbanks also originate their loans in areas with somewhat higher average year-over-year house price appreciation, and both groups of nonbanks lend to neighborhoods with greater average shares of minority residents (32%–33% of the population compared with 26% for both banks and credit unions).[14]

Loan Size. Recent research has shown that lenders have become less likely to originate smaller mortgages. An Urban Institute report notes that high fixed costs of loan originations have negatively impacted the availability of purchase loans of $70,000 or less, which are important for buyers purchasing less expensive properties (McCargo, Bai, George, and Strochak, 2018). Because fintech lenders have automated parts of the origination process, their fixed costs should be smaller than traditional lenders, which may result in them originating more small-dollar loans. However, we find no evidence of this. Like traditional nonbanks, fintech lenders' median loan sizes are larger than those of depository institutions, and a significantly smaller share of their loans are below the $70,000 mark. As shown in Table 4, 3.9% of fintech loans and 3.4% of traditional nonbank loans were small dollar, compared with 7.4% of bank-originated and 11.9% of credit union-originated mortgages.

Refinance versus purchase lending. Fintech loans are much more likely to be used for refinancing a prior mortgage rather than purchasing a property. This is likely driven by both demand and supply sides. On the supply side, Buchak et al. (2018) speculate that refinance mortgages have fewer activities that make automation more difficult, such as title checks, home inspections, and negotiation between buyers and sellers, thus providing a comparative advantage for fintech in refinancing. On the demand side, when purchasing a home, buyers often work with lenders that have been referred to them by their real estate agents. Given that most real estate agents tend to have limited experience with fintech, they are less likely to refer borrowers to fintech lenders, though over time, this is likely to change. In refinancing, borrowers do not have the agent's influence to guide them toward nonfintech lenders.

We next estimate a series of linear probability regressions with the dependent variable taking the value 100, if the mortgage is originated by a fintech lender, and 0, if other nonbank. As nonbanks face similar regulatory burdens and funding environments, this comparison is most appropriate to isolate any impact of the technological differences. Except where noted, we restrict

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[14] Although there is no consistent evidence that fintech lenders are currently less likely to originate mortgages in communities of color, new technology in mortgage lending merits continued scrutiny, particularly since nonbank lenders are not subject to as regular and intensive supervision under the Equal Credit Opportunity Act and the Fair Housing Act as are depository institutions. Evans (2017) and Courchane and Ross (2018) provide thorough discussion of the risks and opportunities presented by fintech lending.

the regression sample to originated loans for which the applicant's income was reported and the income was at least $1,000/year. The main results are presented in Table 5, with additional robustness checks as well as bank and credit union results in the Appendix. We cluster the standard errors at the Census tract level. [15]

IV.3 Fintech Lending and Traditional Measures of Credit Access

Fintech lenders have a larger market share in zip codes with greater (lagged) nonfintech mortgage denial rates. After controlling for the characteristics in Table 1, a one-standard-deviation increase in nonfintech denial rates in the previous calendar year is associated with an increase in fintech conventional lending market share of 2.18 percentage points and 0.88 percentage point in FHA lending. Fintech lenders originate about 21% of all nonbank loans, so these effects would result in a 5%–10% increase in the mean zip code. Results comparing banks and fintech lenders are similar and presented in the Appendix in Table A4.

Given that previous literature has presented limitations of using raw HMDA denial rates as a proxy of credit access (Li and Goodman, 2015), we examine the robustness of this finding to an alternative measure: In the last two columns of Table 5, we instead control for the mean Equifax Risk Score (credit score) in each Census tract for consumers with an inquiry for credit logged on their credit reports during this time period (as a proxy for mortgage shopping). For these loans, a one-standard-deviation increase in tract mean Risk Score is associated with 1.9 (1.14) percentage point decrease in fintech lending for conventional (FHA) mortgages.

Overall, our results indicate that fintech lenders originate comparatively more mortgage loans in lower-credit-score areas and in areas with a higher mortgage-denial-rate by nonfintech lenders. We show that these findings also hold when considering only loans made in metro counties (Table A5). These results are also robust to splitting the sample by loan purpose (purchase versus refinance) as shown in Table A6. Results comparing fintech lenders to credit unions, as presented in Table A7, are similar, except in the case of conventional mortgages, for which fintech lenders actually have a greater market share in neighborhoods with higher credit scores.

Given that several firms in our sample only recently began originating enough mortgages to require HMDA reporting, we separately test whether these newer entrants are different from traditional banks. These new entrants do have higher market share in high denial rate and low

[15] There are several other patterns in fintech lending. First, fintech loans are much less likely to be secured by manufactured housing. Second, fintech lenders have so far not been active in Farm Service Agency and Rural Housing Service lending, which helps low-income households purchase homes in designated rural areas, as determined by the U.S. Department of Agriculture. (Regression results for these types of loans can be found in the Appendix.)

credit score neighborhoods, but the effects are more muted than when comparing the full set of fintech firms to traditional nonbanks. See Table 6.

IV.4 Fintech Activity in Nonmetropolitan Areas

In trying to evaluate how fintech activity differs from other nonbanks in nonmetro counties, it is vital to understand how HMDA reporting requirements differ for loans originated inside and outside metropolitan statistical areas (MSAs). Potentially the most problematic, small banks and even banks of any size with no branches in an MSA are not required to report originations.[16] As a result, we suspect that HMDA data are missing a substantial number of nonmetro bank loans. It speaks to the importance of banks in these areas that, even despite this limitation of HMDA data, banks, and especially community banks, have a comparatively large HMDA-reported market share in nonmetro areas.

Nondepository lenders are required to report if they have originated five or more loans within an MSA and are sufficiently large.[17] These requirements are stricter, and we hypothesize that few nonbank loans are not reported to HMDA; however, we are unaware of any evidence that speaks to this hypothesis or attempts to estimate the number of missing loans.[18] As a result, we believe that our nonbank results are not greatly impacted by these requirements; however, any nonreporting by traditional nonbanks would bias our results toward finding a greater fintech market share (as all fintech firms in our sample are required to report).

Although a small percentage of mortgage loans in our sample (9%) are originated in nonmetro areas, we find fintech lenders' market share in these areas (among nonbank lending) is greater than in metro areas. In Table 5, we show that loans originated in nonmetro areas are 5.5–9.5 percentage points more likely to be originated by fintech firms than those in metro areas. This result holds across loan type (FHA, conventional) and controlling for collateral type, loan purpose (purchase versus refinance), and year of origination. However, in Table 6, we show that among newer fintech firms, this result does not hold.

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[16] For 2016 and 2017 reporting years, the asset threshold was $44 million to qualify as a small bank as of December 31 of the previous calendar year.

[17] For 2016 and 2017, nondepository institutions were required to report if they had over $10 million in assets as of December 31 of the previous calendar year or originated 100 or more residential mortgages in the preceding year. Detailed instructions on requirements for each reporting year can be found at https://www.ffiec.gov/hmda/guide.htm.

[18] See Critchfield, Dey, Mota, and Patrabansh (2018) for a comparison of HMDA data to the National Mortgage Database (NMDB). While the authors find that the NMDB, which is a nationally representative sample of mortgages, is similar to HMDA in its composition of metro, nonmetro, and rural loans, but it is not without discrepancy. Further, the small number of nonmetro loans means that the discrepancy they do find (which may be because of nonreporting) may still have a meaningful impact on nonmetro analysis. They do not evaluate differences by bank versus nonbank lenders.

As mentioned previously, banks are still comparatively important in nonmetro areas. Even with the possibility that HMDA data is missing bank originations, a loan originated in a nonmetro area is 4 percentage points less likely to be originated by a fintech firm (in a sample of only bank and fintech loans) than in a metro area (see Table A2 in the Appendix). Results from the National Survey of Mortgage Originations are consistent with this finding. For 2013–2016, surveyed borrowers in nonmetropolitan areas were more likely to report that having a local office or branch nearby as important to their choice of mortgage lender (see Figure 7).

Figure 8 provides additional context. Although nonbanks dominated HMDA-reported conventional conforming-size loans in metro areas in 2016–2017, in nonmetro areas, the top providers of these loans were community banks (institutions with assets < $10 billion). In fact, community banks have surpassed nonbanks in conventional conforming-size loan originations in nonmetro areas since at least 2000, although in FHA lending, nonbanks have been more active and have gained significant market share when the larger banks exited the market.

An additional potential data issue arises: HMDA-reporting institutions that are not subject to CRA are not required to give precise geographic information on all of the loans they originate.[19] Specifically, these lenders are permitted to not disclose the Census tract, county, MSA, or even state in which the collateral property is located, if the property is not located in an MSA or is located in an MSA where the institution does not have a home branch or office. However, even in these cases, the lender must still report the loan and all of its other characteristics (e.g., race and ethnicity of borrower, origination date). Confirming earlier information provided by Avery, Brevoort, and Canner (2007), we find that in the vast majority of cases (99.8% of originated loans), HMDA reporters choose to provide full geographic location information (including Census tract).

As a robustness test, we first assume that all loans with missing geographic information (0.2% of the sample) were originated in nonmetro areas, though it is possible that some are originated in MSAs in which a non-CRA lender does not have a branch or office. Since we lack geography-based control variables for these loans, we estimate a set of simpler models and find a similar effect of being in a nonmetro area on fintech market share when we assume all missing-geography loans are in nonmetro areas. We show in Table A3 of the Appendix that the coefficients change little if we instead reclassify all of these loans as being originated in metro areas.

