The Heterogeneity of Bank Responses to the Fintech Challenge

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Abstract

We examine the impact of fintech lenders on mortgage lending done by traditional banks, as well as the heterogeneity in their effect. Fintech reduces total lending volume of traditional banks, the brunt of which is carried by small banks. This effect is greater for all banks in the refinancing sector. In the home purchase sector, mortgage costs increase for both types of banks in the presence of more fintech, but this effect is not seen in the refinancing sector. We view our results as evidence that fintech acts as a direct competitor to traditional banks in the refinancing sector of the mortgage market, but fragments the market in the home purchase sector. [1]

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1 Introduction

From 2010 to 2019, the share of mortgage loans originated annually by traditional bank lenders in the United States fell from almost 70% to little more than 43%.[2] Shadow bank lenders have rapidly filled the void left by depository banks. Amongst these shadow bank lenders, fintech lenders (i.e. lenders that use technology and automation to originate loans) have become an increasingly important presence of the mortgage market, going from 4% market share in 2010 to 15% market share in 2019.[3] The amount of loans originated by fintech lenders has more than quadrupled during that time frame, going from $69 billion dollars in 2010 to $395 billion in 2019. Quicken Loans, the largest fintech lender in terms of origination volume, accounts for 5% of total U.S. loan origination volume in 2019. The U.S. mortgage market is slowly being taken over by lenders heavily relying on online platforms and automated algorithms to originate mortgage loans. These fintech lenders almost never meet their borrowers in person, and aren't subject to the same regulatory oversight as traditional banks.

The rapid expansion of fintech lending begs the question of how the growth of fintech lending has impacted traditional banks in the mortgage market. The rapid decline of traditional bank lending volume coincides with the growth of fintech lenders, but whether fintech lenders are responsible for the decline is another question. It is possible that fintech lenders directly compete traditional banks by targeting the same borrower pool. However, it is also possible that fintech lenders attract new borrowers to a market or specialize in specific segments of the borrower pool.

There exists significant heterogeneity between traditional banks in terms of size, lending practices, and geographic outreach. Larger banks tend to have a presence in multiple state mortgage markets across the U.S., and rely more on hard information, such as credit scores, income statements, and other quantitative measures to make a lending decision. Smaller banks, by contrast, tend to be more geographically constrained, and rely more on soft information and borrower relationships to attract a customer base and make lending decisions. (Howell et al. (2021), Liberti and Petersen (2018))

Fintech lenders have been almost exclusively shadow banks in the past decade, but they differentiate themselves from traditional banks and other shadow banks in their use of information and automation.[4] Fintech lenders rely almost entirely on hard information such as credit scores and financial statements to determine borrower credit-worthiness. While large banks also rely heavily on hard information, fintechs tend to specialize in artificial intelligence and machine learning

[2]We define traditional bank lenders as depository institutions active in the mortgage market excluding credit unions.

[3]Statistics are based on our classification and summation of lending activities from HMDA and are presented in more detail in Section 2.

[4]Fintech lenders also compete with traditional bank lenders in terms of regulatory arbitrage, as papers such as Buchak et al. (2018) show. However, this is not due to the technological advantages of fintech lenders over bank lenders, but rather due to the status of fintech lenders as shadow banks which free them from regulations that apply to depository institutions in the U.S. mortgage market. We control for some regulatory differences between states in our analysis, but it is not the main focus of our paper.

(AI/ML) technology, which allows them to better leverage those information sets. (Balyuk, Berger, and Hackney (2020), Liberti and Petersen (2018)) In contrast, small banks rely on more soft information and borrower relationships to make lending decisions. Furthermore, small banks have been slower to adopt AI/ML technology than large banks, as a 2018 Fannie Mae survey demonstrates.

Thus, fintech lenders' usage of AI/ML technology creates competition with both small and large banks, but in different ways that affect the nature of competition for different bank types. Fintech lenders and large banks rely on hard information to make lending decisions, meaning that they are more likely to compete with the same set of potential borrowers that are more credit worthy on paper in terms of financial statements and credit scores. In addition, customers may have heterogeneous preferences that affect their preferences for different services that are offered by different lender types. For instance, some borrowers would prefer to get a loan online with minimal human contact, while others would strongly prefer to have a closer relationship with a loan officer, something that small banks tend to specialize in.

The mortgage market can be subdivided into home purchase mortgages and refinancing mortgages, which are roughly equal in size. [5] Several previous papers have found that fintech lenders are more concentrated in refinancing mortgages compared to other lenders. (Buchak et al. (2018), Fuster et al. (2019)) Thus, if fintech is taking away mortgage business from banks, any effects on total mortgage lending volume are likely to be stronger for refinancing loans than for home purchase loans. Furthermore, the nature of competition could be different for different bank types in each sector of the market. If fintech has divergent interaction with traditional banks in different sectors of the mortgage market, it is important for academics and policy makers to consider how their policy recommendations may impact different segments of the market.

Our paper examines how banks have responded to the challenges of fintech lending, and the heterogeneous responses of different types of traditional bank lenders to this challenge. We examine the heterogeneity in terms of both credit access (defined as the total volume of traditional bank lending), and credit availability (defined as the average amount of credit extended in a single mortgage loan in terms of size and costs). We examine the types of banks that are being pushed out of the market by fintech, and explore the changes in behavior in the presence of fintech, as well the possible reasons why some banks are more affected by fintech than others.

Our data combines both the entire universe of residential mortgages provided by the Home Mortgage Disclosure Act (HMDA) with borrower risk and loan performance data from the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac. While combining HMDA and GSE data at loan has been attempted in previous papers such as Buchak and Jørring (2021), we use tools from the record linkage literature Cohen et al. (2021) to implement our own two-stage matching algorithm in order to combine the datasets on both the loan level and lender level. The GSE data gives us access to a rich set of control variables such as credit scores which are essential to some aspects of our analysis.

[5] For 2019, home purchase loans compromise 50% of total dollar volume in originated loans in HMDA, while refinancing compromise 45% of dollar volume. The remainder of loans fall under home improvement.

In terms of credit access, when we examine the impact of fintech exposure (defined as the market share of fintech lenders in a county), we find a significant negative relationship between a county's fintech exposure and traditional bank total lending volume. A 1% increase in fintech market share is associated with a 3.38% drop in bank lending volume in terms of both dollar amount and number of loans originated. Significant differences exist in terms of effects between different types of banks; a 1% increase in fintech market share is associated with a 4.8% and 5.12% drop in small bank lending volume, in terms of dollar volume and number of loans, respectively. By contrast, large banks are less effected, as fintech is associated with a 1.17% and 0.486% drop in large bank lending volume in terms of dollar volume and number of loans, respectively. When we split mortgage loans by purpose, we see a larger effect of fintech on both small bank and large bank volume for refinancing loans than for home purchase loans.

In terms of credit availability, the impact of fintech on traditional bank mortgages differs by bank type and loan purpose. When we examine bank lending behavior in areas with higher fintech exposure, we find that increased fintech exposure is correlated with significant increases in the average loan amount of a traditional bank mortgage. A 1% increase in fintech market share is associated with a 0.265% increase in small bank loan sizes, and a 0.496% increase in large bank loan sizes. The effect for home purchase loans than for refinancing loans - for refinancing loans, fintech's effect on bank loan sizes becomes statistically insignificant for small banks, and shrinks in magnitude for large banks.

In terms of costs, fintech lenders charge more than small bank lenders in terms of interest rates, and more than both small banks and large banks in terms of non-interest costs. When we examine home purchase loans, a 1% increase in fintech market share translates to a 0.239 basis point increase in small bank interest rates, and a 1.422 and 0.637 basis point increase in non-interest costs for small banks and large banks respectively. However, for refinancing loans, fintech's effect on bank loans disappears across the board. These results suggest that the nature of fintech's competition with banks differs across mortgage sector. Surprising, for home purchase loans, more fintech leads to traditional banks increasing their costs. This suggests that fintech does not act as a direct competitor to traditional banks in the home purchase sector, but rather may be fragmenting the market by specializing in different borrower pools than traditional banks. However, for the refinancing sector, we see that costs for traditional bank mortgages are unaffected by the presence of more fintech, suggesting that fintech lenders may be acting more as a direct competitor for this sector.

To better understand the cost results, we explore how borrower composition has changed in the presence of fintech competition. For the home purchase sector, we find that in areas with a greater fintech market share, bank borrowers tend to have higher incomes and smaller loan-to-value (LTV) ratios, but also higher debt-to-income ratios. However, for the refinancing sector, we most strongly see a drop in credit scores for bank borrowers in areas with more fintech. It is ambiguous how borrower quality is changing in the home purchase sector, but quality is unambiguously deteriorating for traditional banks in the refinancing sector.

Taken together, our results show significant evidence that the growth of fintech lending has reduced credit access provided by both small and large banks, and this effect is particularly strong for small banks. In terms of credit availability, small banks and large banks both increase mortgage sizes in areas with more fintech, yet the rising costs of small bank loans suggests that fintech competes with traditional banks in terms of lending volume, but not costs. Furthermore, for refinancing loans, we see stronger negative effects for traditional bank credit access, but little to no changes in credit accessibility and negative effects on borrower quality. These results suggest that fintech substitutes for banks more strongly amongst refinancing loans, an area in which fintech is more dominant, leaving traditional bank lenders less able to adapt or take advantage of their existing customer base amongst the refinancing segment of the mortgage market.

What these results suggest about the relationship between fintech lenders and traditional bank lenders is that the competitive advantage of fintech lenders lies in their focus on refinancing loans and automation to make lending decisions. Smaller banks, which focus more on soft information and forming relationships between banks and customers, are losing ground faster than larger banks which are better suited to compete with fintechs in terms of technology and infrastructure. In response, we see small banks passing on increasing costs for customers more than large banks. The substitution of bank loans for fintech loans is even stronger in the refinancing section of the mortgage market, where banks are less able to adapt and less able to pass on higher costs to their borrowers.

Our paper's contribution is to provide novel evidence on fintech's impact on the mortgage market as whole, as well as its impact on existing depository institutions. We focus on the heterogeneity that exists both between different bank types, and between the different mortgage sectors, affects the nature of fintech's competition with traditional banks in the mortgage market. Our results suggest not only that small banks are losing ground faster than large banks to fintech, but that fintech competes in different sectors of the mortgage market in different ways, acting more as a direct competitor in refinancing loans, while fragmenting the home purchase market where banks are better able adapt to an increasing fintech presence.

The rest of the paper is structured as follows. The remainder of Section 1 covers the literature review and outlines the hypotheses we will be testing in our paper. Section 2 covers the data sources and summary statistics of the lenders and counties included in our sample. Section 3 shows baseline results for fintech's impact on traditional bank lending credit access. Section 4 covers fintech's impact on traditional bank credit availability. Section 5 examines changes in traditional bank lender composition associated with fintech exposure. Section 6 uses an alternate border identification strategy as a robustness check for aggregate lending volume results in Section 3. Section 7 concludes the paper.

1.1 Literature review

The potential for fintech to significantly improve financial efficiency has been receiving greater attention in recent years. Philippon (2015) argues that although policy measures put in place after 2009 to regulate bank activity have made the financial sector safer, they have also made it harder to disrupt current incumbents and make the deep structural changes that are necessary to make the financial sector more efficient. Building on that paper, Philippon (2016), Thakor (2020) and Buckley, Arner, and Barberis (2016) argues that compared to current incumbents, fintech's lessened dependence on leverage, lower risk aversion, and lack of legacy technologies makes them suited to disrupting the current financial paradigm to significantly improve the efficiency of the financial system. Empirically, C.-C. Lee et al. (2021) finds that the growth of fintech in the Chinese market has significantly improved bank efficiency, in terms of both cost and technology. Fintech may also bring significant benefits in terms of financial inclusion, via the democratization of financial services, particularly amongst poorer and more marginal borrowers, communities, and even countries. (Makina (2019), Philippon (2019), and Sahay et al. (2020)).

However, the financial innovation brought about by fintech may also carry potential downsides to financial stability and costs to financial services. Weller and Zulfiqar (2013), Fung et al. (2020) and Vučinić et al. (2020) find that fintech can bring significant risks to financial stability via cybersecurity threats or via institutional diversity raising liquidity constraints by reducing economies of scale. In addition, Weller and Zulfiqar (2013) and Parlour, Rajan, and Zhu (2022) state that under certain conditions, increased fintech competition with traditional bank lenders may actually raise lending costs for consumers, even for loans originated by bank lenders.

