Fintech and Minority Welfare: Evidence from the Mortgage Market

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June 9, 2022

Abstract

We examine the impact of fintech lenders on the minority credit access and availability and minority borrower quality in terms of credit risk. Fintech expansion in the mortgage market is associated with greater minority credit access amongst both home purchase and refinancing sectors. Fintech lenders significantly reduce costs for refinancing mortgages originated to minority borrowers in terms of both interest rates and non-interest costs. The reduction in costs varies across minority borrowers with Asian, Hispanic, and lower quality borrowers benefiting more than others. [1]

[1]We would like to thank Professors Maureen O'Hara, David Ng, Andrew Karolyi, and Scott Yonker for the comments and suggestions for this paper.

1 Introduction

Discriminatory outcomes in lending towards under-represented minorities, in the United States, particularly in the mortgage market, has been a persistent and ongoing issue. Before laws expressly prohibiting discrimination were passed, practices such as redlining denied ethnic minority communities access to credit on the basis of perceived higher lending risk, directly contributing to the substantial gaps in housing and inter-generational wealth between non-minority and minority families. (Louis Lee Woods (2012)) Although race-based lending discrimination was made illegal under the Fair Housing Act, a substantial literature going back to at least Black, Schweitzer, and Mandell (1978) still finds persistent discrimination for minorities in the likelihood and costs of receiving a mortgage.

In recent years, the growth of fintech - short for financial technology - has received significant attention for its potential in reducing lending discrimination and bridging the racial wealth gap. (Philippon (2019), Bartlett et al. (2022), Broady (2021)) By primarily relying on big data and machine learning algorithms, fintech lenders have a potentially lower amount of implicit and explicit biases towards minority borrowers compared to traditional lenders which still rely on human agents to make face-to-face lending decisions. However, there is also potential that fintech algorithms could inherit existing societal prejudices based on the data input, which would lead to unchanged or even worsening discrimination in lending outcomes.[2] (Barocas and Selbst (2016), Favaretto, De Clercq, and Elger (2019))

It is unclear whether the rise of fintech has benefited minority borrowers. Papers such as Bartlett et al. (2022) suggest that fintech lenders are significantly less discriminatory in terms of interest rates charged to minorities amongst FHA mortgages, and Fuster et al. (2021a) suggest that fintech lenders significantly increased mortgage lending supply to underserved minorities during the outbreak of COVID-19. However, the impact of fintech in terms of non-interest costs remains unclear, as well as whether the general growth of fintech in the years prior to COVID-19 has helped bridge the gap between minority and non-minority consumer outcomes. Furthermore, the heterogeneity in outcomes between different minority groups in terms of credit-worthiness and in racial and ethnic composition is still unclear to the best of our knowledge.

In this paper, we examine how the growth of fintech has impacted both credit access

[2]Such an inheritance would not even have to be a conscious choice on the part of the programmers. An algorithm built with data containing discriminatory outcomes could lead to the algorithm replicating the pre-existing discrimination contained in the data.

and credit availability for minority borrowers in the mortgage market. We explore how both the total mortgage lending and the costs of mortgages have changed for minority borrowers with the rise of fintech. We also explore the heterogeneity in outcomes within minority groups in terms of ethnic composition, borrower quality, and segment of the mortgage market. We also examine the relative the credit-worthiness of minority borrowers that choose fintech lenders, as well as how fintech lenders can complement or substitute for more traditional lenders in terms of minority lending.

First, we examine how the growth of fintech has impacted minority credit access. We find that fintech market power is associated with an increase in total lending for minorities. A 1% increase in fintech market share is correlated with a 0.7 basis point increase in total lending towards minorities. On average, from 2010 to 2019, minorities received an additional $150 million in mortgage lending associated with the growth in fintech. However, when we examine census tracts that are eligible for the Community Reinvestment Act (CRA), we find little to no evidence of fintech growth expanding minority credit access, suggesting that the benefit in credit access for minorities mainly accrue to borrowers located in less economically disadvantaged locations.