IV.5 Fintech Lending and Market Competition

We next study how the amount of competition between mortgage lenders in an area relates to the rate of fintech lending. Our first measure of competition is the number of lenders reporting

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[19] Even institutions subject to CRA have the option to report only the state, county, and MSA of a loan but not the Census tract, if the loan is located in a county with population less than 30,000 as of the 2010 Census.

that tract t is part of their CRA assessment area. Banks provide lists of their assessment areas (the places in which they will be assessed for CRA compliance) as part of their annual CRA reporting (Federal Financial Institutions Examination Council, 2019). Information on these assessment areas is made public by the FFIEC for institutions above a certain asset size, about $1.2 billion in 2016–2017. We use this information as a measure of bank activity in a Census tract.

We show in Table 7 that loans originated in Census tracts that are included in fewer than 10 banks' CRA assessment areas are more likely to be fintech compared with loans originated in tracts with more assessment areas. The relationship between number of assessment areas and fintech share is fairly monotonic: Areas with fewer assessment areas have a greater fintech market share. This result holds for all loan types, but the largest effect sizes are found in the FHA market. Recalling that fintech loans make up about 21% of this sample, the magnitude of even the smaller effect sizes is substantial.

Because the number of assessment areas in a tract is correlated with whether the tract is in a metro area, we next estimate the model on a sample excluding nonmetropolitan areas. Once nonmetro areas are removed, only 0.12% of loans are originated in tracts with zero or one assessment area. However, the general finding is that tracts with fewer assessment areas (and those with less than 10) have a greater fintech market share. The assessment area results are strongest in areas with eight or fewer assessment areas, which is approximately the 10th percentile of tracts. However, among new fintech firms, there is no clear pattern between assessment areas and market share (Table 8).

We also estimate models that measure lender competition using HHI. We show that having a zip-code-level, one-year-lagged lender HHI greater than 625 (the 90th percentile value) is associated with a 3.7 percentage points greater fintech loan share, which is in line with the mean of the assessment area coefficients (Table 9). We interpret this combined evidence as indicating that fintech lenders are serving areas that have less market competition, as measured by areas with fewer local CRA banks and areas with greater HHI mortgage market concentration index. This is consistent with Buchak et al. (2018)'s finding that a linear measure of county HHI is positively correlated with fintech market share.

Last, we study the impact of bank branch density, as captured by branches per square mile in the property's three-digit zip code, according to the FDIC's Summary of Deposits, lagged one year. The last two columns in Table 9 show that below the 10th percentile of bank branch density, fintech lending is actually *less* common, but the result decreases below the 25th percentile. These results complement Fuster et al. (2018b), which show the fintech share increasing in bank branch density (using a similar measure of branch density).

V. Conclusions and Policy Implications

Literature on fintech mortgage lending has been sparse. Existing studies have focused mainly on pricing, defaults, and application processing speed. We test whether fintech lenders serve borrowers and communities with similar characteristics as traditional lenders and find that fintech lending differs in several observable ways.

First, we find that fintech lenders made comparatively more mortgage loans in areas with higher (lagged) mortgage denial rates and in areas with lower median credit scores (Equifax Risk Scores). The denial rate result is robust across nearly all subsamples (conventional, FHA, or VA) and comparison groups (other nonbanks, banks, or credit unions). Relatedly, a lower median tract Equifax Risk Score increases the probability that a loan is made by a fintech lender, suggesting that fintech mortgage lenders may have helped to expand credit access in areas that are underserved.

In addition, we show that fintech lenders expand mortgage access in nonmetropolitan areas. While banks and credit unions have continued to provide the majority of mortgage credit in nonmetropolitan areas, fintech lenders have been more effective than other nonbanks in making inroads, with a given loan being 5–10 percentage points more likely to be fintech loan, if it is in a nonmetro tract than if it is in a metro tract. Even when evaluating a sample of bank and fintech loans, an FHA loan is 2 percentage points more likely to be fintech when it is made in a nonmetropolitan tract compared with a metro tract.

Evidence of fintech credit expansion is notable in areas that are served by few banks. We find that a loan is more likely to be fintech compared with other nonbanks, if the tract falls in the CRA assessment area of fewer than 10 banks, with the result strengthening as the number of banks serving the tract falls. This result is robust to restricting our sample to only loans made in metropolitan areas, but the result is not robust to restricting our sample to new fintech firms. Time will tell if these new fintech firms expand their business to include areas that are less banked.

We note that these findings are based on the fintech activities as of 2016–2017. During this time, the majority of fintech-originated loans are sold to Fannie Mae and Freddie Mac, which provide automated underwriting platforms Desktop Underwriter and Loan Prospector, respectively, to mortgage originators. These automated platforms give rapid feedback to originators about whether perspective loans meet the GSE's underwriting guidelines. The widespread uptake of this technology almost certainly contributes to the similarities between fintech and nonfintech loans on observable characteristics. If fintech firms stop selling such a large percentage of their loans to GSEs, these similarities may diminish and greater scrutiny of the implications of the technology would be particularly important. Additionally, some fintech data intermediaries recently have begun to partner with the GSEs to provide cash flow and bank transaction data for mortgage underwriting, which can be useful in modeling income for self-employed borrowers, for example (Freddie Mac, 2019). The GSEs are also expected to pursue credit score alternatives to FICO, such as Vantage. We expect the GSEs to increasingly use alternative data for future originations.

Given the dramatic growth of fintech innovations in recent years and their disruptive nature, we expect that the industry will continue to change at a rapid pace. In fact, Bartlett et al. (2019) report that, by the end of 2018, nearly 45 percent of mortgage originators offered an online application. The distinction between fintech and nonfintech loans may become less clear going forward, as several fintech platforms have also started to provide white-label services to allow traditional lenders to digitalize their credit decision process, which would likely impact future fintech mortgage lending. This continued evolution of technology in the mortgage market provides an immense number of opportunities for future research.

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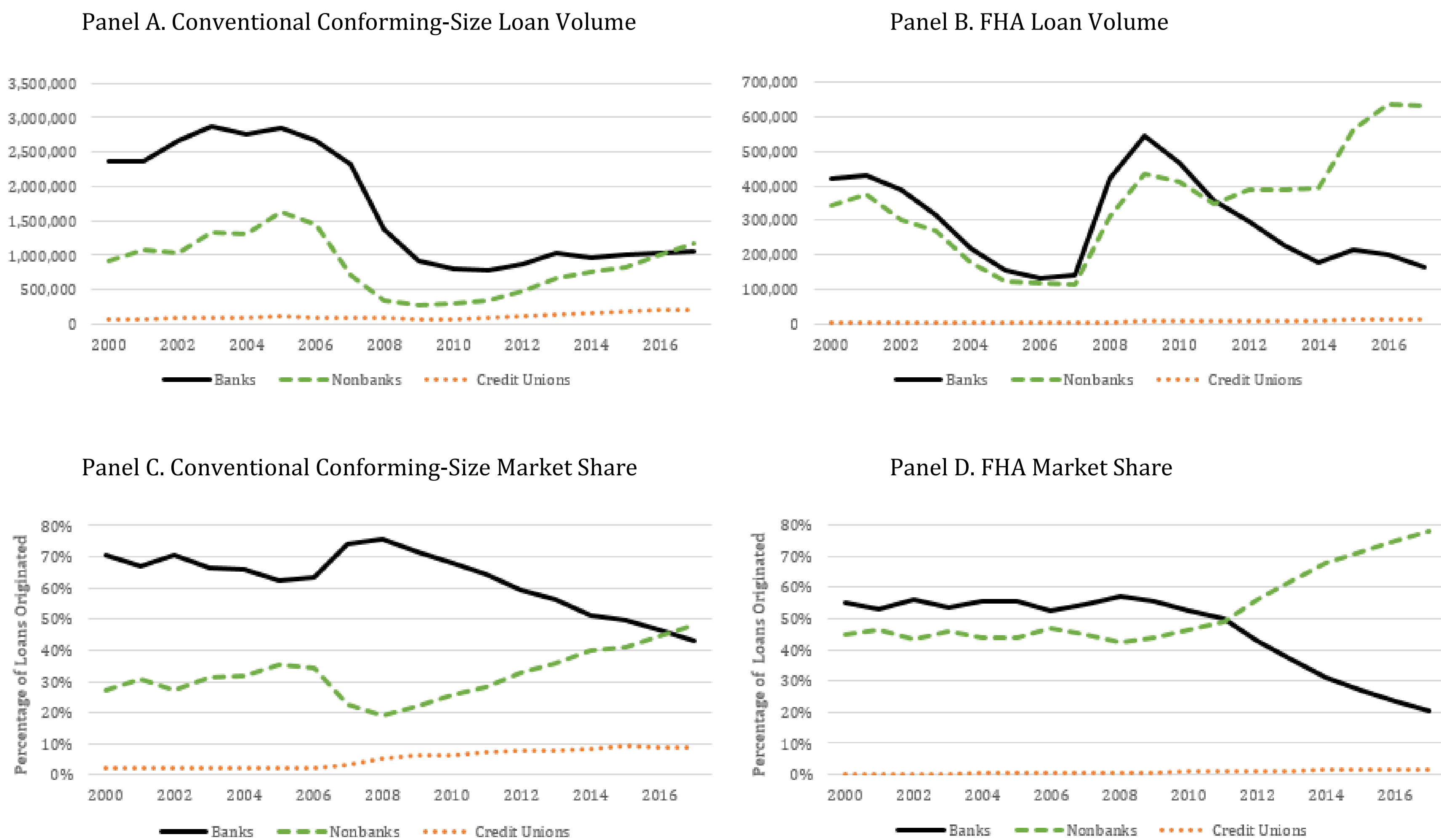
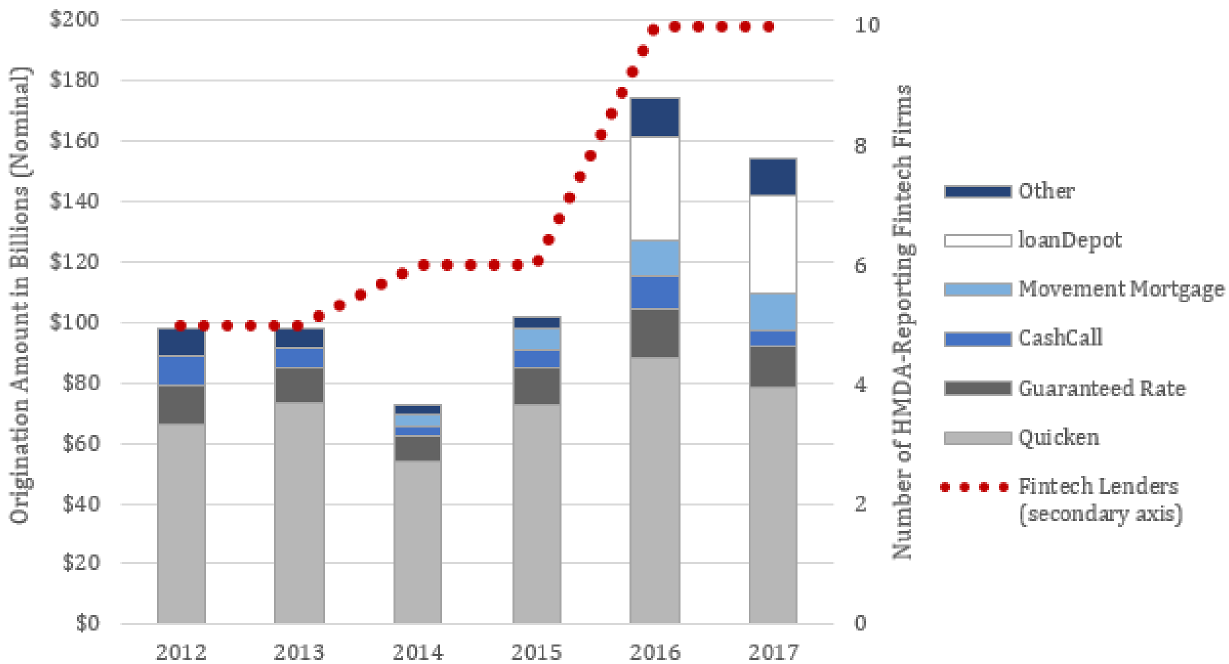
Figure 1. Bank, Nonbank, and Credit Union Origination Volume and Market Share of Conforming-Size Conforming and FHA Purchase Mortgages, 2000–2017