Further questions on the nature of fintech competition has been raised, including whether fintech substitutes or complements for bank lending. Balyuk, Berger, and Hackney (2020) hypothesizes that fintech's competitive advantage lies in their information processing efficiency, which puts them in direct competition with large banks but not small banks. Thus, according to the hard information hypothesis, small banks' reliance on soft information and relationship lending puts them at a competitive advantage compared to large banks relative to new fintech entrants. Both Tang (2019) and Gopal and Schnabl (2022) find significant supporting evidence in both the small business and P2P markets that fintech lenders have substituted for bank lenders after regulatory shocks to bank credit access. However, Tang (2019) also finds fintech complementing bank lending in terms of providing small loans to relatively underserved segments of the population. Similarly, Di Maggio and Yao (2020) finds fintech both substituting and complementing bank lenders, in that fintech lenders target lower quality borrowers when they first enter a market, but over time take higher quality borrowers away from traditional bank lenders.

The mortgage market is an area where there is significant interaction between traditional banks and fintech lending. Fuster et al. (2019) and Buchak et al. (2018) both observe that fintech has significant technological advantages compared to lenders, such as greater convenience and faster processing times. However, they also note the higher costs of fintech loans after controlling for borrower quality and loan size, suggesting that borrowers are willing to pay a premium in return for this processing efficiency. Both Fuster et al. (2019) and Buchak et al. (2018) find little evidence that fintech lenders are "bottom-fishing" the mortgage market by targeting lower quality borrowers in the search for yield. They find that borrowers that go to fintech lenders tend to have similar default rates compared to borrowers from traditional banks. Allen, Shan, and Shen (2020) challenges the view that stricter regulatory structure lead to a drop in traditional bank market share. Using natural disasters as a exogenous shock, they find that areas dominated by stress-tested traditional banks saw a greater increase in mortgage lending due to favorable regulatory treatment. Thus, regulatory oversight may act as both a hindrance and a benefit for traditional banks in different environments.

The increase in regulatory burdens post-2008 on traditional depository institutions is commonly cited as a reason for the displacement of traditional lending institutions with shadow banks in recent year. (Begley and Srinivasan (2020), Gete and Reher (2020), and Buchak et al. (2018)) Begley and Srinivasan (2020) finds that post-2008 regulatory burdens placed on the 4 largest banks (Bank of America, Citi, JP Morgan, and Wells Fargo) in the mortgage market caused them to retreat the market from 2009-2013. Gete and Reher (2020) finds that 22% of shadow bank growth in the overall mortgage market is due to spillover effects of liquidity regulation on securitization, particularly for FHA loans. Buchak et al. (2018) attributes the growth of shadow bank lending in mortgage market post-2008 as 60% due to regulatory arbitrage.

1.2 Hypothesis development

Our paper proposes three main hypotheses on the impact of fintech on traditional bank lending volume and behavior.

H1: Areas with more fintech see a reduction in total lending volume for both small banks and large banks.

Fintech lenders have been noted to substitute for traditional bank lending in the P2P lending market. (Cornaggia, Wolfe, and Yoo (2018), Tang (2019)) Furthermore, the drop in market share by the largest banks in the mortgage market has accompanied by the rise of fintech lenders in the mortgage market. (Begley and Srinivasan (2020)) We expect to find that like the P2P market, fintech lending has been directly substituting for traditional bank lending in the aggregate.

H1.A: The effect is greater for refinancing loans than for home purchase loans.

Previous papers such as Buchak et al. (2018) and Fuster et al. (2019) have found that fintech lenders focus more of their origination activity in the refinancing sector of the mortgage market than on the home purchase sector of the market. Therefore, we hypothesize that fintech lenders act more as a direct competitor to traditional bank lenders in the refinancing sector than in the home purchase sector, as fintech lenders take a greater amount of lending activity away from bank lenders for refinancing loans than for home purchase loans.

H1.B: The effect is greater for large banks than small banks.

Due to their specialization with AI/ML technology over human interaction, fintech lenders are more reliant on hard information when originating and pricing loans (Di Maggio and Yao (2020)). In the context of small business lending, Balyuk, Berger, and Hackney (2020) finds that fintech lenders tend to replace large/out-of-market banks more than small/in-market banks, which they suggest is due to fintech's more efficient processing of hard information. Large banks are more reliant than small banks are on hard information as well, as small banks focus more on cultivating relationships and forming human interactions with potential borrowers to make loans. Thus, we predict that as fintech lending expands in an area, large bank lending volume will be reduced more than small bank lending volume.

H2: The growth of fintech lending creates competitive pressure on traditional banks, causing them to expand credit availability to their remaining pool of customers. This leads to larger loan sizes and reduced costs for individual borrowers.

When fintech displaces traditional bank lending in the mortgage market, we hypothesize that banks respond by making credit easier to obtain for the lenders that remain with them. Holding all other borrower characteristics, loan characteristics, local demographics, and local economic conditions constant, we hypothesize that a mortgage loan originated by traditional banks are larger and have lower costs in areas where fintech is more dominant.

We also hypothesize that the type of banks for which fintech has the strongest effect on their credit access are most affected in terms of credit availability. For example, if fintech displaces total lending volume for large banks more than small banks, then large banks will increase their credit availability more than small banks.

H3: Areas with greater fintech exposure are associated with significant changes in the traditional bank borrower pool, particularly towards more risky borrowers.

Fuster et al. (2019) finds no evidence that fintech lenders target borrowers with lower incomes or worse credit histories. Di Maggio and Yao (2020) finds that fintech lenders initially target higher-risk borrowers, but over time shift their lending towards lower-risk borrowers. As fintech becomes more dominant in an area, established fintech lenders will move a higher quality borrower pool, leaving more risky, lower quality borrowers left in the borrower pool for traditional banks.

2 Data

Our analysis combines several commonly-used datasets in the mortgage and banking literature. In this section we describe the sources of the key variables used in our empirical exercises. Our primary data source for mortgage applications and originations is the public data released through the Home Mortgage Disclosure Act (HMDA). While HMDA is one of the richest datasets on mortgages available, it only contains records of loan originations and it lacks some important information on borrower quality such as credit scores. To overcome these limitations, we utilize techniques from the record linkage literature and the tools developed in Cohen et al. (2021) to combine HMDA with loan-level information from the public Fannie Mae and Freddie Mac data sets. Within this matched sample we observe each borrower's credit score at the time of origination and can track loan performance over time. Details on the record linkage algorithm are found in appendix A.1. Finally, our loan-level data is supplemented with county and state-level controls from a variety of sources.

2.1 Data sources

HMDA: Covering the near universe of U.S. mortgage applications, HMDA is the most comprehensive public dataset on mortgages available. HMDA not only records detailed information on mortgage originations, but it also tracks mortgage applications that were denied or withdrawn for a variety of reasons. Some of the information available in HMDA includes lender identity, application outcome, loan type (conventional vs. non-conventional), loan purpose (refinancing vs. home purchase), loan size, year of origination, securitization outcome, and location at the census tract level. It also contains limited demographic information on applicants, notably race and income. Starting in 2018, the publicly available HMDA data was expanded to include additional information on borrower financials and mortgage costs such as loan interest rate, non-interest-rate charges (including origination charges, discount points, and lender credits), loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio.

We supplement the HMDA data with the Robert Avery lender file to incorporate information about each lender's ultimate parent company as well as fundamentals from call reports.[6] Information on ultimate parents helps the record linkage algorithm by providing additional variables to match on while improving the algorithm's efficiency by shrinking the pool of potential matches. Information from the call reports includes the lender's total asset size by year, which can be used to classify them as either small banks or large banks. We define small banks as banks with total assets below $10 billion, and large banks as the rest.

Fannie Mae and Freddie Mac: Fannie Mae and Freddie Mac are government-sponsored enterprises (GSEs) who provide liquidity to the mortgage market by specializing in purchasing and securitizing 30-year fixed rate conforming loans. From 2010 to 2019, about two-thirds of all mortgages were sold to Fannie Mae or Freddie Mac. In our analysis this GSE data is primarily used to collect information on borrower creditworthiness as they provide variables such as FICO scores, interest rates, LTVs, and DTIs prior to this information becoming available in HMDA. While HMDA contains information on whether a mortgage was sold to Fannie Mae or Freddie Mac, there are no publicly available identifiers to link loans between these sources. This necessitates the

[6] The Robert Avery file is available on Neil Bhutta's website at https://sites.google.com/site/neilbhutta/data.

use of record linkage techniques to create such a mapping.

Fintech definition: To distinguish fintech and non-fintech shadow banks, we start with the classification proposed by Fuster et al. (2019) which classifies fintech lenders based on whether the lender implemented an online process that pulls a hard credit check and can result in preapproval without contacting a loan officer. They proceed to use web archives from the Wayback Machine to approximate when lenders started having this ability, covering the time span of 2010 through 2017. Since our goal is to examine how non-depository lenders who heavily utilize automation impact the behavior of traditional banks, we want to be as broad as possible when classifying fintech lenders. We merge this classification with that of Buchak et al. (2018) and their subsequent 2019 update. Beyond the inherent subjectivity of manual classification, the paper and the updated classification primarily differ from Fuster et al. (2019) by shifting the definition of a fintech lender to be one that offers a contractual quote without human contact rather than a preapproval and by extending the sample through 2019. We use the Wayback machine to approximate the year in which these additional lenders fit the definition of fintech. This combined classification leaves us with a sample of 55 unique fintech lenders by 2019.

Supplemental data: For regional economic and demographic data for local mortgage markets, we collect data from the US Census and American Community Survey between 2010 and 2019. We collect population, population density, racial and ethnic characteristics, education, income and poverty, and homeownership statistics on a census tract level. In addition, to control for the level and growth of house prices, we collect data on house price indexes on a census tract level from the FHFA website, [7] which we then deflate using the national GDP price index.

To control for differences in the regulatory climate between states, we collect information on various mortgage regulations. Information on mortgage broker net worth requirements and annual auditing requirements are available from NMLS. Information on state-wide recording taxes and brick-and-mortar requirements were hand-collected from state regulatory websites. These state-level regulations are frictions of operation that apply to all mortgage lenders, but brick-and-mortar requirements in particular pose an additional barrier on fintech lenders that most non-fintech lenders would satisfy through normal operations. Specific definitions of the mortgage regulation data that can we collect can be found in A.2.

2.2 Summary statistics

Table 1 displays summary statistics for key HMDA variables between 2010 and 2019 for three categories of lenders: Small banks, large banks, and fintech. Panel A summarizes the activity of each type of lender. Fintech lenders tend to have the widest scope of operation, with the median fintech lender operating in over 20% of counties in the United States. Their total volume of lending is similar to large banks with the median lender originating nearly 2 billion dollars of mortgages

[7] https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx

between 2010 and 2019. Small banks tend to be the most likely to accept loan applications, and fintech has the most skewed acceptance rates with large lenders driving the mean acceptance rate significantly below the median. It should be noted that the classification procedure focuses on the biggest players, and there may be numerous smaller fintech lenders that are missing from the sample.

Panel B summarizes loan-level characteristics by lender type. The table shows several facts about fintech lenders, some of which are new. In line with the literature, we find that fintech lenders originate a higher proportion of loans as refinancing loans. Fintech lenders are more likely to securitize their loans, consistent with a business model that is focused on volume and collecting fees rather than retaining and servicing mortgages. Fintech lenders are less focused on conventional loans than traditional bank lenders, and are more likely to originate FHA or VA loans. On average, fintech lenders serve a higher proportion of female and minority borrowers than either type of traditional lender. [8] Within the matched sample of conforming loans, we observe that borrower creditworthiness is not substantially different between the three types of lenders, however fintech lenders charge the highest interest and non-interest costs while small banks charge the lowest. As suggested by Buchak et al. (2018) and Fuster et al. (2019), these differences in cost may be a convenience yield that fintech lenders are able to extract due to their online platforms and quicker processing times.

3 Changes in Bank Credit Access

Since the global financial crisis, the mortgage market has seen dramatic shifts in both market share and loan volume. Figure 1 depicts the changes in the annual market share by bank type over our sample. Since 2010 there has been an expansion in market share for both fintech and non-fintech shadow banks, with fintech more than tripling their market share from 4% in 2010 to about 15% by 2019, and non-fintech shadow banks rising to about 35% market share. Between 2010 and 2015 there was a concurrent growth in market share for non-fintech shadow banks and decline for large banks. This has leveled off since 2015, with a new pattern emerging of concurrent growth and decline for fintech shadow bank lenders and small banks respectively. Figure 1 suggests that the recent growth in shadow banking may be driven by different forces across time, and that fintech has become more important in the most recent years. Looking at total lending volume in Figure 2, we see that traditional bank lending volume has not changed much throughout our sample apart from a temporary drop in 2014. In contrast, total lending done by shadow banks has exploded from 2010 to 2019, totaling over $1 trillion dollars in loan origination volume in 2019.

In this section we address hypothesis **H1** by formally exploring these dynamics and documenting the heterogeneous impact that fintech growth has had on the aggregate lending behavior of

[8] A borrower is classified as a minority if they are recorded as Hispanic in ethnicity, or are not recorded as white or Asian in race.

traditional banks. We begin by using a fixed-effects regression model to document whether fintech growth is at all associated with changes in the aggregate lending behavior of traditional bank. To capture the heterogeneity of these effects, we split the sample across both bank size and loan type. Finally, to get a glimpse on whether these effects are driven by supply-side or demand-side effects we run a similar fixed-effects model to example how traditional bank selectivity captured through rejection rates have changed in the presence of fintech competition.