Second, turning to credit availability, we examine whether fintech lenders are less discriminatory towards minorities than non-fintech lenders, both in terms of interest rates and non-interest costs. Similar to Bartlett et al. (2022), we find that fintech lenders are comparatively less discriminatory than non-fintech lenders to minority borrowers in the refinancing market, but not in the home purchase market. [3] For a refinancing mortgage, controlling for risk and lender and time heterogeneity, minority borrowers are charged a premium of 1.25 basis points and 17.25 basis points in terms of interest rates and non-interest costs, respectively. However, fintech lenders charge minority borrowers 1.36 basis points and 8.53 basis points less in terms of interest rates and non-interest costs, respectively. On average, fintech lenders save minority refi borrowers $209.03 in total non-interest costs, and $32.51 in annual interest rate payments. For high-quality minority borrowers, we find little evidence that fintech lenders reduce costs, suggesting that the growth in credit availability has mainly accrued to lower-quality borrowers.

We also examine how the discrimination in minority costs and overall costs of mortgages change as fintech becomes more dominant in an area. In areas with higher fintech market share, we find that the difference in costs for refi mortgage between minorities

[3] More specifically, however, Bartlett et al. (2022) finds fintech lenders are less discriminatory to minority borrowers in the refinancing market (1) in terms of interest rates only, and (2) for mortgages sold to Ginnie Mae. By contrast, our sample is composed of mortgages sold Fannie Mae and Freddie Mac, and we find that fintech lenders are less discriminatory in terms of non-interest costs as well.

and non-minorities increases for interest rates and decreases total non-interest costs. We also find that refi total non-interest costs for fintech minority borrowers rise in areas where fintech has greater market share. However, costs for non-fintech mortgages for minorities do not change as fintech becomes more dominant, suggesting that the increase in minority premiums for non-interest costs are driven mainly by fintech lenders in markets where they are more dominant.

Lastly, we examine the types of borrowers that apply to fintech lenders for a mortgage, focusing on differences in minority status and mortgage sector. For home purchase loans, both minority and non-minority borrowers have higher incomes, but worse credit scores, loan-to-value (LTV) ratios, and debt-to-income (DTI) ratios, suggesting that fintech lenders attract higher income, but also lower quality borrowers. For refinancing loans, however, fintech borrowers also have worse credit scores and LTV ratios, but better DTI ratios, suggesting that fintech borrower quality is more mixed in the refinancing sector. We also find that as fintech becomes more dominant and takes a greater market share, the remaining pool of minority borrowers for non-fintech lenders have higher incomes in the home purchase sector, and worse credit and LTV scores in the refinancing sector. Thus, we find that the evidence suggests that fintech lenders target higher income but worse quality borrowers in the home purchase sector, but target a similar quality borrowers as non-fintech lenders in the refinancing sector.

Taken together, our results suggest that the growth of fintech lenders in the mortgage market has expanded both credit access and credit availability for minority borrowers. In terms of credit access, the main minority beneficiaries of the expansion of fintech are those looking for a home purchase mortgage, and reside outside a CRA-eligible tracts. In terms of credit availability, however, the main beneficiaries are riskier, less credit worth borrowers looking to get a refinancing loan. Furthermore, fintech acts more as a complement to non-fintech lenders in the home purchase sector, but acts more as a substitute in the refinancing sector.