Source: HMDA. Note: Includes first-lien, purchase mortgages secured by 1- to 4-family properties. Lien type and property type identifiers were not available in HMDA prior to 2004, so for those years, loans are not filtered on those fields. “Banks” include commercial banks and thrifts. “Nonbanks” include fintech in these charts.

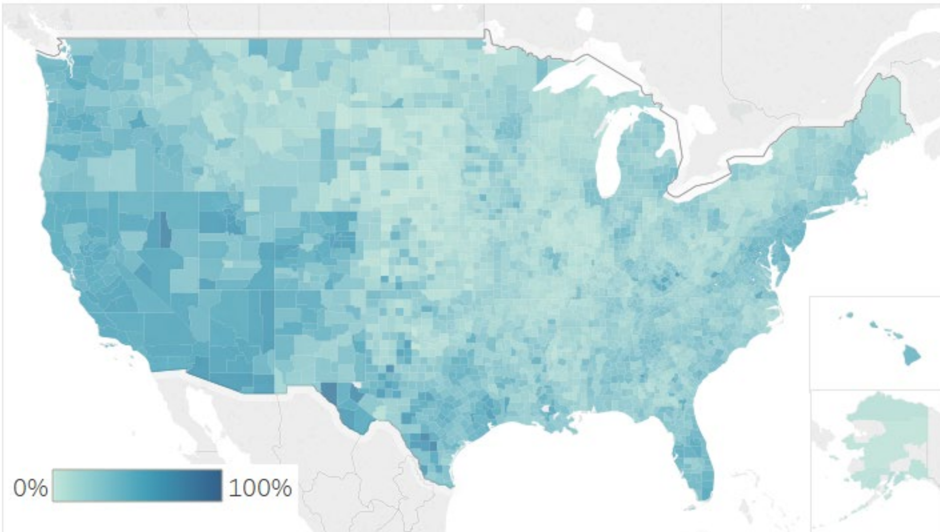
Figure 2. Fintech Origination Volume by Lender — All Mortgage Product Types
Origination Years 2012–2017



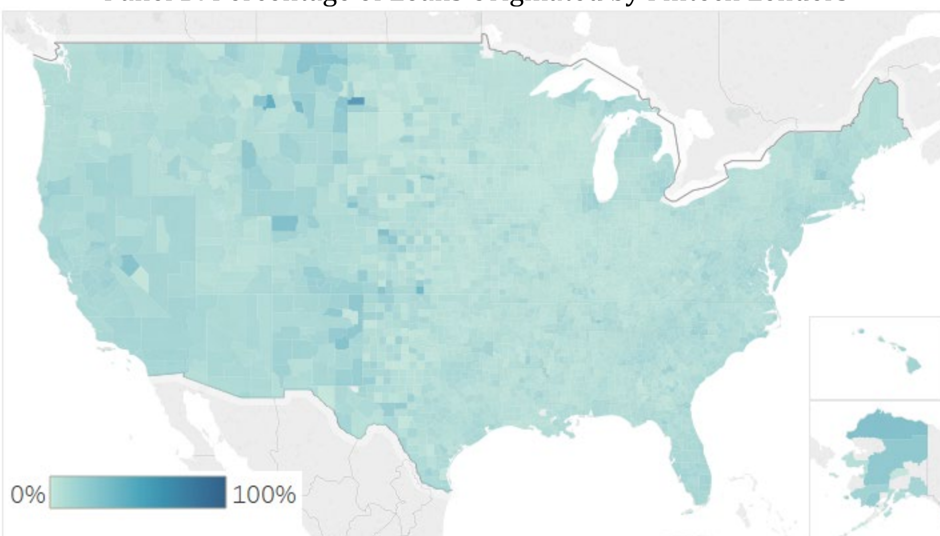
Source: HMDA. Note: Includes first-lien mortgages secured by 1- to 4-family and manufactured homes. Excludes loans with origination amount exceeding county conforming loan limit. Includes conventional, FHA, VA, and Rural Housing Service loans.

Figure 3. Conventional Conforming-Size Mortgages Originations by County, 2016–2017

Panel A: Percentage of Loans Originated by Traditional Nonbank Lenders



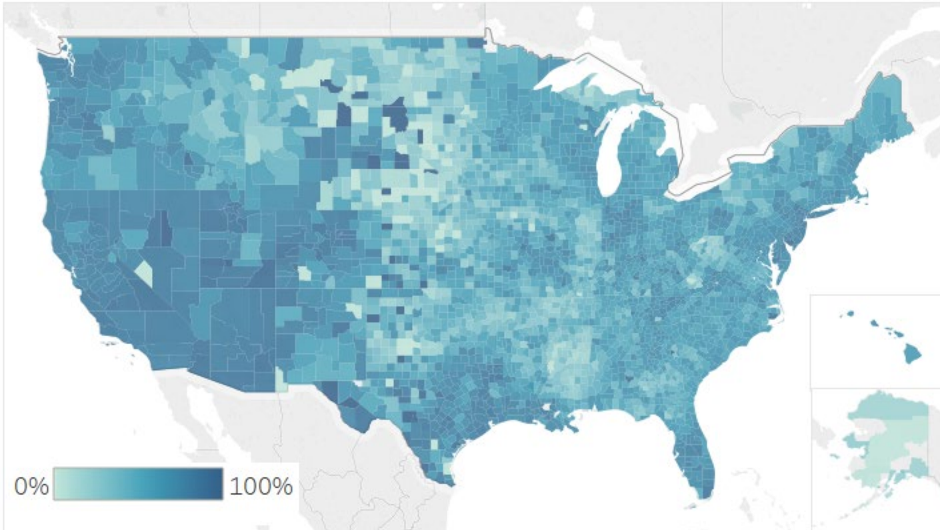
Panel B: Percentage of Loans Originated by Fintech Lenders



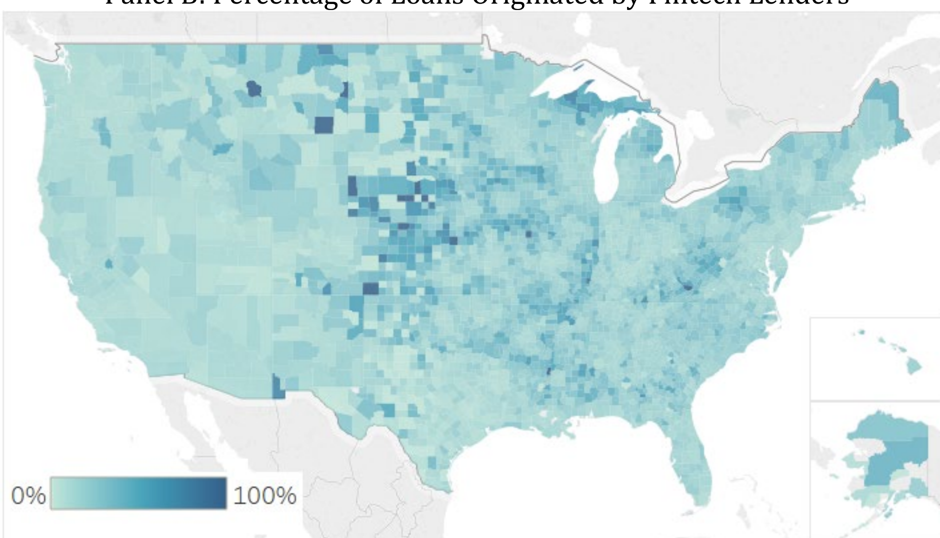
Source: HMDA. Note: Includes first-lien mortgages secured by 1- to 4-family properties and manufactured homes.