3.1 Empirical Strategy

When evaluating the impact of fintech exposure on aggregate traditional bank behavior, we use a fixed-effects model with county-year observations of the form

$$\text{Dependent Variable}_{c,t} = \beta_1 \text{Fintech Market Share}_{c,t-1} + \mu X_{c,t-1} + \delta_s + \pi_t + \varepsilon_{c,t}, \tag{1}$$

where *Fintech Market Share*$_{c,t-1}$ is the share of mortgage lending taken by fintech lenders in year $t-1$ in county c. $X_{c,t-1}$ are county level control variables which include statewide mortgage regulations and county-level variables such as population, population density, proportion of minority (defined as non-white and non-asian), educational attainment, median income, poverty rates, homeownership rates, house prices, house price growth, and the HHI of the county's mortgage market. δ_s are state fixed effects, and π_t are year fixed effects.

The goal of this model is to isolate shifts in fintech market share that cannot be explained by local market conditions. In the current section we consider measures of bank lending volume and rejection rates as our dependent variable. We always run the model with year fixed-effects, and we also run the model with and without state fixed-effects. With all fixed-effects active, our source of heterogeneity is coming from differences in counties within a state and year. Our control variables are chosen to absorb economic and demographic factors that could explain both fintech presence in a region and our dependent variables. We do not believe that the dependent variables themselves are a concern for reverse-causality, however it is possible that some unobserved forces influence both fintech market share and our dependent variables. In section 6, we run a robustness which takes advantage of fintech lenders' online presence and how they effectively choose to operate in states rather than individual counties.

3.2 Total lending

We run the fixed effects model with a measure of county-level lending activity as the dependent variable. In Table 2 local lending activity is measured by the log dollar amount of mortgages, while Table 3 uses log number of mortgages originated. Each table reports results split by bank size (small vs. large) and loan purpose (home purchase vs. refinancing) with and without state fixed effects. Interpretation of this model can be tricky, as there is a mechanical relationship between fintech market share and lending volume by non-fintechs when holding the market sized fixed. Unless fintech lenders are attracting a mutually exclusive set of borrowers into the market, we expect to observe that other lenders on average are losing lending volume as fintech market share increases. Thus, our main interest in which banks are losing more ground across each segment of the market.

For the value of total lending in Table 2, we see that fintech market share is associated with a statistically significant drop in the aggregate lending activities of both large and small banks across all specifications. When considering heterogeneity on bank size, the drop in aggregate lending activity is burdening small banks much more strongly than large banks. For Table 2 Panel A, Columns (4) and (6) show that a 1% increase in fintech market share is associated with a 4.8% drop in lending volume for small banks, and a 1.17% drop for large banks.

Splitting the sample by loan purpose, fintech market share displaces traditional bank lending more strongly for refinancing loans with small banks still taking the brunt of the impact. Panel B shows that for home purchase loans, a 1% increase in fintech market share in the home purchase sector is associated with a 3.43% drop in lending volume for small banks, and a 0.84% drop for large banks. For refinancing loans, Panel C displays much stronger results, with a 1% increase in fintech market share in the refinancing sector associated with a 4.15% drop in lending volume for small banks, and a 1.68% drop for large banks.

The results from Table 3 are similar with significant drops in aggregate lending activity of traditional banks in almost every specification. We still observe that small banks are affected the most, and the effect is strongest for refinancing loans. In unreported results we verify that these coefficients are largely robust across time. Splitting the sample on the cutoff year 2015, we do not see a large changes in coefficients or significance. Most notably the coefficient for large banks loses significance in the first half of our sample, and become stronger in the second half.

Figure 3 shows the impact of fintech on bank lending volume when we rerun our specification for each year of our sample. The figure shows that our results are qualitatively consistent across time for both small and large banks, and that small banks are consistently more affected by fintech competition than large banks are.

We find two main takeaways from this section. First, we confirm hypothesis **H1** but reject textbfH1.B by observing that small banks are being pushed out of the mortgage by fintech more than large banks are being pushed out. Second, we confirm hypothesis **H1.A** by observing that fintech lenders push out traditional bank lending more strongly in the refinancing sector than in the home purchase sector of the mortgage market. We see that in aggregate, borrowers are more attracted to fintech lenders when it comes to refinancing their loans than when they have to purchase a new house.

We conduct several robustness checks to validate and better understand these results. In section 6 we conduct an analysis that relies on cross-border differences between states for identification, and find similar patterns (albeit with higher standard errors). In appendix A.3 we consider alternative cuts of the data, one where we focus on shadow banks instead of fintechs and another where we compare Quicken Loans to the rest of the fintechs. We find that while similar patterns persist for non-fintech shadow banks, the effects are much stronger for the fintechs. In addition, the results of this section are stronger for Quicken Loans but still persist for the rest of the fintechs.

3.3 Rejection rates

So far we have observed a reduction in aggregate lending activity from traditional banks in the presence of fintech competition. However, it is unclear precisely how fintech competition is influencing traditional bank lending behavior. We are observing that small banks lose ground more quickly than large banks in the presence of fintech competition, but we do not know anything about the mechanisms driving these changes. In this section we explore how willing banks are to supply credit to the market by examining how their selectivity has changed in the presence of fintech competition. While fintech competition may be attracting new customers to the mortgage market, they may also be attracting customers who would have otherwise patronized a traditional bank. It is unclear how the presence of a fintech competition should impact the selectivity of traditional banks. On the one hand, the residual borrower pool might be deteriorating in quality leading to higher selectivity. On the other hand, a shrinking borrower pool may leave traditional banks with excess liquidity and make them more willing to approve mortgages.

In Table 4 we run a fixed effects model of the form 1 with observations at the application-level and traditional bank application rejection rates as the dependent variable. We include control variables for borrower quality such as debt-to-income ratio and loan-to-value ratio, as well as other borrower characteristics such as log amount borrowed, log income, loan purpose, owner occupancy, and lien status. However, we are unable to control for credit score as this information is not available in HMDA for the most years and our GSE matched sample only contains accepted conventional loans.

We once again split the sample based on bank size (small vs. large) and loan purpose (home purchase vs. refinancing). Panel A contains coefficients for the universe of applications. We observe that a 1% increase in fintech market share is associated with a .96% increase in rejection rates, and this coefficient is being driven by small banks in particular. Splitting the sample by loan purpose we observe that large bank selectivity is impacted by fintech presence only for home purchase loans. Small banks are being affected across the board, and are the only type affected for refinancing loans.

We see that small banks are becoming particularly more selective in their lending activity while reducing their lending activities in the presence of fintech competition. This indicates that there might be a supply-side channel driving our aggregate results, but this exercise by itself is not conclusive. Since HMDA lacks detailed borrower information, this relationship may be driven by unobserved shifts in borrower quality. In Section 5 we explore how fintech competition affects the borrower profile conditional on loan acceptance, and utilize our GSE matched sample to see if small banks are lowering their standards for acceptance in the presence of fintech competition.

4 Changes in Bank Credit Availability

Having established that fintech lending has a significant negative effect on traditional bank credit access, we now turn to examine if fintech affects traditional bank credit availability. In hypothesis **H2**, we argued that fintech competition should lead to larger loan sizes and reduced costs for borrowers. Both loan size and costs are important to examine in terms of credit availability. A larger loan means that an individual borrower can get a greater amount of credit, but higher costs for a mortgage will mean that the borrower has to pay more for that credit. If a borrower can get a larger mortgage, but has to pay more in interest rates and non-interest costs, we cannot conclude that their access to credit has truly increased.

In terms of traditional bank loan sizes, we find that greater fintech market share is associated with larger loan sizes for both small banks and large banks. When we split apart mortgages by purpose, we find that in the refinancing sector, the effect becomes statistically insignificant for small banks, and economically smaller for large banks. Regardless of whether this effect is demand-driven or supply-driven, the difference in effect seems to indicate that bank lenders are less able to adapt to fintech competition in the refinancing sector.

In terms of traditional bank loan costs, fintech is associated with higher costs for both small and large banks, and the effect is greater for non-interest costs compared to interest rates. However, when we focus only on refinancing loans, we find no effect of fintech on bank costs. Combined with our previous findings, these results suggest that fintech acts more as a direct competitor to traditional banks in the refinancing sector.

4.1 Size of loans

We examine the effect of fintech exposure on traditional bank loan sizes using the following fixed effects model:

$$Log(\text{Loan Size})_{i,c,t} = \beta_1 \text{Fintech Market Share}_{c,t} + \beta_2 \text{Loan Controls}_{i,c,t} + \mu X_{c,t} + \gamma_i + \delta_s + \pi_t + \varepsilon_{i,c,t}, \tag{2}$$

where *Fintech Market Share*$_{c,t}$ is the market share of fintech lenders in county c for time t, *Loan Controls* are the owner occupancy status, lien status, and number of borrowers for the loan, as well as the log income, sex, credit score, loan-to-value ratio (LTV), and debt-to-income ratio (DTI) of the borrower. LTV and DTI values are binned. $X_{c,t}$ are the aforementioned county level controls from Equation 1, γ_i are lender fixed effects, δ_s are state fixed effects, and π_t are month of origination fixed effects. We run these regressions for (a) all traditional banks in our sample, (b) small banks only, and (c) large banks only. We also run these regressions for different sectors of the mortgage market, either for both home purchase and refinancing purposes, or for only home purchase loans or refinancing loans separately.

Table 5 shows the results of our fixed effect model for fintech's effect on traditional bank loan sizes. For Table 5 Panel A, we find that the share of a county's mortgage market that is taken by fintech lenders is positively associated with larger traditional bank loan sizes. Holding all other variables constant, Table 5 Panel A Columns (2) and (3) show that a 1% increase in fintech market share is associated with an approximately 0.265% and a 0.496% increase in small bank and large bank mortgage sizes respectively. Table 5 Panel B shows similar results for home purchase mortgages only. For home purchase loans, Columns (2) and (3) show that a 1% increase in fintech market share is associated with an approximately 0.27% and a 0.489% increase in small bank and large bank mortgage sizes respectively.

However, when we look at refinancing loans only, Table 5 Panel C shows much smaller effects of fintech market share on traditional bank loan sizes, for both small and large banks. The effect of fintech on small bank loan sizes becomes statistically insignificant, while for large banks the effect drops to a 0.335% increase in loan size per 1% increase in fintech market share.

We cannot say for certain whether the increase in mortgage loan sizes is demand-driven or supply-driven, but the difference in impact between home purchase loans and refinancing loans is nonetheless significant. If the effect is demand-driven, then the increase in bank loan sizes could be due to changes in unobserved borrower preferences or in the traditional bank borrower pool composition. Regardless, a smaller effect for refinancing loans suggests that the preferences or the composition of borrowers for traditional banks are less changed when fintech enters an area, suggesting that banks are less able to target a separate segment of the borrower pool for refinancing loans compared to home purchase loans. However, if the effect is supply-driven, then banks are the ones making the decision to be more generous with credit. Smaller increases in loan sizes for refinancing loans suggest that banks are less able or willing to adapt to fintech competition in the refinancing sector compared to the home purchase sector.

4.2 Costs of loans

We now turn our attention to the effect of fintech on traditional bank mortgage costs. We begin by comparing costs directly between lender types to understand more about fintech compares with other lenders. Next, we examine the impact of fintech exposure on the lending costs of banks. By learning about the premium that fintech charges to its borrowers and how fintech causes banks to raise their own costs in certain sectors of the mortgage market, we can better understand the heterogeneous nature of fintech's interaction with traditional bank lenders.

4.2.1 Direct comparisons

First, we directly compare costs by lender type to better understand how fintech impact bank mortgage costs. We regress the different measures of mortgage costs on indicator variables for the type of lender, while using the same control variables as Equation 2. The two measures of mortgage costs are interest rates and total non-interest costs.[9] The results of these regressions are shown in Table 6.

Table 6, using *Small Bank* as the default lender type, compares costs for different lender types. Columns (1) and (4) show that for interest rates, large banks and fintech lenders charge both higher interest rates and non-interest costs compared to small banks. In line with previous papers such as Buchak et al. (2018) and Fuster et al. (2019), we find that fintech lenders charge a higher interest rate premium compared to both large and small banks. The large bank interest rate premium is about 5.2 basis points compared to small banks, and the fintech interest rate premium is 7.6 basis points. The non-interest rate premium is even greater for both large banks and fintech lenders, and the difference between premiums for large banks and fintech lenders are even greater. Fintech lenders charge a 62.6 basis point premium in non-interest costs, while large banks charge a 16.7 basis point premium. As such, if fintech lenders become more dominant in a county, we can expect the average costs of loans to rise in that county, especially in terms in non-interest costs, and especially if the county's mortgage market was previously more dominated by small bank lenders.