The mechanism behind the differences in costs of fintech loans, both between minorities and non-minorities, and within minority groups, is still open for debate. It is possible that minority borrowers that select fintech lenders are comparatively more likely to engage in price shopping, thus earning them better mortgage prices. Lenders may be extracting monopoly rents from minority borrowers, who may be less prone to shopping around on average. (Woodward (2008) and Woodward and Hall (2012)) By moving the mortgage application process to an online venue, fintech lenders may lower informational costs for contacting multiple lenders for minority borrowers, allowing them to more effectively shop around and thus earn better interest rates and fees. The fact that credit availability gains to minorities center entirely on refinancing loans is consistent with the interpretation that price shopping is harder, and thus lender monopoly rent extract easier, amongst home purchase mortgages, where the time frame and borrower experience with the mortgage lending process is generally shorter than for refinancing loans. However, the fact that we see no reduction in costs for high quality borrowers, which would be more associated with high financial literacy, would speak against the price shopping interpretation. It is also possible that the algorithms driving fintech lenders offer lower costs to minority borrowers by reducing human bias involved in lending decisions. Neither explanation is mutually exclusive, and further study into the nature of fintech and minority mortgage pricing would be helpful in clarifying the mechanism.

1.1 Literature review

Research into the economics of discrimination stretches back to Becker (1957), which modeled how discriminatory outcomes were driven by differences in tastes for discrimination. For the housing and mortgage markets in particular, the economic disadvantages suffered by black and other ethnic minority homeowners in the U.S. has been well-documented. (Cloud and Galster (1993), Zenou and Boccard (2000), Taylor (2019), Quillian, Lee, and Honoré (2020)) The practice of redlining during the 1930s rationed mortgage credit to potential racial and ethnic minority homeowners, denying them opportunities to build inter-generational housing wealth that was afforded to white mortgage borrowers, leading to significant negative effects on home-ownership and poverty rates that have lasted to this day. (Appel and Nickerson (2016), Aaronson, Hartley, and Mazumder (2021)) Bayer, Ferreira, and Ross (2016) and Reid et al. (2017) find that minority homeowners were especially vulnerable to economic shocks brought on by the 2008 financial crisis, leading to higher rates of mortgage delinquency and default.

Though statistical and taste-based discrimination have been made illegal in the U.S., mortgage lenders have argued that differences in mortgage approvals and costs for minorities have been driven by ”business necessities” due to risk factors such as credit histories and debt-to-income ratios. (Glantz and Martinez (2018)) The literature on minority outcomes in the mortgage market, frequently disputes this claim by lenders. Charles and Hurst (2002), Bayer, Ferreira, and Ross (2016) and Bartlett et al. (2022) find that compared to non-minority borrowers, even after controlling for credit scores and other risk factors, Black and Hispanic borrowers were more likely to be rejected for a mortgage, and pay higher interest rates when accepted for one. Ambrose, Conklin, and Lopez (2020) finds that disparities in mortgage broker fees depend on the race of both the broker and the borrower. However, Bhutta and Hizmo (2020) disputes that the differences in interest rates charged for minorities are offset by the discount points paid by different minority groups, and do not appear to reflect discrimination by lenders.

The growth of fintech in recent years has attracted significant attention for its impact on minority outcomes. Philippon (2019) predicts that by using big data, fintech lenders will reduce overall lending discrimination in the credit markets, even if their machine learning algorithms manage to credit indirect proxies for group membership. Broady (2021) details how fintech can mitigate the racial wealth gap in the U.S. by reducing costs and prices, increasing convenience, and expanding access to credit for under-served populations. By contrast, Barocas and Selbst (2016) argue that big data algorithms could worsen discrimination by being built on top of data that reflect existing societal prejudices. Similarly, Fuster et al. (2021b) predicts in the context of the mortgage market that fintech's innovations in statistical technology will benefit mainly non-Black and non-Hispanic mortgage borrowers, and that the interest rate spread between minority and non-minority borrowers will widen with the growth of fintech lending.

The empirical evidence for the impact of fintech on minority outcomes tends to support the viewpoint espoused by Philippon (2019). In the context of small business lending, fintech lenders have been found to reduce racial disparities during the Paycheck Protection Program (PPP). (Erel and Liebersohn (2020), Fei and Yang (2021), Howell et al. (2021)) In the context of the mortgage market, Bartlett et al. (2022) finds that fintech lenders reduce disparities in interest rates for mortgages insured by the Federal Housing Agency (FHA) going to minorities. Haupert (2022) finds that minority borrowers are less likely to be rejected relative to white borrowers by fintech lenders relative to non-fintech lenders.