Figure 4. FHA Mortgages Originations by County, 2016–2017

Panel A: Percentage of Loans Originated by Traditional Nonbank Lenders



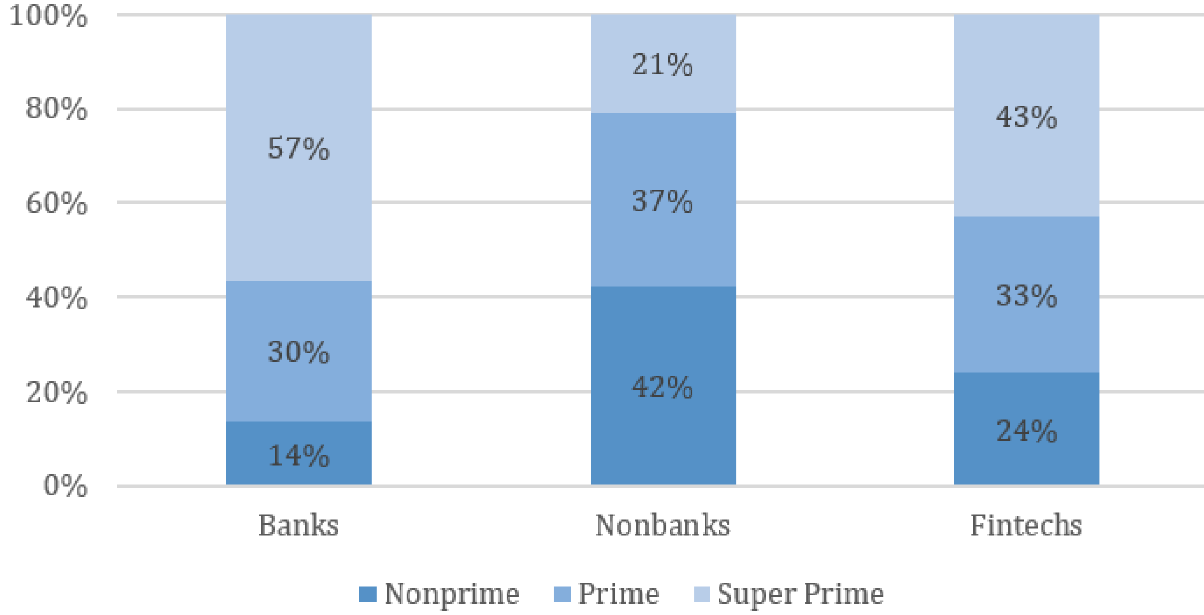
Panel B: Percentage of Loans Originated by Fintech Lenders



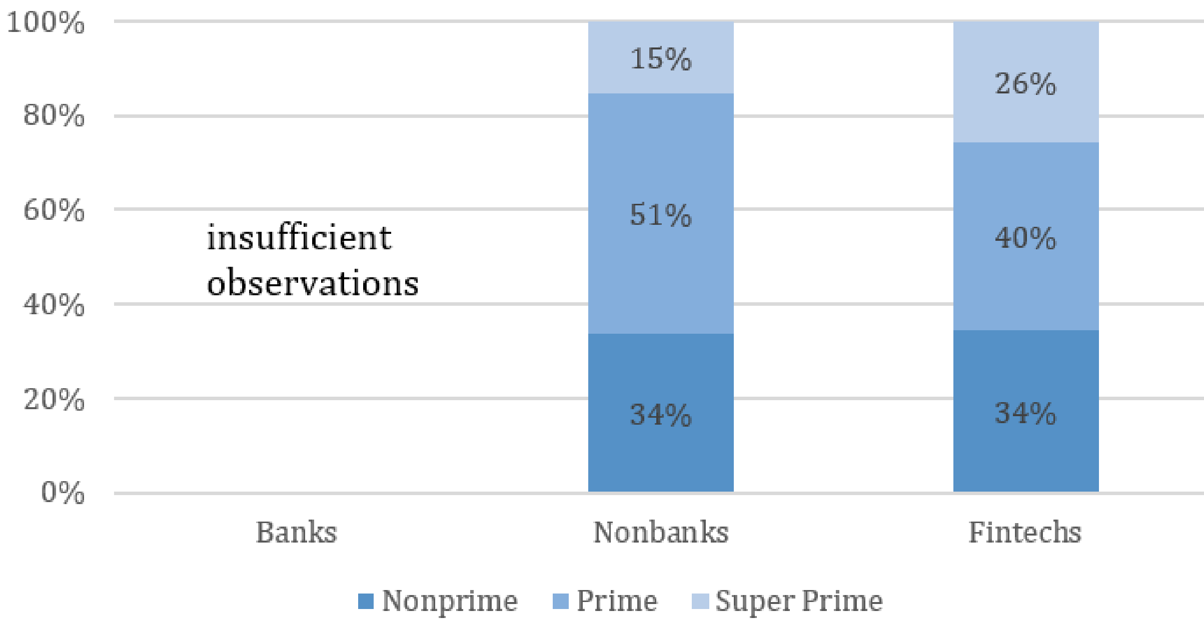
Source: HMDA. Note: Includes first-lien mortgages secured by 1- to 4-family properties and manufactured homes.