When we split loans by purpose, for home purchase loans, we find that the interest rate premium for large bank lenders loses statistical significance, but the premiums for fintech lenders remain significant. For refinancing loans, however, the premium becomes economically larger for both large banks and fintech lenders, rising to a 10 basis point and 40.5 basis point premium for interest rates and non-interest costs respectively for large banks, and to a 10.1 basis point and 95.1 basis point premium for interest rates and non-interest costs respectively for fintech lenders.

Fintech lenders having a comparatively higher non-interest cost premium compared to their interest rate premium is consistent with their business model. Papers such as Buchak et al. (2018) have found that shadow bank lenders securitize almost all of their loans via the originate-to-distribute model. Thus, fintech lenders would not collect interest payments on the mortgages they originate, and thus would be relatively more incentivized to charge borrowers higher non-interest costs. With an additional advantage in processing times for fintech loans (Fuster et al. (2019)) it is possible that fintech lenders charge a convenience premium for their loans, which allows them to

[9] Total non-interest costs are scaled by the mortgage principal. Both costs are expressed in terms of percentage points.

raise their costs above those originated by traditional banks.

4.2.2 Fintech's effect on traditional bank costs

Next, we look at how increased fintech exposure may have affected the costs that traditional bank lenders charge to borrowers. We use the following fixed effects model to measure the effect of fintech exposure on traditional bank mortgage lending costs:

$$\text{Cost of Loan}_{i,c,t} = \beta_1 \text{Fintech Market Share}_{c,t} + \beta_2 \text{Loan Controls}_{i,c,t} + \mu X_{c,t} + \gamma_i + \delta_s + \pi_t + \varepsilon_{i,c,t}, \tag{3}$$

where *Cost of Loan*$_{i,c,t}$ is either the interest rate or the total non-interest costs of the mortgage. Costs are expressed in terms of percentage points, which means that the effect of β_1 can be interpreted as the effect on costs of a 1% increase in fintech market share in terms of basis points. The controls and fixed effects for the model are the same as for Equation 2.

Table 7 shows the results of our model for the effect of fintech market share on traditional bank mortgage costs. Panel A displays the results for interest rates, while Panel B displays the results for non-interest costs. For all traditional bank loans, Columns (1) and (2) suggest that fintech exposure has a stronger positive association with non-interest costs compared to interest rates. β_1 is both statistically and economically less significant for interest rates compared to non-interest costs. For Column (3), β_1 is insignificant for both interest rates and non-interest costs, which suggests that for refinancing loans, the costs of traditional bank loans are less affected than those of home purchase loans.

Columns (4) through (6) show that greater fintech market share is associated with higher small bank costs. For Columns (4) and (5), β_1 is greater in magnitude for non-interest rate costs compared to interest rate costs. A 1% increase in fintech market share raises interest rates for small bank mortgages by 0.26 basis points, and non-interest costs by 1.06 basis points. For home purchase loans, the effect changes to 0.23 basis points for interest rates, and 1.42 basis points for small bank mortgages. The pattern disappears for refinancing loans, as shown by Column (6), where we see no significant effect for either interest rates or non-interest costs.

For large banks, Columns (7) to (9) show no effect for fintech exposure on large bank interest rates, and a positive effect on non-interest costs but only for home purchase mortgages. Furthermore, the effect of a 1% increase in fintech market share is only a 0.64 basis point increase in non-interest costs for home purchase loans for large banks, compared to a 1.42 basis point increase for small banks. As such, we can see that compared to small banks, fintech has a much smaller impact on lending costs for large banks.

Referring back to Table 6, interest rates of mortgages originated by small banks are less than those originated by fintech lenders, and both small and large bank non-interest mortgages costs are less than those for fintech mortgages. Fintech lenders may be competing with traditional bank lenders in terms of lending volume, but the same cannot be said for costs. For home purchase loans, it is possible that fintech lenders are fragmenting the market into different segments. Banks may have greater market power over their remaining pool of customers, which allows them to charge higher interest rates and non-interest costs. However, large bank mortgage costs are greater than those of small banks, which means that they would be less able to raise their costs in the presence of more fintech.

For refinancing loans, we see no effect for fintech for bank mortgage costs. Tying back into our results for Section 3, fintech lenders have a stronger effect on both small bank and large bank credit access for refinancing loans compared to home purchase loans. It is possible that fintech lenders act more as direct competitors to traditional banks in the refinancing sector. Therefore, not only would they be competing for a similar borrower pool, but in the presence of more direct competition from fintech, bank lenders are less able to pass on higher costs to their borrowers out of fear of losing even more lending volume to fintech lenders.

In summary, the effect of the growth of fintech on traditional bank lending costs differs between both bank type and loan purpose. Small banks raise both interest rates and non-interest costs in areas with more fintech, while large banks raise non-interest costs at most. Furthermore, we only see a rise in costs for home purchase loans compared to refinancing loans, which suggest that fintech lenders act more as direct competitors to banks in the refinancing sector of the mortgage market, whereas for the home purchase sector, fintech lenders may be fragmenting the market into different segments.

In appendix A.3 we repeat this cost exercise with a sample of just loans originated by Quicken Loans, and another sample that omits these observations and only considers other fintechs. We find that the cost results are robust across the board, but they are most strongly present with Quicken Loans, suggesting that they have played an important role in how the mortgage lending landscape has transformed over the past decade.

5 Has Fintech Changed the Traditional Bank Customer Profile?

We next explore the impact of fintech on the typical borrower profile for traditional banks. As fintech takes a greater slice of the mortgage market, what is left of the borrower pool for traditional banks remains as question. It is possible that fintech lenders target specific segments of the borrower pool, such as by cream-skimming higher quality borrowers, or bottom-fishing lower quality borrowers. In such a case, we would expect to see the composition of the borrower pool for traditional banks to also shift in quality towards the segments that are not targeted by fintech lenders. It is also possible that fintech lenders simply target the entire borrower pool, which would lead to an overall decrease in the volume of lending for traditional banks, but would not change the composition of the borrower pool for those banks. In hypothesis **H3** we assert that traditional banks in areas with greater fintech exposure shift towards riskier borrowers.

We run the following fixed effects model to measure the association between fintech market share and different measures of borrower quality for traditional banks:

$$\text{Borrower Quality}_{i,c,t} = \beta_1 \text{Fintech Market Share}_{c,t} + \beta_2 \text{Loan Controls}_{i,c,t} + \mu X_{c,t} + \gamma_i + \delta_s + \pi_t + \varepsilon_{i,c,t} \tag{4}$$

We run the model for four different measures of Borrower Quality: log income, credit score, LTV, and DTI. Loan Controls are lien status, owner occupancy, sex, and minority status of the borrower, while the remaining local economic and demographic controls and fixed effects are the same as Equation 2.

Table 8 shows our results for Equation 4 for the relationship between greater fintech exposure and the change in traditional bank borrower profile. For the home purchase sector, Panels A and B show mixed results in terms of fintech's impact on traditional bank borrower quality. Columns (1) to (3) show that only large bank borrowers become relatively higher income earners in areas with greater fintech exposure. For both small and large bank borrowers, Columns (4) to (6) show no association between fintech exposure and credit scores, Columns (7) to (9) show a negative association with LTV ratios in Panel B, and Columns (10) to (12) show a positive association with DTI ratios. Overall, for home purchase loans, traditional bank borrowers are becoming higher income earners, but also more leveraged in the presence of more fintech exposure.

However, Panel C shows a different story for the refinancing sector. Columns (1) to (3) and (7) through (12) show little to no significant association between fintech exposure and income, LTV, or DTI. However, Columns (4) to (6) show a significant negative association between fintech exposure and credit scores for refinancing loans. Thus, for refinancing loans, fintech lenders are at least partially cream skimming more credit-worthy lenders, leaving behind more risky lenders amongst the remaining pool of borrowers for banks.

Taken together, these results may partially explain why fintech has had a different impact on traditional bank lending volume and behavior for home purchase loans and for refinancing loans. Fintech reduces total traditional bank lending volume less for home purchase loans than for refinancing loans, and banks raise average loan sizes and costs for purchase loans more than for refinancing loans. Turning back to Table 8, traditional banks shift their customer profile towards higher income but also more leveraged borrowers for home purchase loans. For refinancing loans, however, fintech shifts their borrower pool towards lower credit score borrowers.

This evidence suggests that traditional banks are better able to adapt against fintech competition in the home purchase sector, allowing them to gain access to relatively high-quality borrowers compared to refinancing loans. For the home purchase sector, fintech lenders seem to be targeting borrowers based on additional factor than on-paper borrower quality. For refinancing loans, the deterioration in credit scores amongst traditional bank borrowers in the presence of more fintech competition indicates that fintech lenders are targeting higher quality borrowers in this sector. Therefore, fintech seems to be acting more as a direct competitor to traditional banks in the refinancing sector compared to the home purchase sector.

6 Fintech Exposure Effects Using a Cross-border Approach

Our main results depend on a fixed-effects model that attempts to control for factors that could influence fintech lenders' presence in local markets. The presence of a fintech lender in a market is largely driven by their decision to operate in a state. Lenders must go through a licensing process and develop an infrastructure that conforms to local regulations in order to offer their mortgage products to a state. Once they are operational within a state, potential borrowers can simply go the lender's website or download their mobile application to begin applying for a mortgage. Unlike traditional banks, fintech lenders have no need to open numerous physical branches across the state to reach potential customers. For this reason, state fixed effects go a long way in controlling for unobserved factors that attract fintech lenders to operate in particular state markets.

However, there may be unobserved factors within a state that influence both our county-level fintech exposure as well as our dependant variables. As a robustness check, we run an alternative specification that utilizes border-pair fixed effects. We assume that counties that share a state border also share similar market conditions, and what changes by crossing the border is that borrowers have access to a different pool of fintech lenders. Furthermore, since fintech lenders make the choice to operate in states as a whole, their decision should be unrelated to the heterogeneity of market conditions within the state. We replicate our regressions in Section 3 using the subset of counties that exist on a state border, replacing state fixed effects with border fixed effects. We further detach from local conditions by using state-level fintech market share as our fintech exposure variable, as opposed to the county-level market share used in our main results. State-level market share should be unrelated to county-level economic conditions, and captures the ease of accessing a fintech lender who is operating in the state.

Figures 4 through 6 contains plots the market share of fintech lenders by state in between 2010 and 2019. There are some regional patterns, such as mid-western states generally having low levels of fintech exposure and coastal states having higher levels of fintech exposure. Overall there is a lot of variation in the degree of fintech exposure across the country, although this variation becomes more subdued over time. Table 9 compares summary statistics of counties on the border with all counties in our sample. Overall the two groups appear similar to each other, with none of our demographic or economic variables being significantly different between them.

Table 10 measures the effect of fintech exposure on total lending volume, replicating Table 2 with the cross-border methodology. Using this approach, our overall results are weaker in magnitude but qualitatively similar and statistically significant. The standard errors of the cross-border approach are much higher which makes it more difficult to compare the magnitude of each coefficient, but we still see the same pattern as before that the level of fintech competition affects small banks' lending volume most strongly for refinancing loans. For home purchase loans we still see a reduction in loan volume for both types of banks, though there is no longer a significant difference between bank type.

Table 11 measures the effect of fintech exposure on the number of loans, recreating Table 3 with the cross-border methodology. We see no changes in how fintech exposure impacts small banks using this alternative methodology, however the results for large banks become insignificant. We also see a weakening of coefficients for home purchase loans specifically. Overall however, these results are consistent with our original conclusion that small banks are struggling more than large banks in the presence of fintech competition, and this is especially true for the refinancing segment of the mortgage market.

7 Conclusion

In this paper, we examine how the growth of fintech lending has impacted the size and behavior traditional bank lending, as well the heterogeneity of the impact in terms of different bank types and different sectors of the mortgage market. We examine the impact of fintech on banks in terms of credit access, credit availability, and borrower quality to see how fintech has changed the total amount and average amount of credit extended by traditional banks.

We find that greater fintech exposure is associated with less total lending volume for both small and large banks, but the impact is greater for small banks than for large banks. Furthermore, the effect is greater in the refinancing sector than in the home purchase sector of the mortgage market. When we examine the impact of fintech on the costs of loans, more fintech in an area is associated with higher lending costs for both small and large bank mortgages for home purchase loans, but not for refinancing loans. Furthermore, fintech's impact on traditional bank borrower quality trends toward higher income but higher leveraged borrowers in the home purchasing sector, but lower credit score borrowers in the refinancing sector.

Taken together, our results suggest that the effect of fintech on traditional bank lending behavior differs not only for different types of banks, but also for different sectors of the mortgage market. For the home purchase sector, fintech acts less as a direct competitor to banks, but instead may be fragmenting the market into different segments that allow banks to act with market power towards their own segment of the borrower pool, passing on higher mortgage costs to their customers. However, for the refinancing sector, fintech acts more as a direct competitor to banks, reducing their ability to adapt and forcing them to target riskier, lower quality borrowers.