1.2 Hypothesis development

Our paper proposes three main hypotheses on the impact of fintech on minority mortgage outcomes.

H1: Fintech lenders expand credit access for minority borrowers.

The existing literature for small business lending have found that fintech lenders expand credit access to minorities. Erel and Liebersohn (2020) and Howell et al. (2021) find that during the beginning of the COVID-19 pandemic, fintech lenders increased PPP lending to minority borrowers disproportionately more than non-fintech lenders, and that they expand the overall supply of financial services rather than redistributing it. We hypothesize that in the context of the mortgage market, fintech serves a similar role in expanding the overall credit supply for minorities by increasing the total amount of mortgages that are originated to minority borrowers.

H2: Fintech lenders expand credit availability in terms of lowering costs for minority borrowers, in terms of both interest rates and non-interest costs. Furthermore, fintech market dominance is associated with smaller price differences between minority and non-minority borrowers.

Bartlett et al. (2022) finds that controlling for risk and time fixed effects, fintech lenders are less discriminatory towards minority borrowers in terms of interest rates charged for FHA-insured loans. Though our paper focus on government-sponsored enterprise (GSE) mortgages,[4] we extend our analysis to include non-interest costs, both in total as well as for individual categories such as origination charges, discount points. We hypothesize that fintech lenders reduce discrimination in mortgage prices in terms of both interest rates and non-interest costs. Our reasoning is that fintech lenders' reliance on algorithms for lending decisions reduce the human bias involved in the decision making process, thereby reducing the differences in prices charged to minority borrowers relative to non-minority borrowers. Furthermore, we hypothesize that as fintech becomes more dominant in a market, discrimination in mortgage pricing for all minority borrowers should decrease as well.

H3: Minority borrowers that approach fintech lenders tend to be lower quality, in terms of income and *ex-ante* risk measures. As fintech grows in market share, the remaining pool of minority borrowers left for non-fintech lenders will be of similar or higher quality as before the fintech expansion.

In the context of personal loans, Di Maggio and Yao (2020) finds that fintech lenders acquire market share by first lending to higher-risk borrowers before expanding to safer borrowers. Likewise, Tang (2019) finds that peer-to-peer (P2P) lending platforms serves as a substitute to bank lenders in terms of serving infra-marginal borrowers. We hypothesize that similar to other credit markets, fintech lenders target lower quality borrowers amongst minority borrowers in the mortgage market, in terms of income, credit score, LTV, and DTI. Furthermore, as fintech expands in market share, we hypothesize that the quality of borrowers left over for non-fintech lenders will be unaffected (if fintech is expanding credit access for minorities, and thus complementing non-fintech lenders), or will increase

[4] We define GSE mortgages as mortgages sold to Fannie Mae or Freddie Mac.

(if fintech does not increase credit access, and thus substitutes for lending by non-fintech lenders).

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. (2018) 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

Mortgage originations and performance: Our primary data source is the HMDA-GSE match that was utilized in Law and Mislang (2022). This dataset combines the detailed mortgage origination data available via the Home Mortgage Disclosure Act (HMDA) with the loan performance data available from the government-sponsored enterprises (GSEs) Freddie Mac and Fannie Mae. For the period between 2010 and 2019, these data sources are matched using fuzzy data matching techniques that utilize overlapping information between the data sources to identify unambiguously matching loans. This matched data allows us to combine racial and ethnic information from HMDA with borrower quality (such as LTV, DTI, and FICO scores) and loan performance information (such as late payments and defaults) from the GSE data sources for the entirety of our sample. Since we are relying on the GSE data, our sample is restricted to 30-year fixed rate conforming loans. This data is supplemented with the Robert Avery lender file to incorporate information about each lender's ultimate parent company as well as fundamentals from call reports.[5]

Definitions: Using the demographic information provided by HMDA, we define an underrepresented minority as an individual who self-reports to HMDA as hispanic or as a race that is not White or Asian. Since race is self-reported to HMDA, there is a concern that measurement error and self-censorship may bias the results of our regressions. While we cannot directly address these concerns in our analysis, we find it reassuring that the results of Bartlett et al. (2022) are robust to an alternative specification that uses an algorithm to map borrower names into racial groups.