Figure 5. Distribution of Offers by Consumer VantageScore Segments

Panel A: Conventional Mortgage Offers

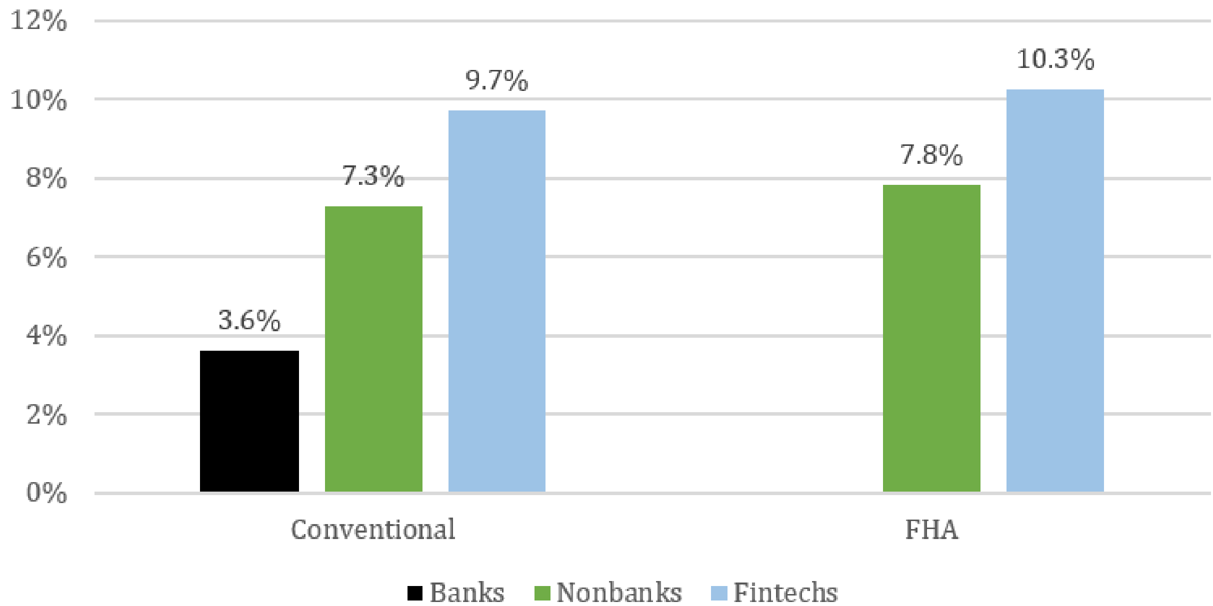


Panel B: FHA Mortgage Offers



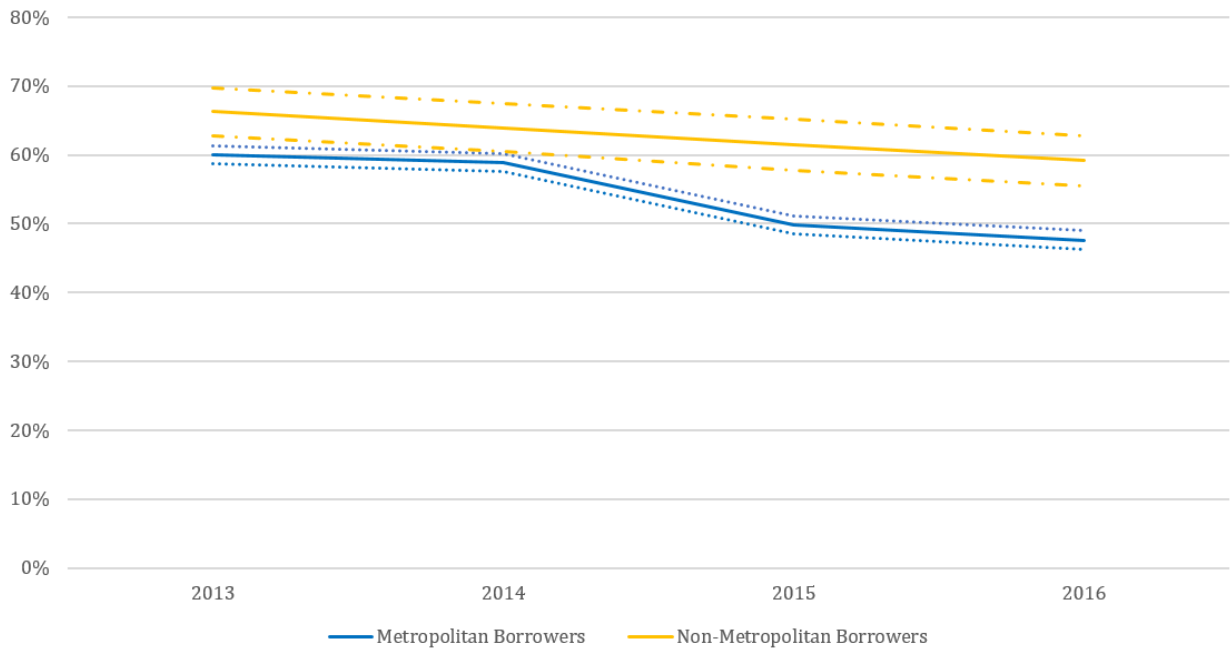
Source: Mintel Comperemedia, Inc. Direct Mail Monitor Data and TransUnion LLC Match File. Note: Bank institutions have a small number of FHA observations, so their distribution is not reported. VantageScore bins are based on Vantage 3.0 and are defined as follows: nonprime (< 661), prime (661–780), and super prime (> 780), following Experian (2015).

Figure 6. Share of Mortgage Offers That Are Made to Borrowers Living in Nonmetropolitan Counties



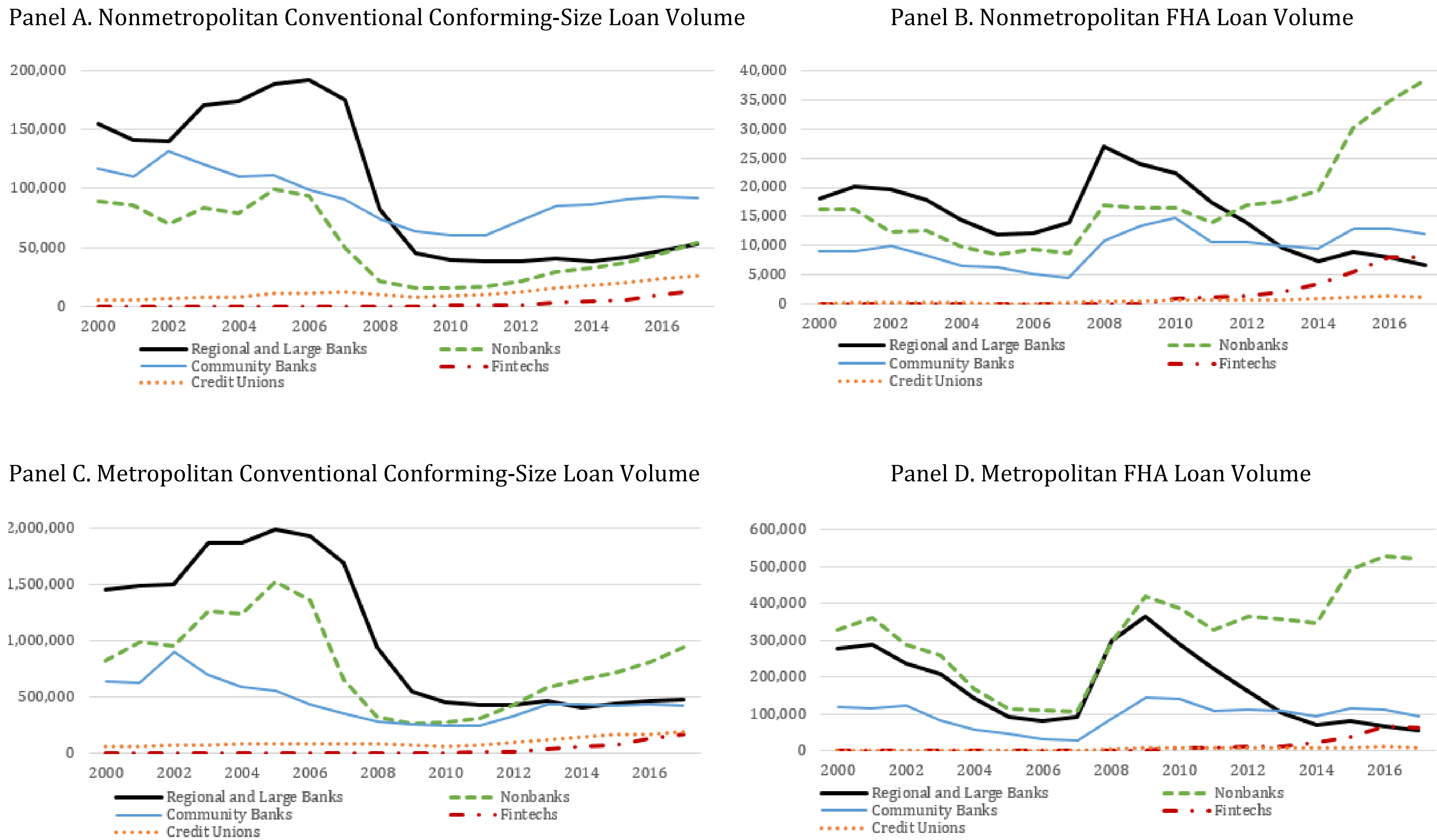
Source: Mintel Comperemedia, Inc. Direct Mail Monitor Data and TransUnion LLC Match File. Note: Bank institutions have a small number of FHA observations, so their distribution is not reported.

Figure 7. Percentage of NSMO Respondents Indicating That Proximity to Branch/Office Important for Choice of Lender



Source: National Survey of Mortgage Originations (NSMO) Public Use File, available at https://www.fhfa.gov/nsmodata.

Figure 8. Purchase Mortgage Origination Volume in Nonmetropolitan and Metropolitan Counties, 2000–2017



Source: HMDA. Note: Includes first-lien, purchase mortgages secured by 1- to 4-family properties. Lien type and property type identifiers were not available in HMDA data prior to 2004, so for those years, loans are not filtered on those fields. "Banks" include commercial banks and thrifts. "Nonbanks" exclude fintech in these charts.

Table 1. Descriptive Statistics for Originated Mortgages in 2016–2017

	All Lender Types				Means by Lender Type			
Variable	Mean	SD	Min	Max	Fintechs	Nonbanks	Banks	Credit Unions
Panel A. Full Sample								
[n = 11.98 million]								
Loan Type								
Conventional (d)	0.67	0.47	0	1	0.65	0.54	0.80	0.90
FHA (d)	0.20	0.40	0	1	0.22	0.30	0.10	0.03
VA (d)	0.11	0.31	0	1	0.12	0.14	0.08	0.07
Farm Service Agency/Rural Housing Service (d)	0.02	0.14	0	1	0.01	0.03	0.02	0.00
Panel B. Conventional, FHA, and VA								
[n = 11.75 million]								
Nonmetropolitan (d)	0.09	0.29	0	1	0.09	0.07	0.12	0.11
Manufactured housing (d)	0.02	0.14	0	1	0.00	0.03	0.02	0.03
Refinance (d)	0.44	0.50	0	1	0.65	0.37	0.44	0.51
2017 (d)	0.46	0.50	0	1	0.48	0.48	0.44	0.47
Panel C. Omitting Missing Census Tracts								
[n = 11.72 million]								
Nonfintech lagged denial rate	19.1	6.8	0	100	19.6	19.3	18.9	18.7
Mean Equifax Risk Score	674	38	381	834	673	672	677	675
CRA loan (d)	0.35	0.48	0	1	0.35	0.36	0.34	0.36
No income reported (d)	0.06	0.23	0	1	0.04	0.09	0.04	0.01
Tract percent minority	30.2	24.4	0	100	32.0	33.6	26.4	26.1
Assessment areas	16	8	0	25	17	17	15	14
1-year house price appreciation (%)	5.13	4.05	-24.7	35.6	5.32	5.49	4.71	4.72

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), Federal Reserve Bank of New York/Equifax Consumer Credit Panel, CoreLogic Solutions House Price Index, and Community Reinvestment Act data from the FFIEC. Note: Dichotomous variables are denoted by (d). Panel A includes owner-occupied mortgages originated 2016–2017 and secured by 1- to 4-family properties or manufactured homes, excluding loans with an amount in excess of the single-family conforming loan limit (a proxy for jumbo loans). Panel B limits Panel A's loans to conventional, FHA, and VA loans (that is, excluding Farm Service Agency/Rural Housing Service loans). Panel C restricts Panel B's loans to those that had the Census tract of the collateral property reported. CRA loan is a dummy that is coded as 1 if the borrower's income reported in HMDA < 80% of area median income (AMI) and/or the collateral property is located in an LMI or distressed/underserved Census tract. Assessment areas captures the number of CRA-regulated banks that have included the Census tract in their CRA assessment areas and is top coded at 25.