Our paper does not make any conclusions on how fintech's effect on traditional bank behavior impacts overall consumer welfare, which is an interesting avenue for further exploration. Nonetheless, our paper presents interesting and surprising results on how the rise of fintech lenders have impacted other lenders in the mortgage market that have previously been dominant. The retreat of small banks from the mortgage market has significant implications about the changing preferences of borrowers in the U.S. mortgage market and the costs they are willing to pay for greater convenience and automation. Furthermore, the difference in the impact of fintech on different sectors of the mortgage market highlights the importance of considering bank heterogeneity when assessing policy decisions regarding fintech.

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A Appendices

A.1 HMDA GSE Linkage Process

When two datasets share observations of the same identity but lack an identifier that can directly link them, techniques from the record linkage (or "data matching") literature may be used to create such an identifier. In our case both HMDA and the GSE datasets share observations from the universe of loan originations, but there is no publicly available mapping file to merge these datasets together. However, there are many overlapping variables between these datasets that can be leveraged to successfully merge them together. The success of this process depends on how much identifying information is contained in these shared fields. Intuitively, this identifying information makes up a "fingerprint," which can be cross-checked between the two datasets. The amount of identifying information is increasing in the number of shared variables, as well as how refined the information in each variable is.

One challenge to matching data is managing computational efficiency. A direct approach towards data matching is to check each record pair between two datasets. If one dataset has n observations and the other m observations this would mean performing $n \times m$ comparisons, which swiftly becomes unmanageable when datasets start to exceed a million observations. This difficulty is compounded by the fact that not all truly matching pairs will share the exact same values in their shared variables, which necessitates the use ”fuzzy data matching” techniques that involve more complex operations with tolerances that allow for information to be close but not exact.

To link HMDA to the GSE datasets, we apply a multistage process using tools from the R package ”Fedmatch” that was created by Cohen et al. (2021). The tools of this package handles the messy aspects of comparing two datasets, and is largely plug-and-go once the user knows the matching criteria that they want to set. To reduce dimensionality and keep computation times manageable, we partition each dataset based on geography and lender ID before running the matching algorithm at the loan-level. Since lenders also do not share an identifier between each dataset, we split the matching process into two stages and begin with a lender-level match.

Each GSE dataset contains lender names, and the Robert Avery file can be used to merge lender names into HMDA. While the Robert Avery file is complete in linking names to HMDA, the GSE datasets censor the names of the smaller lenders. For each year we use Jaccard string similarity to create a list of potential name matches, which we then filter by hand into an accurate name match.

The second stage of the matching process involves preprocessing selected variables in each dataset to be able to conform with one another. For example, if a variable is binned in one dataset but not the other, we must bin the variable in the dataset where it is unbinned to facilitate comparisons. We then split each dataset based on the lender ID and geographic information. For geographic information, we make use of public zipcode crosswalk files to match census tracts in HMDA to 3-digit zip codes in Freddie Mac, and we match counties in HMDA and 3-digit zip codes for Fannie Mae. While this is not a perfect mapping of geographic information, it goes a long way in disambiguating sets of potential matches that coincidentally share information but exist in different parts of the state. Within these filtered datasets we find records that have an exact match on observable characteristics at the time of loan origination.

For both GSEs, prior to 2018, these characteristics are loan amount, property type, owner occupancy status, and loan purpose. Starting in 2018 we also include interest rate, manufactured property status, and loan purpose while removing variables no longer available in HMDA. Unfortunately there is no way to manually verify whether matches are correct, so we must assume that any records that uniquely match perfectly on these criteria are correctly matched. In cases where multiple records match perfectly, we remove them from the sample as there is no way to distinguish which is the true match. While this process is more likely to filter out records that are more modal in shared characteristics, we are not too concerned with this biasing our results.

A.2 Robustness check: Statewide mortgage regulations

We collect data on a year-by-year basis from the Nationwide Multistate Licensing System & Registry (NMLS) and by hand on the following statewide mortgage regulations:

Brick and Mortar Laws: A state with brick and mortar laws require any mortgage lender operating in the state to have a physical location open in that same state. Some states such as Texas allow some lenders to apply for an exemption from brick-and-mortar requirements, but these exemptions typically only apply on a city or county basis - a lender that wants to operate in other parts of the state either still needs to have a physical location open, or apply for additional exemptions. For brick and mortar laws, we use an indicator variable to record whether a state has brick-and-mortar regulations on their books for the year.

Recording Tax: Several states charge a tax for a home purchaser to record a mortgage. The amount of the recording tax is based on the principal of the mortgage, and can range from 0.1% in Alabama to 1.925% in New York. These taxes are levied upon the borrower, not the lender, but the additional taxation burden placed onto the borrower in a state with such a tax may significantly affect the decision to enter or remain in the market, or on the amount or costs a lender is willing to loan/charge a borrower. For our data, we record the size of the recording tax (in percentage points) for each state for each year. If a state does not have a recording tax, we mark the recording tax as zero.

Net Worth Requirements: A net worth requirement for a state is the minimum amount of assets that a lender is required to have on their balance sheet in order to be allowed to operate in that state. We record the dollar amount of the net worth requirement for each state in each year of our sample. If a state does not have a net worth requirement, we record the net worth requirement to be zero.

Annual Auditing Requirements: Some states require any lender operating in that state to submit annual audited financial statements. We use an indicator variable to record whether a state that has any annual auditing requirements. Some states require lenders to only submit an annual unaudited financial statement - we record these states as having no annual auditing requirements.

A.3 Are the results being driven by Fintech?

In our main analysis, our narrative focuses on the nature of fintech competition. However, without further exploration our results are not necessarily special to the set of financial institutions we define as fintech. In particular, it could be the case that the results are driven purely by the largest player in our sample, Quicken Loans. Alternatively, it could be that our results do not depend on fintech lending at all and instead are being driven by the shadow banking sector as a whole. To better understand these possibilities, we repeat our analysis with varying definitions of market share. At the end of this exercise, we conclude that there is something special about the effect that fintech lenders have on the mortgage market that isn't purely driven by Quicken Loans.

A.3.1 Alternative specification: Quicken Loans

As a robustness check for whether our aggregate results are being driven solely by Quicken Loans, we repeat our previous analysis for volume and costs of bank mortgages, replacing fintech market share with only the market share of Quicken Loans, and again with fintech market share excluding Quicken Loans. We start by repeating the exercise of table 2 on the sub-samples. Table 12 contains results for Quicken Loans while Table 13 contains results for all other fintech lenders.

Across the board, we see that the magnitude of the effect of fintech competition on traditional bank lending volume is larger for Quicken Loans than other fintech lenders, with a one percent increase in the market share of Quicken having about twice the impact as a one percent increase in the market share of other fintech lenders. The effect on large banks for non-Quicken fintech lenders loses significance, otherwise the rest of the results are qualitatively unaffected. These patterns persist for the home purchase sector alone, where the differences in the effect of Quicken vs. non-Quicken fintech lenders becomes even stronger. However, these differences disappear for the refinancing sector.

When repeating the cost regressions replacing fintech market share with the Quicken (Table 14) and non-Quicken (Table 15) market share respectively, we lose statistical significance, but many of the results remain qualitatively unchanged. Changes in the market share for Quicken Loans is only significant for interest costs when considering the overall sample, which seems to be driven purely by the effect on small banks. For non-interest costs, the results are significant only for the home purchase sector and this seems to be driven more by large banks. For the rest of the market, we only observe significant effects for the interest costs of small banks which seem to be increasing across the board.

Overall, we take this as evidence that Quicken plays an important role in the story of fintech competition, but it is not the sole driver of the patterns we observe in this paper. For the refinancing sector in particular, Quicken seems to have similar effects as other fintech lenders. However the significant coefficients within the home purchase sector seem to be mostly driven by Quicken. We believe that this could be an interesting topic for future research.

A.3.2 Alternative specification: Non-fintech Shadow Banks

Fintech lenders primarily differ from traditional banks in two ways: Use of technology and regulatory arbitrage. Fintech lenders are special in their use of technology, however they are not the only lenders who can take advantage of the regulations that traditional banks face. Every fintech lender in our sample is a shadow bank, but not all shadow banks are fintech lenders. If our main results are driven mostly by regulatory arbitrage, then they should be preserved when considering competition from the rest of the shadow banking sector. If this is not the case, then technology use may have played an important role in mortgage market competition since the global financial crisis.

(Table 16) contains aggregate results on the effect of non-fintech shadow bank competition on traditional banks across bank types and market segments. Compared to Table 2, we observe statistically significant differences in coefficients with the estimated effect being approximately cut in half for most specifications.

We take this to mean that both technology use and regulatory arbitrage both play an important role in banking competition. However, fintech lenders make up a substantial portion of nonbank lenders in the mortgage market while the biggest differences we observe in competition occur for large banks who make up the majority of the traditional banking sector. With this in mind, fintech lenders are contributing substantially to the way mortgage lending has evolved over the past decade.