We use the same definition of fintech as in Law and Mislang (2022), which combines the classifications proposed by Fuster et al. (2019) and Buchak et al. (2018). In general, a lender is considered to be fintech if they are capable of preapproving a loan application without forcing the borrower to speak with a loan officer. This capability acts as a proxy for the existence of a sophisticated automated backend that streamlines the mortgage origination process. Finally, the Wayback machine is used to approximate the year in which each lender's website displays features that indicate that they fit the definition of fintech. This process leaves us with 55 lenders who are classified as a fintech lender at some point between 2010 and 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, [6] 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

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

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

found in A.2.

2.2 Summary statistics

There are significant differences in the average borrower profile for various racial and ethnic groups. Table 1 contains summary statistics for key borrower quality and loan costs variables. Panel A splits the sample by minority status, with minority being defined as anyone who either identifies as hispanic, or who identifies themself as not white or asian. Panel B splits the sample further into racial and ethnic groups, namely white, asian, black, hispanic, and all others. We observe that on average, minority borrowers take more discount points, pay higher interest rates, and have more expensive origination charges. At the same time, they are slightly more leveraged than non-minority borrowers and have an average credit score of about 15 points lower.

As a percentage of loan amount, we see that Black and Hispanic borrowers pay the most in non-interest costs while Asian borrowers pay the least. This disparity in non-interest costs is present both in the origination charges as well as the discount points. Overall, we observe that minority borrowers are less creditworthy on average while paying higher interest and non-interest costs for their mortgages. The existence of a cost disparity does not necessarily mean that we are observing discrimination in the mortgage market. As we explore further in section 3, numerous other factors could be driving this disparity. We observe that minority borrowers are more likely to patronize fintech lenders, whose business model focuses on collecting flat fees and securitizing the loans. The disparity could also be driven by differences in borrower quality, or in the extent to which different borrowers shop around for their mortgage.

3 Minority Credit Access

In our first empirical exercise we examine whether the recent boom in fintech lending has expanded credit access to minority borrowers. Table 2 shows the relationship between fintech market share and the log dollar volume of mortgage lending to various minority groups at the census tract level, with census tract control variables (including the size of the mortgage market in each census tract) and fixed effects at the census tract, state, and year level. Overall, we see that an expansion in fintech market share is associated with

Table 1: Summary statistics by race and ethnicity

Panel A: Minority Status

	Non-minority				Minority			
	Min	*Mean*	*Max*	*SD*	*Min*	*Mean*	*Max*	*SD*
Interest Rate	2.25	4.234	6.875	0.589	2.25	4.348	7	0.601
Rate Spread	-1.58	0.301	3.14	0.402	-1.34	0.405	3.14	0.445
Origination Charges ($)	0	1805.695	405463.2	1835.898	0	2135.513	45678.78	2087.192
Origination Charges (%)	0	0.855	131.268	0.805	0	1.005	9.582	0.898
Discount Points ($)	0	1099.722	66375	1739.749	0	1409.793	28454.4	1987.276
Discount Points (%)	0	0.492	25.047	0.71	0	0.635	7.352	0.799
Total Non-interest Costs ($)	0	3995.346	4713074	5400.65	0	4541.457	952883.68	4381.297
Total Non-interest Costs (%)	0	1.9	2547.608	2.681	0	2.166	374.881	1.846
Loan Amount ($000s)	10	236.707	1470	122.64	10	228.597	1305	120.281
Income ($000s)	0	114.601	911124	1113.916	0	95.712	180066	500.586
Credit Score	300	751.413	842	45.354	442	736.658	842	49.095
LTV	2	75.283	504	18.749	3	76.875	978	19.915
DTI	1	34.579	62	9.579	1	36.857	56	8.87
Observations	2851889				460259			