Table 2. Lenders' Mean Area Denial Rates, Risk Scores, and CRA-Relevant Lending by Product Type

		Nonfintech Lagged Denial Rate		Tract Equifax Risk Score		CRA Loan (d)	
		Fintechs	Nonbanks	Fintechs	Nonbanks	Fintechs	Nonbanks
Purchase	Conventional	18.4	18.2	678	679	0.32	0.33
	FHA	21.7	21.0	653	655	0.49	0.50
	VA	20.1	19.5	664	665	0.32	0.33
Refinance	Conventional	19.0	18.3	680	685	0.32	0.30
	FHA	21.2	20.8	659	663	0.49	0.51
	VA	20.2	19.9	668	668	0.40	0.34

Source: HMDA and Federal Reserve Bank of New York/Equifax Consumer Credit Panel. The analysis includes owner-occupied mortgages originated 2016–2017 and secured by 1- to 4-family properties or manufactured homes, excluding loans with an amount in excess of the single-family conforming loan limit.

Table 3. Additional Characteristics of Originated Mortgages in 2016–2017

Variable	All Lenders	Fintechs	Nonbanks	Banks	Credit Unions
Tract Median Family Income/AMI					
Low (< 50% AMI)	2%	2%	2%	2%	2%
Moderate (50 - 79.9% AMI)	13%	13%	14%	12%	13%
Middle (80 - 119.9% AMI)	46%	46%	46%	46%	50%
Upper (>= 120% AMI)	39%	39%	37%	41%	35%
Borrower Income/AMI, Where Reported					
Low (< 50% AMI)	7%	6%	7%	7%	6%
Moderate (50 - 79.9% AMI)	20%	19%	21%	19%	20%
Middle (80 - 119.9% AMI)	27%	28%	29%	26%	27%
Upper (>= 120% AMI)	46%	46%	43%	49%	47%
Borrower Income Not Reported	6%	4%	8%	4%	1%
Race/Ethnicity, Where Reported					
Asian	6%	5%	6%	6%	4%
Black	7%	8%	8%	5%	6%
Hispanic	11%	10%	14%	8%	9%
Other minority	1%	1%	1%	1%	1%
White	76%	75%	71%	80%	80%
Race/Ethnicity Uknown	10%	27%	7%	8%	10%
Sex, Where Reported					
Male	69%	67%	69%	70%	65%
Female	31%	33%	31%	30%	35%
Sex Unknown	6%	21%	3%	6%	6%

Source: HMDA and U.S. Census Bureau data from the FFIEC. Note: AMI = area median income. This is the median family income of the metropolitan division or core-based statistical area in which a tract is located. For nonmetropolitan counties, this is the median family income for the nonmetro portion of the state in which the collateral property is located. For borrower income ratio, the AMI used is the area estimate calculated annually by the FFIEC. For the Census tract income ratio, the AMI is the 2010 Census value for loans originated in 2016 and the 2011–2015 American Community Survey for loans originated in 2017. The analysis includes owner-occupied mortgages originated in 2016–2017 and secured by 1- to 4-family properties or manufactured homes, excluding loans with an amount in excess of the single-family conforming loan limit.

Table 4. Loan Size at Origination

Panel A. Median Loan Size

Lender Type	**All Loans**	**Metropolitan**	**Nonmetropolitan**	**Purchase**	**Refinance**
Fintech lenders	$200,000	$207,000	$132,000	$207,000	$195,000
Traditional nonbanks	$215,000	$221,000	$142,000	$211,000	$223,000
Bank	$190,000	$200,000	$129,000	$196,000	$184,000
Credit union	$163,000	$170,000	$120,000	$176,000	$150,000
All lenders	$200,000	$209,000	$133,000	$202,000	$198,000

Panel B. Percentage of Loans $70,000 or Less

Lender Type	**All Loans**	**Metropolitan**	**Nonmetropolitan**	**Purchase**	**Refinance**
Fintech lenders	3.9%	3.0%	12.4%	3.9%	3.9%
Traditional nonbanks	3.4%	2.7%	11.8%	3.6%	3.0%
Bank	7.4%	5.6%	19.0%	6.3%	8.8%
Credit union	11.9%	10.6%	22.2%	8.6%	15.1%
All lenders	5.6%	4.4%	16.2%	5.0%	6.4%

Source: HMDA. The analysis includes owner-occupied mortgages originated in 2016–2017 and secured by 1- to 4-family properties or manufactured homes, excluding loans with an amount in excess of the single-family conforming loan limit.

Table 5. Linear Probability Model Results, Likelihood of Mortgage = Fintech

	Dependent Variable: Fintech = 100; Nonbank = 0			
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.32***	0.13***		
	(0.01)	(0.01)		
Mean tract Risk Score			-0.05***	-0.03***
			0.00	0.00
Nonmetro (d)	5.56***	9.12***	6.68***	9.56***
	(0.18)	(0.18)	(0.18)	(0.18)
Manufactured (d)	-20.67***	-18.20***	-19.76***	-17.83***
	(0.11)	(0.13)	(0.10)	(0.13)
Refi (d)	20.05***	14.77***	20.27***	14.90***
	(0.08)	(0.09)	(0.08)	(0.09)
1-year HPA	-0.32***	-0.23***	-0.34***	-0.25***
	(0.01)	(0.01)	(0.01)	(0.01)
2017 (d)	3.59***	0.99***	2.47***	0.49***
	(0.06)	(0.06)	(0.05)	(0.06)
Intercept	8.61***	9.17***	47.37***	31.72***
	(0.19)	(0.17)	(0.85)	(0.91)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	3,745,021	1,878,219	3,745,021	1,878,219
Adj. R2	0.065	0.046	0.064	0.046

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), Federal Reserve Bank of New York/Equifax Consumer Credit Panel, and CoreLogic Solutions House Price Index data. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table 6. Linear Probability Model Results, Likelihood of Mortgage = Fintech
Excluding Fintech Lenders that Reported to HMDA Prior to 2016

	Dependent Variable: Fintech = 100; Nonbank = 0			
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.10***	0.05***		
	(0.01)	(0.01)		
Mean tract Risk Score			-0.02***	-0.02***
			0.00	0.00
Nonmetro (d)	-0.53***	-0.67***	-0.26*	-0.52***
	(0.11)	(0.11)	(0.11)	(0.11)
Manufactured (d)	-7.03***	-5.79***	-6.94***	-5.66***
	(0.07)	(0.07)	(0.07)	(0.07)
Refi (d)	2.87***	1.18***	2.96***	1.28***
	(0.06)	(0.07)	(0.06)	(0.07)
1-year HPA	0.01	0.03***	0	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
2017 (d)	0.91***	1.34***	0.55***	1.15***
	(0.04)	(0.05)	(0.04)	(0.05)
Intercept	4.23***	4.37***	19.40***	16.17***
	(0.14)	(0.13)	(0.62)	(0.76)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	3,078,456	1,683,161	3,078,456	1,683,161
Adj. R2	0.005	0.003	0.005	0.003

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), Federal Reserve Bank of New York/Equifax Consumer Credit Panel, and CoreLogic Solutions House Price Index data. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table 7. Linear Probability Model Results, Likelihood of Mortgage = Fintech Lender Concentration

	Dependent Variable: Fintech = 100; Nonbank = 0			
	All Counties		Metropolitan Counties	
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.31***	0.12***	0.32***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
Nonmetro (d)	3.25***	4.42***		
	(0.26)	(0.25)		
Manufactured (d)	-21.09***	-18.95***	-18.68***	-15.64***
	(0.12)	(0.13)	(0.12)	(0.14)
Refi (d)	20.04***	14.73***	19.69***	14.01***
	(0.08)	(0.09)	(0.08)	(0.10)
1-year HPA	-0.30***	-0.19***	-0.29***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)
2017 (d)	3.54***	0.89***	3.49***	0.91***
	(0.06)	(0.06)	(0.06)	(0.07)
No. of Assessment Areas Tract Falls Inside				
0	2.09**	10.54***	-3.78	7.00*
	(0.74)	(0.88)	(2.95)	(3.31)
1	1.07*	8.39***	-3.48**	2.58
	(0.54)	(0.65)	(1.10)	(1.32)
2	2.80***	9.20***	1.22	9.01***
	(0.49)	(0.54)	(0.86)	(0.96)
3	3.54***	6.36***	1.51	7.67***
	(0.47)	(0.45)	(0.87)	(0.93)
4	4.98***	5.33***	5.40***	4.59***
	(0.46)	(0.37)	(0.75)	(0.54)
5	2.18***	3.85***	2.68***	4.39***
	(0.35)	(0.31)	(0.47)	(0.41)
6	2.41***	4.08***	2.28***	3.51***
	(0.29)	(0.29)	(0.35)	(0.33)
7	2.12***	3.14***	2.06***	3.25***
	(0.24)	(0.23)	(0.26)	(0.25)
8	2.31***	3.10***	2.35***	3.08***
	(0.24)	(0.23)	(0.25)	(0.24)
9	0.32	0.95***	0.19	1.07***
	(0.30)	(0.25)	(0.32)	(0.26)
10	0.16	1.46***	0.08	1.37***
	(0.22)	(0.22)	(0.22)	(0.22)
Intercept	8.49***	8.74***	8.41***	9.11***
	(0.19)	(0.17)	(0.21)	(0.18)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	3,745,021	1,878,219	3,523,232	1,723,794
Adj. R2	0.065	0.047	0.059	0.036

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), CoreLogic Solutions House Price Index data, and Community Reinvestment Act data from the FFIEC, and FDIC Summary of Deposits data. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. T-statistics are displayed in parentheses. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table 8. Linear Probability Model Results, Likelihood of Mortgage = Fintech Lender Concentration
Excluding Fintech Lenders that Reported to HMDA Prior to 2016