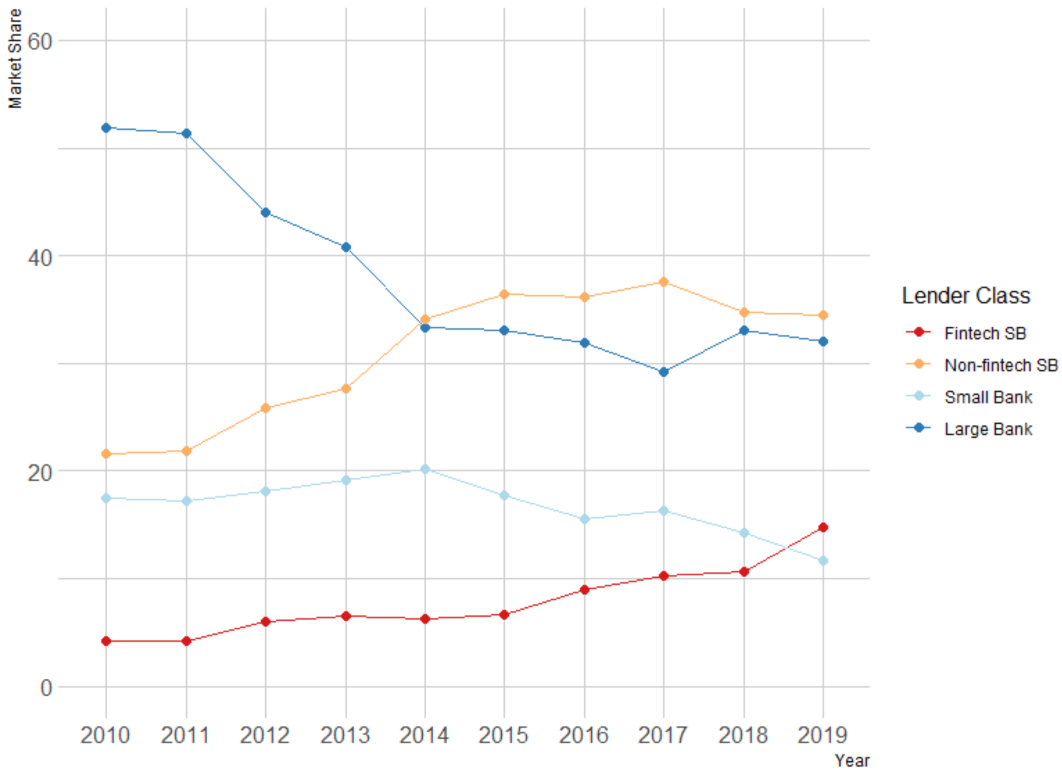

Figure 1: Lender Type Market Share by Year

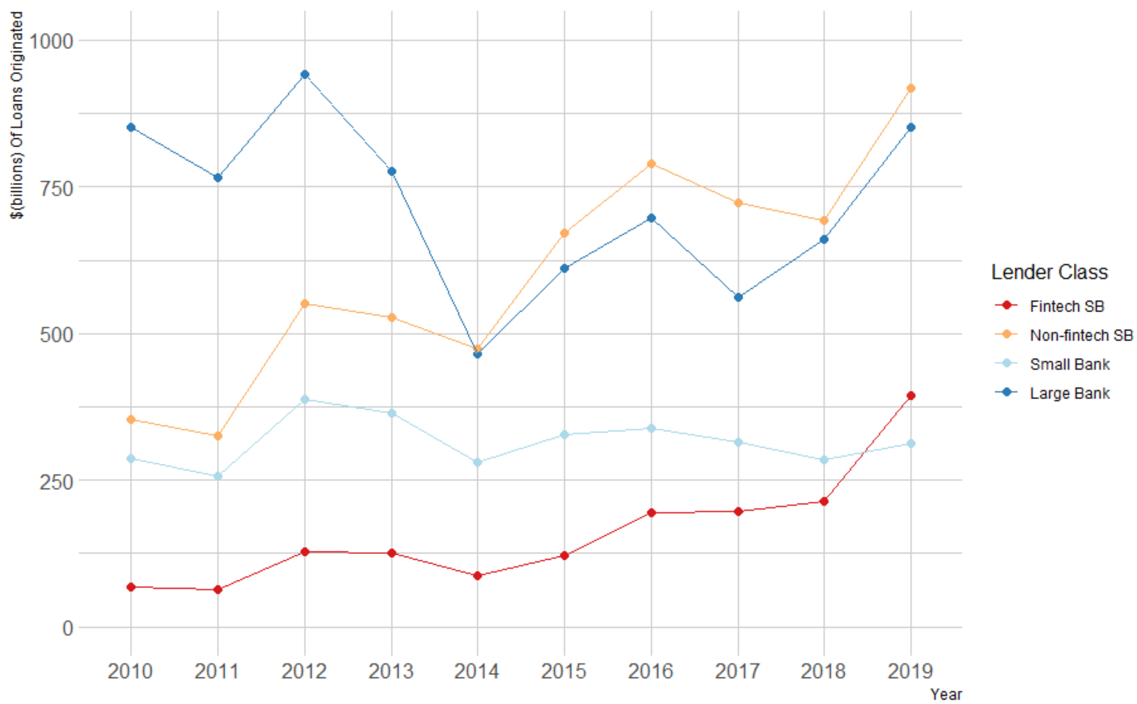

Figure 2: Total Lending by Year

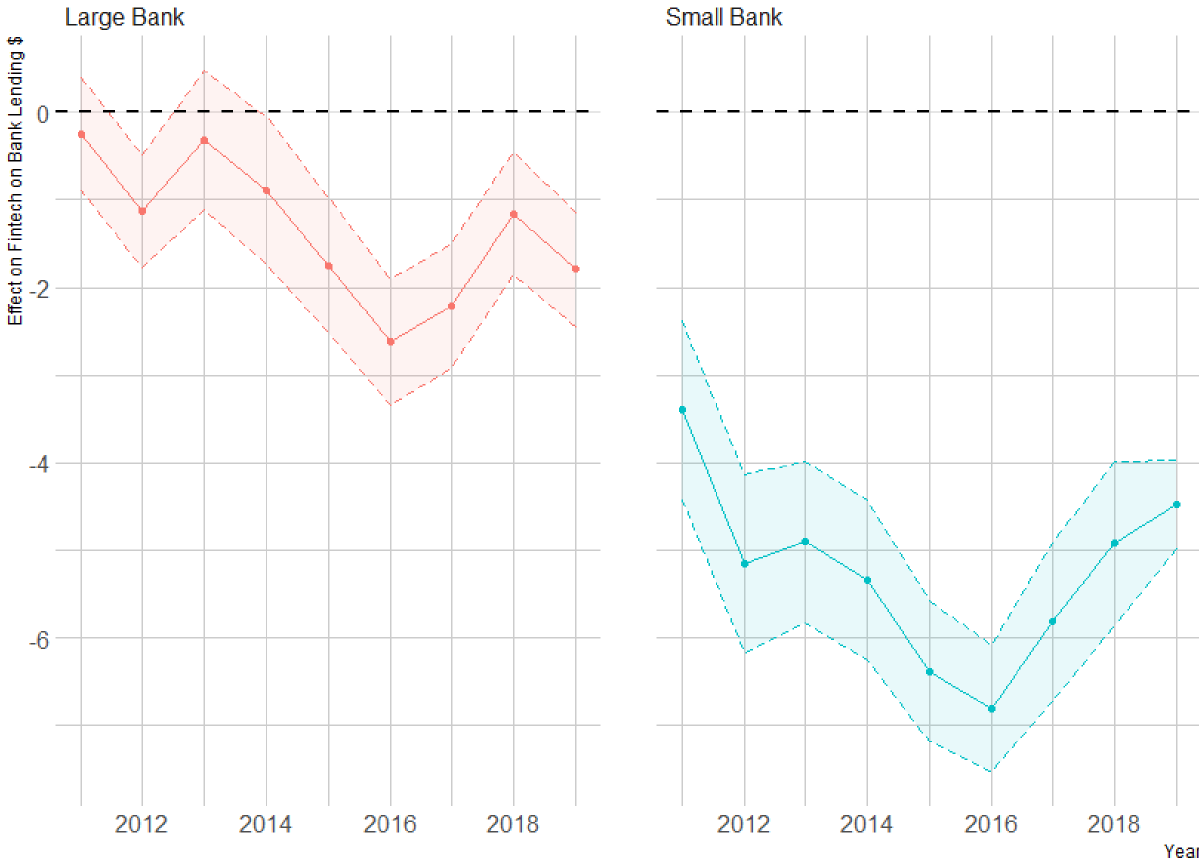

Figure 3: Time variation in fintech's impact on bank lending volume

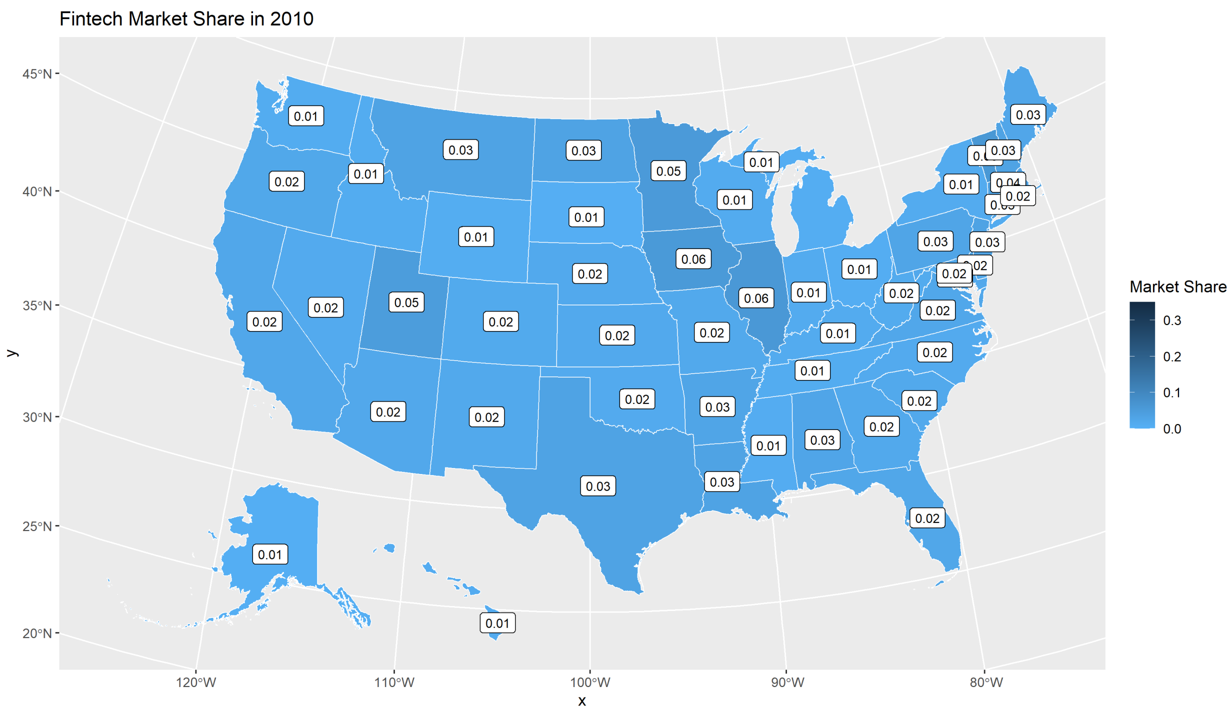

Figure 4: Fintech Market Share by State in 2010

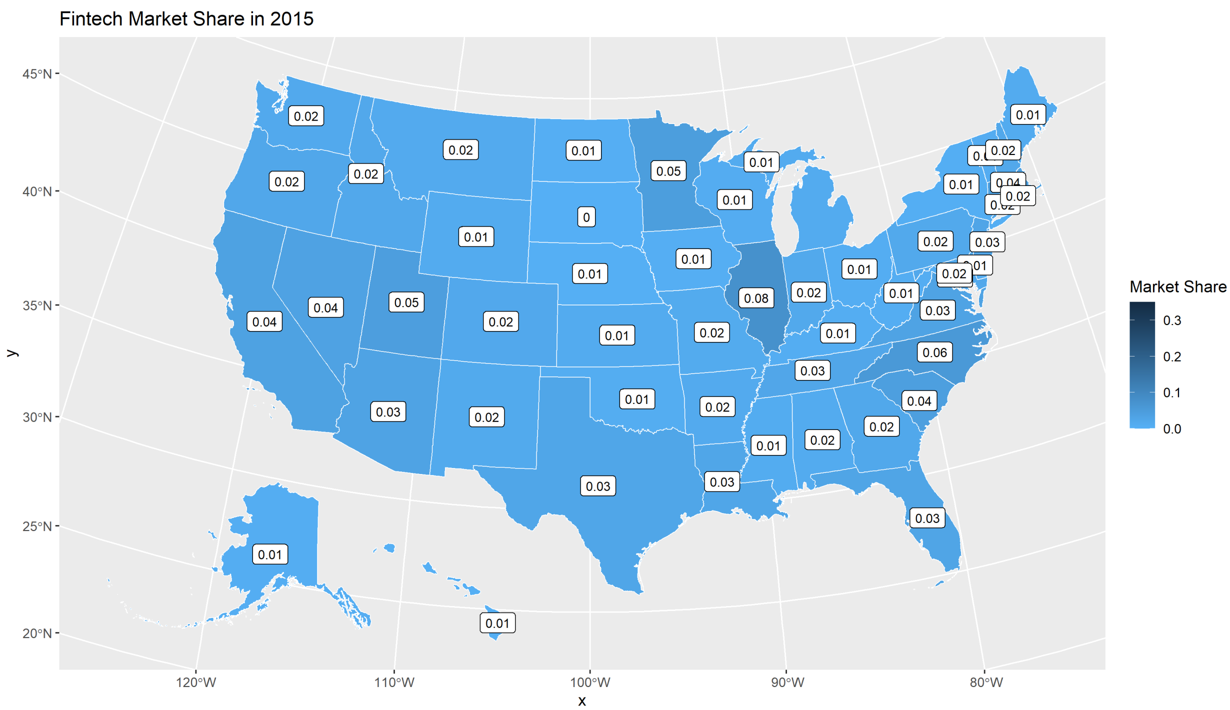

Figure 5: Fintech Market Share by State in 2015

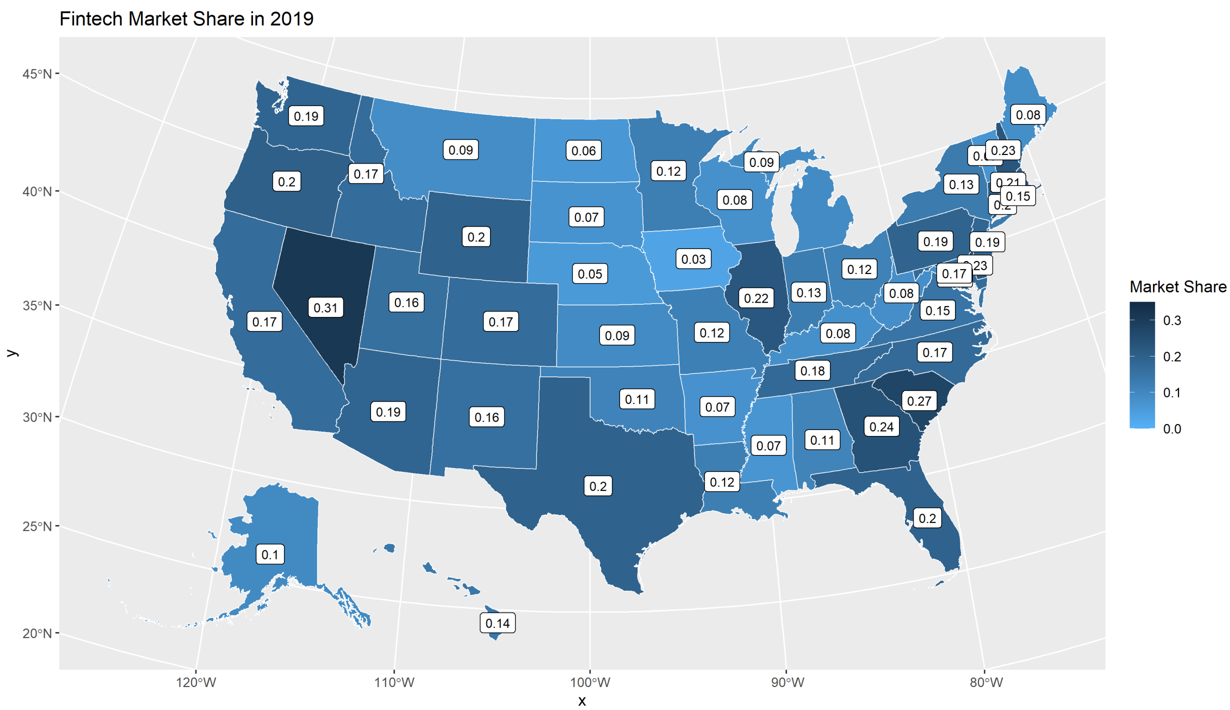

Figure 6: Fintech Market Share by State in 2019

Table 1: Sample summary statistics

Panel A				**Lender Statistics**					
Lender Type	Small Bank			Large Bank			Fintech Lender		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Dollar Volume ($millions) Originated	89.33	19.42	380.13	7185.6	1813.36	21370.02	8258.02	1951.91	18152.33
Number of Loans Originated	421.74	115	1581.15	26248.5	5849	83710.35	35721.38	9640	80627.067
Counties Active	27.08	10	83.31	510.11	228.5	668.92	898.1	690.5	773.07
Market Share (%)	0.005	0.001	0.021	0.384	0.092	1.178	0.411	0.094	0.873
Acceptance Rate (%)	86.01	88.33	11.59	76.64	78.17	13.92	78.38	86.51	21.09
Observations		5358			184			55	