	Dependent Variable: Fintech = 100; Nonbank = 0			
	All Counties		Metropolitan Counties	
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.10***	0.05***	0.10***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Nonmetro (d)	0.03	-0.28		
	(0.17)	(0.14)		
Manufactured (d)	-6.89***	-5.67***	-6.85***	-5.58***
	(0.07)	(0.08)	(0.08)	(0.09)
Refi (d)	2.87***	1.17***	2.61***	0.85***
	(0.06)	(0.07)	(0.06)	(0.07)
1-year HPA	0	0.02**	0.01	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
2017 (d)	0.91***	1.34***	0.86***	1.27***
	(0.04)	(0.05)	(0.04)	(0.05)
No. of Assessment Areas Tract Falls Inside				
0	-1.35**	-0.63	-1.10	(0.53)
	(0.43)	(0.50)	(1.98)	(1.28)
1	-1.94***	-1.33***	-4.38***	-3.42***
	(0.28)	(0.31)	(0.52)	(0.48)
2	-1.04***	0.30	-2.78***	-1.84***
	(0.28)	(0.41)	(0.43)	(0.41)
3	-0.64*	-0.41	-0.84	0.31
	(0.27)	(0.26)	(0.45)	(0.62)
4	0.04	-0.32	0.65	-0.07
	(0.24)	(0.21)	(0.35)	(0.31)
5	-1.03***	-1.07***	-0.84*	-0.91***
	(0.23)	(0.19)	(0.33)	(0.27)
6	-0.56*	-0.58**	-0.74*	-0.76**
	(0.24)	(0.22)	(0.29)	(0.26)
7	-0.32	-0.60***	-0.24	-0.54**
	(0.17)	(0.16)	(0.19)	(0.18)
8	0.48*	0.01	0.61**	0.08
	(0.20)	(0.16)	(0.22)	(0.18)
9	-1.29***	-0.83***	-1.34***	-0.82***
	(0.16)	(0.16)	(0.17)	(0.17)
10	-1.01***	-0.86***	-1.04***	-0.88***
	(0.16)	(0.16)	(0.16)	(0.16)
Intercept	4.29***	4.54***	4.32***	4.70***
	(0.14)	(0.13)	(0.15)	(0.14)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	3,078,456	1,683,161	2,911,268	1,560,093
Adj. R2	0.005	0.003	0.004	0.002

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), CoreLogic Solutions House Price Index data, and Community Reinvestment Act data from the FFIEC, and FDIC Summary of Deposits data. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. T-statistics are displayed in parentheses. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table 9. Linear Probability Model Results, Likelihood of Mortgage = Fintech Lender Concentration

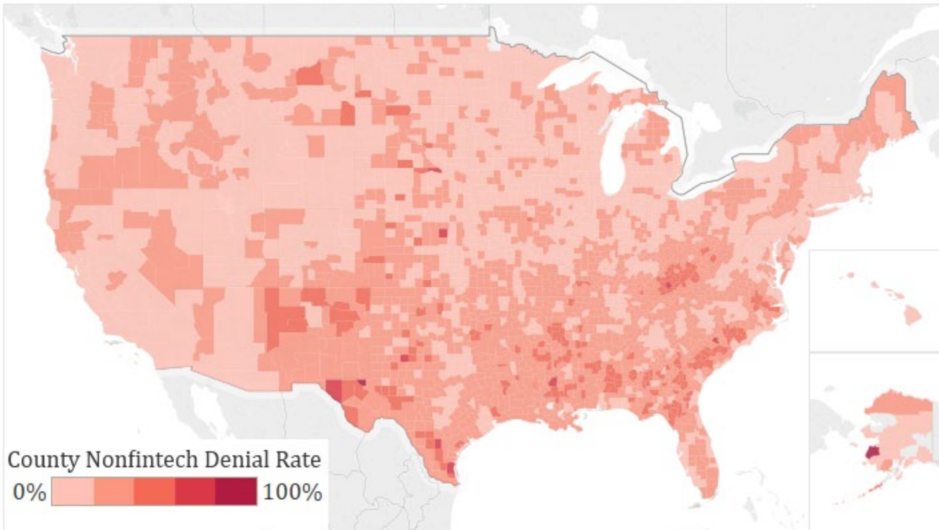
	Dependent Variable: Fintech = 100; Nonbank = 0		
	All	All	All
Nonfintech denial rate	0.16***	0.15***	0.16***
	(0.01)	(0.01)	(0.01)
Nonmetro (d)	4.79***	6.98***	6.69***
	(0.14)	(0.14)	(0.15)
Manufactured (d)	-19.18***	-18.72***	-18.79***
	(0.09)	(0.09)	(0.09)
Refi (d)	18.65***	18.65***	18.65***
	(0.06)	(0.06)	(0.06)
1-year HPA	-0.21***	-0.22***	-0.23***
	(0.01)	(0.01)	(0.01)
2017 (d)	2.26***	2.22***	2.24***
	(0.04)	(0.04)	(0.04)
Lender HHI > 625	3.70***		
	(0.15)		
Branch Dens. < 10th pctile		-3.01***	
		(0.14)	
Branch Dens. <25th pctile			-0.90***
			(0.11)
Intercept	9.60***	10.26***	10.11***
	(0.15)	(0.15)	(0.15)
Sample	F + NB	F + NB	F + NB
Observations	6,529,120	6,528,799	6,528,799
Adj. R2	0.059	0.059	0.059

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), CoreLogic Solutions House Price Index data, and FDIC Summary of Deposits data. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. T-statistics are displayed in parentheses. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

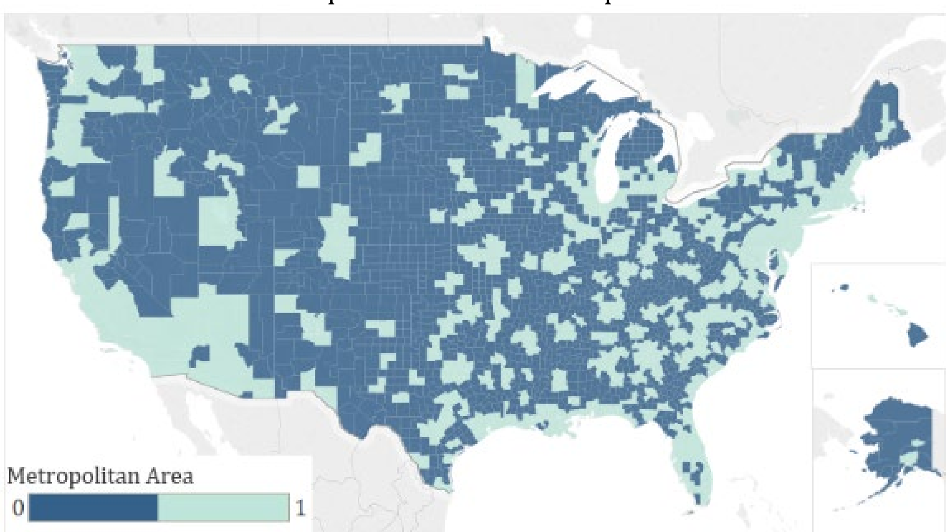
Appendix

Figure A1. Nonfintech Denial Rate and Nonmetropolitan Counties

Panel A: Percentage of Nonfintech Loan Applications Denied



Panel B: Metropolitan and Nonmetropolitan Counties



Source: HMDA. Note: Includes first-lien mortgages secured by 1- to 4-family properties and manufactured homes.

Table A1. List of Sample Fintech Mortgage Lenders

	Fintech Start Date		
Lender	**This Paper**	**Fuster et al. (2018)**	**Buchak et al. (2018)**
AmeriSave Mortgage	2008		2008
Better Mortgage	2016	not included	not included
CashCall Inc.	2008		2008
Everett Financial (Supreme)	2016	2016	
Guaranteed Rate	2010	2010	2008
loanDepot	2016	2016	
Movement Mortgage	2014	2014	2013
SoFi	2016	not included	not included
Quicken	2010	2010	2000

Sources: Fuster, Plosser, Schnabl, and Vickery (2018) and Buchak, Matvos, Piskorski, and Seru (2018). Note: firms with a 2016 start date are treated as new firms in our robustness tests.

Table A2. Linear Probability Model Results, Likelihood of Mortgage = Fintech

Panel A: Fintech vs. Traditional Nonbanks

	Dependent Variable: Fintech = 100; Nonbank = 0			
	All	Conventional	FHA	VA
Nonmetro (d)	6.84***	7.04***	9.57***	5.16***
	(0.44)	(0.63)	(0.34)	(0.35)
Manufactured (d)	-18.00***	-17.92***	-17.82***	-18.68***
	(0.14)	(0.19)	(0.14)	(0.19)
Refi (d)	18.52***	19.99***	14.71***	15.87***
	(0.06)	(0.08)	(0.09)	(0.12)
2017 (d)	1.64***	2.55***	0.44***	0.80***
	(0.04)	(0.05)	(0.06)	(0.08)
Intercept	11.99***	13.09***	10.86***	10.03***
	(0.06)	(0.07)	(0.07)	(0.10)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	6,538,194	3,750,690	1,880,326	907,178
Adj. R2	0.058	0.062	0.044	0.046