Panel B			**Loan Statistics**			
Lender Type	Small Bank		Large Bank		Fintech Lender	
	Mean	Median	Mean	Median	Mean	Median
Loan Characteristics						
Loan Amount ($000s)	211.81	155	273.75	175	231.18	200
Applicant Income ($000s)	177.64	82	139.20	93	103.51	84
Owner Occupied	0.827	1	0.885	1	0.921	1
Securitized	0.603	1	0.640	1	0.915	1
Secured by first lien	0.927	1	0.926	1	0.993	1
Loan Purpose						
Home Purchase	0.492	0	0.335	0	0.384	0
Refinancing	0.421	0	0.579	1	0.608	1
Improvement	0.079	0	0.065	0	0.005	0
Loan Type						
Conventional	0.836	1	0.860	1	0.716	1
FHA	0.097	0	0.082	0	0.186	0
VA	0.046	0	0.052	0	0.091	0
FSA/RHS	0.021	0	0.007	0	0.007	0
Borrower Demographics						
Male	0.738	1	0.712	1	0.677	1
Female	0.262	0	0.288	0	0.323	0
Minority	0.091	0	0.132	0	0.176	0
Non-minority	0.909	1	0.868	1	0.824	1
Borrower Risk Measures						
Credit Score	753.95	763	750.18	760	744.75	752
Loan-to-Value Ratio	74.9	80	76.05	80	76.15	80
Debt-to-Income Ratio	33.04	34	34.34	35	35.66	37
Mortgage Costs						
Interest Rate	4.16	4.13	4.24	4.25	4.3	4.38
Non-Interest Costs	3183.71	2812.55	3903.74	3527.73	4684.33	4219.5
Observations	14632800		26143502		6787062	

This table reports the summary statistics of mortgage loans included in our sample, grouped by lender type. Data on lending volume, loan purpose, loan type, borrower demographics, and age include all loans from 2010-2019 in HMDA. Data on borrower risk measures and mortgage costs come only from loans that are matched between HMDA and GSE data.

Table 2: The effect of Fintech on aggregate bank lending (Log Total Dollar Amount)

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-3.234 ***	-3.376 ***	-5.252 ***	-4.802 ***	-0.426 *	-1.17 ***
	(0.168)	(0.156)	(0.244)	(0.22)	(0.231)	(0.205)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24660	24660	24660	24660	24660	24660
R^2	0.933	0.943	0.844	0.865	0.889	0.919

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-2.162 ***	-2.294 ***	-3.281 ***	-3.43 ***	-0.699 ***	-0.835 ***
	(0.14)	(0.134)	(0.281)	(0.272)	(0.234)	(0.231)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24658	24658	24658	24658	24658	24658
R^2	0.92	0.93	0.78	0.81	0.792	0.818

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-2.568 ***	-2.507 ***	-4.959 ***	-4.145 ***	-1.001 ***	-1.675 ***
	(0.147)	(0.142)	(0.306)	(0.287)	(0.333)	(0.311)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24659	24659	24659	24659	24659	24659
R^2	0.907	0.922	0.696	0.726	0.784	0.821

This table reports the effect of a county's fintech exposure on the annual amount of mortgage lending done in that county, which is measured by the log dollar amount of mortgages originated. *Fintech Market Share* is the fraction of a county's mortgages that are originated by fintech lenders. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3: The effect of Fintech on aggregate bank lending (Log Number of Loans)

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-3.550 ***	-3.376 ***	-5.619 ***	-5.120 ***	-0.378 **	-0.486 ***
	(0.146)	(0.136)	(0.237)	(0.207)	(0.187)	(0.178)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24660	24660	24660	24660	24660	24660
R^2	0.94	0.949	0.826	0.866	0.907	0.934

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-1.944 ***	-2.088 ***	-2.520 ***	-2.842 ***	-0.666 ***	-0.555 ***
	(0.113)	(0.107)	(0.167)	(0.147)	(0.133)	(0.138)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24658	24658	24658	24658	24658	24658
R^2	0.922	0.934	0.813	0.858	0.891	0.912

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-2.715 ***	-2.438 ***	-4.497 ***	-3.672 ***	-0.182	-0.384 ***
	(0.113)	(0.104)	(0.168)	(0.149)	(0.141)	(0.117)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24659	24659	24659	24659	24659	24659
R^2	0.928	0.944	0.804	0.85	0.902	0.932

This table reports the effect of a county's fintech exposure on the annual amount of mortgage lending done in that county, which is measured by the log number of mortgage originated. *Fintech Market Share* is the fraction of a county's mortgages that are originated by fintech lenders. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Fintech Exposure Effects on traditional bank rejection rates

Panel A: All Loans			
Bank Type	All	Small	Large
	(1)	(2)	(3)
Fintech Market Share	0.096 ***	0.101 ***	0.070
	(0.030)	(0.023)	(0.044)
Loan-level Controls	X	X	X
County-level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Observations	39787874	13323309	26464565
R^2	0.068	0.030	0.087

Panel B: Home Purchase Loans			
Bank Type	All	Small	Large
	(1)	(2)	(3)
Fintech Market Share	0.118 ***	0.105 ***	0.127 ***
	(0.028)	(0.026)	(0.038)
Loan-level Controls	X	X	X
County-level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Observations	14235498	6306412	7929086
R^2	0.032	0.029	0.038

Panel C: Refinancing Loans			
Bank Type	All	Small	Large
	(1)	(2)	(3)
Fintech Market Share	-0.013	0.073 **	-0.035
	(0.032)	(0.027)	(0.036)
Loan-level Controls	X	X	X
County-level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Year Fixed Effects	X	X	X
Observations	20726398	5682073	15044325
R^2	0.040	0.035	0.043

This table examines the correlation between a county's traditional bank rejection rates and the market power of fintech lenders by loan type. *Fintech Market Share* equals the countywide fraction of mortgage loans originated by fintech lenders. The dependent variable is a dummy variable which notes whether a loan is accepted or rejected, with accepted being recorded as 0, and rejected recorded as 1. Both the dependent variable and *Fintech Market Share* are on a scale from 0 to 1. Cluster-robust standard errors by lender are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 5: Fintech exposure effects on traditional bank loan sizes

Panel A	**All Loans**		
Bank Type	All Banks	Small Banks	Large Banks
	(1)	(2)	(3)
Fintech Market Share	0.494 ***	0.265 *	0.496 ***
	(0.138)	(0.132)	(0.137)
Loan-Level Controls	X	X	X
County-Level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Month Fixed Effects	X	X	X
Observations	1118065	222473	895592
R^2	0.491	0.38	0.545
Panel B	**Home Purchase Loans**		
Bank Type	All Banks	Small Banks	Large Banks
	(1)	(2)	(3)
Fintech Market Share	0.486 ***	0.27 *	0.489 ***
	(0.124)	(0.138)	(0.123)
Loan-Level Controls	X	X	X
County-Level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Month Fixed Effects	X	X	X
Observations	619067	125414	493653
R^2	0.453	0.34	0.532
Panel C	**Refinancing Loans**		
Bank Type	All Banks	Small Banks	Large Banks
	(1)	(2)	(3)
Fintech Market Share	0.353 **	0.231	0.335 **
	(0.155)	(0.183)	(0.151)
Loan-Level Controls	X	X	X
County-Level Controls	X	X	X
Lender Fixed Effects	X	X	X
State Fixed Effects	X	X	X
Month Fixed Effects	X	X	X
Observations	479198	94058	385140
R^2	0.522	0.445	0.547

This table shows the associated between traditional bank loan sizes and the market share of fintech in the county the loan was originated from. The dependent variable is the log loan amount of a mortgage. Standard errors are clustered by lender and state and are shown in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 6: Mortgage Costs by Lender Type

Dependent Variable	Interest Rates			Non-interest Costs		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank	0.052 **	0.018	0.100 ***	0.167 *	0.030	0.405 ***
	(0.019)	(0.019)	(0.024)	(0.091)	(0.087)	(0.131)
Fintech	0.076 ***	0.052 ***	0.101 **	0.626 ***	0.411 **	0.951 ***
	(0.027)	(0.019)	(0.039)	(0.194)	(0.175)	(0.241)
Loan-Level Controls	X	X	X	X	X	X
County-Level Controls	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X
Observations	1402586	741087	641171	644497	437565	206932
R^2	0.217	0.247	0.195	0.075	0.046	0.224

Standard errors are given in parentheses and are clustered by lender and state. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 7: Fintech Effects on Traditional Bank Mortgage Costs

Panel A				**Interest Rates**					
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fintech Market Share	0.055	0.062	0.028	0.261 ***	0.239 ***	0.223	0.024	0.037	-0.014
	(0.033)	(0.038)	(0.042)	(0.075)	(0.062)	(0.138)	(0.038)	(0.038)	(0.036)
Loan-Level Controls	X	X	X	X	X	X	X	X	X
County-Level Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	1118065	619067	479198	222473	125414	94058	895592	493653	385140
R^2	0.218	0.25	0.192	0.218	0.223	0.175	0.222	0.259	0.199

Panel B				**Non-Interest Costs**					
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fintech Market Share	0.582 **	0.829 **	-0.114	1.062 **	1.422 **	0.242	0.358 *	0.637 **	-0.358
	(0.238)	(0.318)	(0.407)	(0.485)	(0.675)	(0.43)	(0.19)	(0.276)	(0.382)
Loan-Level Controls	X	X	X	X	X	X	X	X	X
County-Level Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	488951	358176	130775	81729	55953	25776	407222	302223	104999
R^2	0.05	0.032	0.207	0.1023	0.146	0.065	0.055	0.035	0.312

This table shows the associated between traditional bank loan costs and the market share of fintech in the county the loan was originated from. The dependent variable in Panel A is interest rates, while for Panel B it is non-interest costs, expressed as a percentage of the mortgage principal. Standard errors are clustered by lender and state and are shown in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 8: Fintech exposure and the composition of traditional bank borrowers

Panel A	**All Loans**											
Dependent Variable	Log Income			Credit Score			LTV			DTI		
Bank Type	All Banks (1)	Small Banks (2)	Large Banks (3)	All Banks (4)	Small Banks (5)	Large Banks (6)	All Banks (7)	Small Banks (8)	Large Banks (9)	All Banks (10)	Small Banks (11)	Large Banks (12)
Fintech Market Share	0.503 ***	2.062	0.292 ***	14.85	-1.333	-1.07	6.338	-1.26	5.74	3.563 ***	2.884 **	3.09 ***
	(0.169)	(1.377)	(0.088)	(5.822)	(7.569)	(5.767)	(7.299)	(4.248)	(8.408)	(1.04)	(1.316)	(1.075)
Loan-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
County-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Observations	1388585	238261	1150324	1357833	233509	1124324	1357966	233565	1124401	1136813	224944	911869
R^2	0.104	0.058	0.123	0.015	0.009	0.016	0.026	0.015	0.029	0.01	0.005	0.011

Panel B	**Home Purchase Loans**											
Dependent Variable	Log Income			Credit Score			LTV			DTI		
Bank Type	All Banks (1)	Small Banks (2)	Large Banks (3)	All Banks (4)	Small Banks (5)	Large Banks (6)	All Banks (7)	Small Banks (8)	Large Banks (9)	All Banks (10)	Small Banks (11)	Large Banks (12)
Fintech Market Share	0.549 ***	2.436	0.321 ***	0.784	4.414	0.067	-4.514 ***	-8.337 ***	-4.627 ***	3.768 ***	3.734 **	3.298 ***
	(0.196)	(11.57)	(0.065)	(4.942)	(11.06)	(4.158)	(1.575)	(2.996)	(1.383)	(0.996)	(1.423)	(1.065)
Loan-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
County-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Observations	648222	129666	518556	628396	126559	501837	628534	126613	501921	628513	126603	501910
R^2	0.1	0.05	0.135	0.018	0.012	0.02	0.029	0.024	0.031	0.009	0.001	0.011