Panel B: Fintech vs. Banks

	Dependent Variable: Fintech = 100; Bank = 0			
	All	Conventional	FHA	VA
Nonmetro (d)	-4.50***	-7.22***	3.40***	2.77***
	(0.20)	(0.16)	(0.32)	(0.28)
Manufactured (d)	-19.38***	-15.74***	-30.28***	-23.60***
	(0.21)	(0.28)	(0.38)	(0.43)
Refi (d)	15.60***	13.67***	40.48***	28.05***
	(0.07)	(0.07)	(0.17)	(0.18)
2017 (d)	4.14***	3.93***	2.53***	5.49***
	(0.04)	(0.04)	(0.12)	(0.13)
Intercept	15.50***	12.69***	27.35***	15.43***
	(0.08)	(0.08)	(0.16)	(0.17)
Sample	F + B	F + B	F + B	F + B
Observations	5,622,391	4,351,466	741,644	529,281
Adj. R2	0.039	0.036	0.15	0.094

Source: HMDA and U.S. Census Bureau (2010 Decennial Census). Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table A3. Linear Probability Model Results, Likelihood of Mortgage = Fintech
Alternative Method of Identifying Metro Areas (Upper Bound)

Panel A: Fintech vs. Traditional Nonbanks

	Dependent Variable: Fintech = 100; Nonbank = 0			
	All	Conventional	FHA	VA
Nonmetro (d)	7.29***	7.68***	9.87***	5.48***
	(0.14)	(0.19)	(0.19)	(0.20)
Manufactured (d)	-18.08***	-18.04***	-17.88***	-18.75***
	(0.09)	(0.11)	(0.12)	(0.17)
Refi (d)	18.51***	19.98***	14.69***	15.86***
	(0.06)	(0.08)	(0.09)	(0.12)
2017 (d)	1.63***	2.54***	0.43***	0.79***
	(0.04)	(0.05)	(0.06)	(0.08)
Intercept	11.97***	13.07***	10.85***	10.01***
	(0.06)	(0.08)	(0.07)	(0.10)
Sample	F + NB	F + NB	F + NB	F + NB
Observations	6,538,194	3,750,690	1,880,326	907,178
Adj. R2	0.058	0.062	0.044	0.046

Panel B: Fintech vs. Banks

	Dependent Variable: Fintech = 100; Bank = 0			
	All	Conventional	FHA	VA
Nonmetro (d)	-4.32***	-7.09***	3.59***	2.84***
	(0.13)	(0.13)	(0.27)	(0.27)
Manufactured (d)	-19.55***	-16.00***	-30.32***	-23.62***
	(0.10)	(0.09)	(0.37)	(0.43)
Refi (d)	15.60***	13.67***	40.48***	28.05***
	(0.07)	(0.07)	(0.17)	(0.18)
2017 (d)	4.14***	3.93***	2.52***	5.49***
	(0.04)	(0.04)	(0.12)	(0.13)
Intercept	15.48***	12.66***	27.33***	15.42***
	(0.09)	(0.08)	(0.16)	(0.17)
Sample	F + B	F + B	F + B	F + B
Observations	5,622,391	4,351,466	741,644	529,281
Adj. R2	0.038	0.036	0.15	0.094

Source: HMDA and U.S. Census Bureau (2010 Decennial Census). Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. T-statistics are displayed in parentheses. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table A4. Linear Probability Model Results, Likelihood of Mortgage = Fintech
Community Characteristics

Fintech vs. Banks

	Dependent Variable: Fintech = 100; Bank = 0			
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.26***	0.44***		
	(0.01)	(0.01)		
Mean tract Risk Score			-0.03***	-0.04***
			0.00	0.00
Nonmetro (d)	-8.00***	1.97***	-7.08***	3.78***
	(0.12)	(0.26)	(0.12)	(0.27)
Manufactured (d)	-17.13***	-31.74***	-16.40***	-30.48***
	(0.09)	(0.38)	(0.09)	(0.37)
Refi (d)	13.33***	40.35***	13.47***	40.52***
	(0.07)	(0.17)	(0.07)	(0.17)
1-year HPA	0.62***	0.56***	0.61***	0.55***
	(0.01)	(0.02)	(0.01)	(0.02)
2017 (d)	4.40***	3.74***	3.56***	2.17***
	(0.05)	(0.13)	(0.04)	(0.12)
Intercept	4.92***	15.15***	29.53***	48.24***
	(0.18)	(0.33)	(0.86)	(1.79)
Sample	F + B	F + B	F + B	F + B
Observations	4,344,381	741,153	4,344,381	741,153
Adj. R2	0.041	0.156	0.04	0.153

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), and CoreLogic Solutions House Price Index.
Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table A5. Linear Probability Model Results, Likelihood of Mortgage = Fintech
Including Loans in Metropolitan Counties Only

	Metro Only				Nonmetro Only			
	0 = Nonbank		0 = Bank		0 = Nonbank		0 = Bank	
	Conventional	FHA	Conventional	FHA	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.33***	0.10***	0.29***	0.45***	0.26***	0.26***	0.12***	0.37***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Manufactured (d)	-18.15***	-14.64***	-19.69***	-29.08***	-23.77***	-25.78***	-13.42***	-35.07***
	(0.11)	(0.12)	(0.11)	(0.49)	(0.25)	(0.24)	(0.12)	(0.55)
Refi (d)	19.70***	14.03***	13.46***	39.19***	25.80***	21.93***	12.24***	48.69***
	(0.08)	(0.10)	(0.07)	(0.18)	(0.25)	(0.27)	(0.14)	(0.36)
1-year HPA	-0.31***	-0.21***	0.64***	0.63***	-0.43***	-0.46***	0.41***	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)
2017 (d)	3.54***	0.98***	4.53***	3.80***	4.14***	0.50*	3.71***	3.21***
	(0.06)	(0.07)	(0.06)	(0.14)	(0.21)	(0.23)	(0.11)	(0.32)
Intercept	8.53***	9.72***	4.12***	14.92***	13.63***	14.27***	1.66***	18.91***
	(0.20)	(0.18)	(0.21)	(0.37)	(0.57)	(0.56)	(0.30)	(0.78)
Sample	F + NB	F + NB	F + B	F + B	F + NB	F + NB	F + B	F + B
Observations	3,523,232	1,723,794	3,856,357	655,023	221,789	154,425	488,024	86,130
Adj. R2	0.059	0.035	0.036	0.145	0.131	0.097	0.045	0.243

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), and CoreLogic Solutions House Price Index.
Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table A6. Linear Probability Model Results, Likelihood of Mortgage = Fintech

Purchase vs. Refinance

	Metro Only				Nonmetro Only			
	0 = Nonbank		0 = Bank		0 = Nonbank		0 = Bank	
	Conventional	FHA	Conventional	FHA	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.22***	0.12***	0.18***	0.47***	0.41***	0.13***	0.33***	0.35***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Nonmetro (d)	2.56***	5.89***	-7.21***	-1.35***	8.46***	14.77***	-8.73***	8.99***
	(0.19)	(0.20)	(0.11)	(0.33)	(0.25)	(0.27)	(0.17)	(0.31)
Manufactured (d)	-17.29***	-12.05***	-11.76***	-24.55***	-36.85***	-30.48***	-25.37***	-66.95***
	(0.11)	(0.13)	(0.10)	(0.37)	(0.23)	(0.18)	(0.12)	(0.70)
1-year HPA	-0.12***	-0.10***	0.53***	0.79***	-0.51***	-0.55***	0.69***	0.07*
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
2017 (d)	1.84***	0.02	2.94***	4.09***	5.39***	3.19***	5.77***	2.93***
	(0.07)	(0.07)	(0.06)	(0.16)	(0.08)	(0.12)	(0.07)	(0.21)
Intercept	10.34***	9.16***	7.28***	13.64***	27.25***	24.45***	16.24***	59.49***
	(0.22)	(0.19)	(0.21)	(0.40)	(0.24)	(0.28)	(0.20)	(0.40)
Sample	F + NB	F + NB	F + B	F + B	F + NB	F + NB	F + B	F + B
Observations	1,958,602	1,295,719	2,058,669	520,199	1,786,419	582,500	2,285,712	220,954
Adj. R2	0.008	0.006	0.013	0.015	0.012	0.024	0.015	0.022

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), and CoreLogic Solutions House Price Index.
Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.

Table A7. Linear Probability Model Results, Likelihood of Mortgage = Fintech Given Fintech or Credit Union

	Dependent Variable: Fintech = 100; Credit Union = 0			
	Conventional	FHA	Conventional	FHA
Nonfintech denial rate	0.29***	0.30***		
	(0.02)	(0.02)		
Mean tract Risk Score			0.04***	-0.03***
			0.00	0.00
Nonmetro (d)	-8.74***	-1.43***	-6.50***	-0.12
	(0.42)	(0.31)	(0.42)	(0.30)
Manufactured (d)	-45.57***	-38.65***	-43.91***	-38.31***
	(0.21)	(1.90)	(0.22)	(1.90)
Refi (d)	14.52***	11.63***	14.53***	11.66***
	(0.15)	(0.17)	(0.15)	(0.17)
1-year HPA	1.01***	0.27***	1.01***	0.26***
	(0.03)	(0.02)	(0.03)	(0.02)
2017 (d)	2.61***	1.17***	1.93***	0.08
	(0.11)	(0.12)	(0.09)	(0.10)
Intercept	31.84***	78.70***	9.24***	103.82***
	(0.55)	(0.46)	(2.24)	(1.44)
Sample	F + CU	F + CU	F + CU	F + CU
Observations	1,744,584	326,405	1,744,584	326,405
Adj. R2	0.044	0.062	0.043	0.057

Source: HMDA, U.S. Census Bureau (2010 Decennial Census), Federal Reserve Bank of New York/Equifax Consumer Credit Panel, CoreLogic Solutions House Price Index. Note: ***, **, and * indicate 0.001, 0.01, and 0.05 levels of significance, respectively. Standard errors are clustered at the Census tract level. Dummy variables are indicated by (d); coefficients for missing income dummy are suppressed.