Panel C	**Refinancing Loans**											
Dependent Variable	Log Income			Credit Score			LTV			DTI		
Bank Type	All Banks (1)	Small Banks (2)	Large Banks (3)	All Banks (4)	Small Banks (5)	Large Banks (6)	All Banks (7)	Small Banks (8)	Large Banks (9)	All Banks (10)	Small Banks (11)	Large Banks (12)
Fintech Market Share	0.268 *	1.391	0.067	-14.18 **	-13.35 **	-17.3 ***	16.88	8.943	17.33	2.179 *	1.082	1.919
	(0.149)	(0.866)	(0.099)	(5.977)	(5.472)	(6.445)	(11.74)	(5.78)	(13.22)	(1.195)	(1.948)	(1.213)
Loan-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
County-level Controls	X	X	X	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X	X	X	X
Observations	719085	105473	613612	708470	103850	604620	708467	103852	604615	488126	95310	392816
R^2	0.11	0.065	0.12	0.012	0	0.014	0.045	0.012	0.049	0.013	0.005	0.015

This table displays the correlation between county-level fintech market share and the change in traditional bank borrower composition. Standard errors are clustered by lender and state and are shown in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 9: Summary statistics of counties - population vs. in-sample

County Demographics: All Counties vs. Border Counties	All Counties			Border Counties		
	Mean	Median	SD	Mean	Median	SD
Economics						
Median Income	47013,96	45401.5	13511.38	47005.94	44859	13008.73
HPI	264.82	209.28	171.43	258.35	204.79	154.34
House Price Growth	1.53	1.74	5.13	1.31	1.59	5.18
Homeownership	71.97	73.20	8.11	71.89	73.03	7.91
Poverty Rate	1.23	0.54	2.66	1.04	0.54	1.77
Demographics						
Total Population	98896.42	26011	317072.5	90389.8	26099	249120.5
Population Density	282.84	46.36	1754.12	288.68	43.09	2436.83
Minority %	16.80	10.25	16.86	16.09	9.07	17.09
Educational Attainment						
<Highschool	10.08	9.20	4.55	10.08	9.14	4.45
Highschool	23.80	24.17	5.46	24.04	24.26	5.21
Some College	20.47	20.34	3.98	20.58	20.39	3.93
Bachelors	9.06	8.44	3.75	8.91	8.34	3.60
Graduate	4.77	3.98	2.78	4.71	4.00	2.70
Observations		32204			11493	

This table reports the summary statistics of county-year pairs included in our sample from 2010 to 2019.

Table 10: The effect of Fintech on aggregate bank lending (Log Total Dollar Amount) - Cross Border Approach

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-1.241 **	-1.818 ***	-4.203 ***	-2.926 ***	1.03	-1.553 *
	(0.609)	(0.562)	(0.875)	(0.834)	(1.015)	(0.857)
Year Fixed Effects	X	X	X	X	X	X
Border Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.922	0.941	0.84	0.873	0.875	0.916

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-1.274 **	-0.771 *	-2.289 ***	-1.242 *	-2.178 **	-1.821 *
	(0.496)	(0.451)	(0.785)	(0.71)	(1.075)	(0.937)
Year Fixed Effects	X	X	X	X	X	X
Border Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.905	0.926	0.741	0.787	0.78	0.817

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-1.912 ***	-2.834 ***	-6.095 ***	-3.989 ***	-2.157 **	-1.655
	(0.66)	(0.69)	(1.168)	(1.342)	(1.027)	(1.063)
Year Fixed Effects	X	X	X	X	X	X
Border Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.9	0.922	0.697	0.734	0.759	0.802

This table displays the results of the cross-border analysis on fintech's effect on traditional bank mortgage lending. *Fintech Market Share* measures the fraction of mortgages are originated by fintech lenders in the state a county is located in. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 11: The effect of Fintech on aggregate bank lending (Log Number of Loans) - Cross Border Approach

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-1.788 ***	-1.421 ***	-4.394 ***	-2.510 ***	-0.590	-0.600
	(0.475)	(0.447)	(0.706)	(0.627)	(0.699)	(0.587)
Year Fixed Effects	X	X	X	X	X	X
Border Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.931	0.947	0.825	0.88	0.899	0.933

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-0.847 **	-0.239	-1.372 ***	-0.805 *	-0.850	-0.286
	(0.380)	(0.346)	(0.585)	(0.477)	(0.570)	(0.465)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.914	0.935	0.813	0.872	0.879	0.91

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Market Share	-2.370 ***	-2.226 ***	-5.302 ***	-3.080 ***	0.689	-1.208 **
	(0.459)	(0.419)	(0.621)	(0.566)	(0.540)	(0.483)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	9000	9000	9000	9000	9000	9000
R^2	0.923	0.942	0.811	0.861	0.897	0.932

This table displays the results of the cross-border analysis on fintech's effect on traditional bank mortgage lending. *Fintech Market Share* measures the fraction of mortgages are originated by fintech lenders in the state a county is located in. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 12: The effect of Quicken Loans on aggregate bank lending

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Quicken Market Share	-5.122 ***	-5.411 ***	-7.807 ***	-7.225 ***	-1.451 ***	-2.647 ***
	(0.257)	(0.235)	(0.385)	(0.358)	(0.345)	(0.29)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24660	24660	24660	24660	24660	24660
R^2	0.934	0.944	0.845	0.866	0.889	0.92

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Quicken Market Share	-4.447 ***	-3.773 ***	-6.391 ***	-5.638 ***	-2.209 ***	-1.459 ***
	(0.272)	(0.236)	(0.537)	(0.476)	(0.516)	(0.499)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24658	24658	24658	24658	24658	24658
R^2	0.92	0.93	0.78	0.808	0.793	0.818

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Quicken Market Share	-3.18 ***	-3.088 ***	-5.738 ***	-4.928 ***	-1.679 ***	-2.34 ***
	(0.189)	(0.187)	(0.374)	(0.354)	(0.411)	(0.386)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24659	24659	24659	24659	24659	24659
R^2	0.908	0.922	0.695	0.726	0.785	0.822

This table reports the effect of a county's exposure to Quicken Loans on the annual amount of mortgage lending done in that county, which is measured by the log dollar amount of mortgages originated. *Quicken Market Share* is the fraction of a county's mortgages that are originated by Quicken Loans. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 13: The effect of Non-Quicken Fintech Loans on aggregate bank lending

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Quicken Fintech Market Share	-2.306 ***	-2.11 ***	-3.564 ***	-3.398 ***	-0.057	-0.316
	(0.197)	(0.197)	(0.288)	(0.268)	(0.282)	(0.281)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	22886	22886	22886	22886	22886	22886
R^2	0.931	0.94	0.845	0.87	0.893	0.921

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Quicken Fintech Market Share	-1.878 ***	-2.19 ***	-2.752 ***	-3.149 ***	-1.011 ***	-1.254 ***
	(0.158)	(0.163)	(0.341)	(0.354)	(0.224)	(0.229)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	20749	20749	20749	20749	20749	20749
R^2	0.92	0.931	0.8	0.831	0.844	0.865

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Quicken Fintech Market Share	-3.085 ***	-2.766 ***	-6.081 ***	-4.853 ***	-1.861 ***	-2.192 ***
	(0.228)	(0.212)	(0.604)	(0.541)	(0.496)	(0.474)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	20231	20231	20231	20231	20231	20231
R^2	0.921	0.934	0.733	0.767	0.832	0.865

This table reports the effect of a county's fintech exposure, excluding Quicken Loans, on the annual amount of mortgage lending done in that county, which is measured by the log dollar amount of mortgages originated. *Non-Quicken Fintech Market Share* is the fraction of a county's mortgages that are originated by fintech lenders excluding Quicken Loans. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 14: Fintech Effects on Traditional Bank Mortgage Costs - Quicken Loans

Panel A				**Interest Rates**					
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quicken Market Share	0.186 *	0.010	0.083	0.286 ***	0.113	0.131	0.141	-0.33	0.072
	(0.107)	(0.149)	(0.072)	(0.111)	(0.128)	(0.087)	(0.137)	(0.172)	(0.086)
Borrower and Loan Controls	X	X	X	X	X	X	X	X	X
County Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	1,867,796	892,982	974,814	364,125	190,180	173,945	1,503,671	702,802	800,869
R^2	0.594	0.633	0.552	0.603	0.615	0.558	0.593	0.640	0.549

Panel B				**Non-Interest Costs**					
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quicken Market Share	0.764	1.374 **	0.017	1.030	0.937	0.169	0.631	1.433 **	-0.093
	(0.583)	(0.582)	(0.315)	(0.652)	(0.576)	(0.393)	(0.596)	(0.709)	(0.321)
Borrower and Loan Controls	X	X	X	X	X	X	X	X	X
County Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	524,115	366,703	157,412	80,688	54,525	26,163	443,427	312,178	131,249
R^2	0.509	0.488	0.618	0.654	0.654	0.700	0.481	0.456	0.602

This table shows the associated between traditional bank loan costs and the market share of the fintech lender Quicken Loans in the county the loan was originated from. The dependent variable in Panel A is interest rates, while for Panel B it is non-interest costs, expressed as a percentage of the mortgage principal. Standard errors are clustered by lender and state and are shown in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 15: Fintech Effects on Traditional Bank Mortgage Costs - Non-Quicken Loans

Panel A	**Interest Rates**								
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-Quicken Fintech Market Share	0.046	0.056	0.014	0.282 ***	0.161 ***	0.308 ***	0.037	0.054	-0.008
	(0.048)	(0.035)	(0.051)	(0.082)	(0.057)	(0.101)	(0.051)	(0.034)	(0.062)
Borrower and Loan Controls	X	X	X	X	X	X	X	X	X
County Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	1,867,796	892,982	974,814	364,125	190,180	173,945	1,503,671	702,802	800,869
R^2	0.594	0.633	0.552	0.603	0.615	0.558	0.593	0.640	0.549

Panel B	**Non-Interest Costs**								
Bank Type	All Banks			Small Banks			Large Banks		
Loan Purpose	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing	All	Home Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Non-Quicken Fintech Market Share	0.719	0.715	-0.352	0.623	0.820	-0.404	0.675	0.658	-0.370
	(0.436)	(0.449)	(0.233)	(0.677)	(0.702)	(0.333)	(0.424)	(0.423)	(0.272)
Borrower and Loan Controls	X	X	X	X	X	X	X	X	X
County Controls	X	X	X	X	X	X	X	X	X
Lender Fixed Effects	X	X	X	X	X	X	X	X	X
State Fixed Effects	X	X	X	X	X	X	X	X	X
Month Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	524,115	366,703	157,412	80,688	54,525	26,163	443,427	312,178	131,249
R^2	0.510	0.488	0.618	0.654	0.654	0.700	0.481	0.456	0.602

This table shows the associated between traditional bank loan costs and the market share of the fintech lenders other than Quicken Loans in the county the loan was originated from. The dependent variable in Panel A is interest rates, while for Panel B it is non-interest costs, expressed as a percentage of the mortgage principal. Standard errors are clustered by lender and state and are shown in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 16: The effect of Non-Fintech Shadow Bank Loans on aggregate bank lending

Panel A	**All Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Fintech SB Market Share	-1.096 ***	-1.585 ***	-2.486 ***	-2.361 ***	0.532 ***	-0.263 ***
	(0.069)	(0.072)	(0.095)	(0.101)	(0.097)	(0.097)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24660	24660	24660	24660	24660	24660
R^2	0.932	0.944	0.852	0.869	0.89	0.919

Panel B	**Home Purchase Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Fintech SB Market Share	-1.178 ***	-1.515 ***	-2.239 ***	-2.087 ***	-0.017	-0.7 ***
	(0.055)	(0.057)	(0.096)	(0.096)	(0.088)	(0.097)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24658	24658	24658	24658	24658	24658
R^2	0.925	0.936	0.8	0.82	0.792	0.819

Panel C	**Refinancing Loans**					
Bank Type	All Banks		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Fintech SB Market Share	-1.018 ***	-1.285 ***	-2.661 ***	-2.102 ***	0.848 ***	0.2
	(0.084)	(0.088)	(0.164)	(0.17)	(0.143)	(0.152)
Year Fixed Effects	X	X	X	X	X	X
State Fixed Effects		X		X		X
Observations	24659	24659	24659	24659	24659	24659
R^2	0.904	0.92	0.692	0.722	0.785	0.82

This table reports the effect of a county's non-fintech shadow bank exposure on the annual amount of mortgage lending done in that county, which is measured by the log dollar amount of mortgages originated. *Non-Fintech SB Market Share* is the fraction of a county's mortgages that are originated by non-fintech shadow banks. For the dependent variable, Columns (1) and (2) uses mortgage lending done by all bank lenders, Columns (3) and (4) uses mortgage lending done only by small banks, and Columns (5) and (6) uses mortgage lending done only by large banks. Cluster-robust standard errors by county are given in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.