Panel B: Race & Ethnicity

	White	Asian	Black	Hispanic	Other
Interest Rate	4.242	4.168	4.371	4.346	4.284
Rate Spread	0.305	0.259	0.43	0.4	0.356
Origination Charges ($)	1790.556	1956.294	2157.783	2117.77	2202.732
Origination Charges (%)	0.869	0.718	1.088	0.971	1.004
Discount Points ($)	1081.899	1291.536	1521.915	1340.267	1538.52
Discount Points (%)	0.496	0.451	0.726	0.59	0.67
Total Non-interest Costs ($)	3953.608	4403.798	4471.401	4579.154	4452.559
Total Non-interest Costs (%)	1.926	1.641	2.276	2.135	2.073
Loan Amount ($000s)	230.072	299.117	213.627	233.179	240.436
Income ($000s)	113.89	121.073	95.75	93.301	115.314
Credit Score	751.047	754.79	732.241	738.025	740.979
LTV	75.486	73.388	78.533	76.319	75.11
DTI	34.412	36.102	36.347	37.188	35.882
Observations	2578909	276029	133386	290034	31645

This table reports and compares costs and borrower quality of mortgage loans by minority and ethnicity status in our HMDA-GSE matched sample. Panel A reports summary statistics by minority status. Panel B reports summary statistics by ethnicity.

an expansion of lending volume to all minority groups. These effects are strongest among refinancing loans, where a one percent increase in fintech market share is associated with an eleven basis point increase in the volume of lending to minorities. This means that on average, greater fintech competition in an area is associated with greater credit access to all minority groups. There are numerous mechanisms that could be causing this coefficient. It could be that fintech companies are better able to identify creditworthy borrowers within minority groups than traditional banks. It could also be the case that fintech companies select into markets with greater minority presence.

To get a better idea of how the expansion of credit access is distributed, in Table 3 we run a similar set of regressions the left-hand side variable to be the share of borrowers within each census tract who belong to various minority groups. While every minority group has increased credit access in the presence of fintech in absolute terms, it is only the non-asian minorities whose credit access increases to such a degree that they make up a larger percentage of the borrower pool. These effects are most strong for black borrowers who are refinancing with a one percent increase in fintech market share being associated with a 6.4 basis point increase in the black share of borrower loan volume.

Table A.1 and Table A.2 examine the association of fintech market share with the volume and market share of loans borrowed by various minority groups. If fintech lenders have an arbitrage opportunity by selecting themselves into markets where disadvantaged borrowers are being under-served, we would expect this opportunity to not be present in census tracts where the community reinvestment act is active. This is indeed what we observe, fintech presence has no significant effect on lending volume for any minority group for any type of mortgage. There is a significant association black borrowers having increased borrower market share within CRA census tracts, however this is not robust when splitting the sample by loan purpose.

Figures 1 and 2 plot the volume and market share of different types of lenders across different demographic groups. The vertical axis for the volume graphs has logarithmic scaling, so the apparent magnitude of changes should be interpreted as percentages. Over the past decade, both fintech and non-fintech shadow bank lenders have grown exponentially in lending volume, whereas traditional banks have been largely stagnant. The growth of fintech lending volume is present for all borrower types, but the growth has been most concentrated in underrepresented minority groups. In 2010 the market share of lender types was largely homogeneous across demographic groups with large banks taking approximately half of the market, small banks taking under 20 percent, and fintech barely having a presence. Over time, fintech has grown to approximately 20 percent market share across all groups. The striking difference between groups is that non-fintech shadow banks have displaced large banks most strongly among black and hispanic borrowers, with a weaker trend for white and asian borrowers. By 2019, this tend resulted in the lending volume of fintech lenders to be nearly equal to large banks among black and hispanic borrowers. In contrast, white and asian borrowers have more reliance on large banks in 2019.

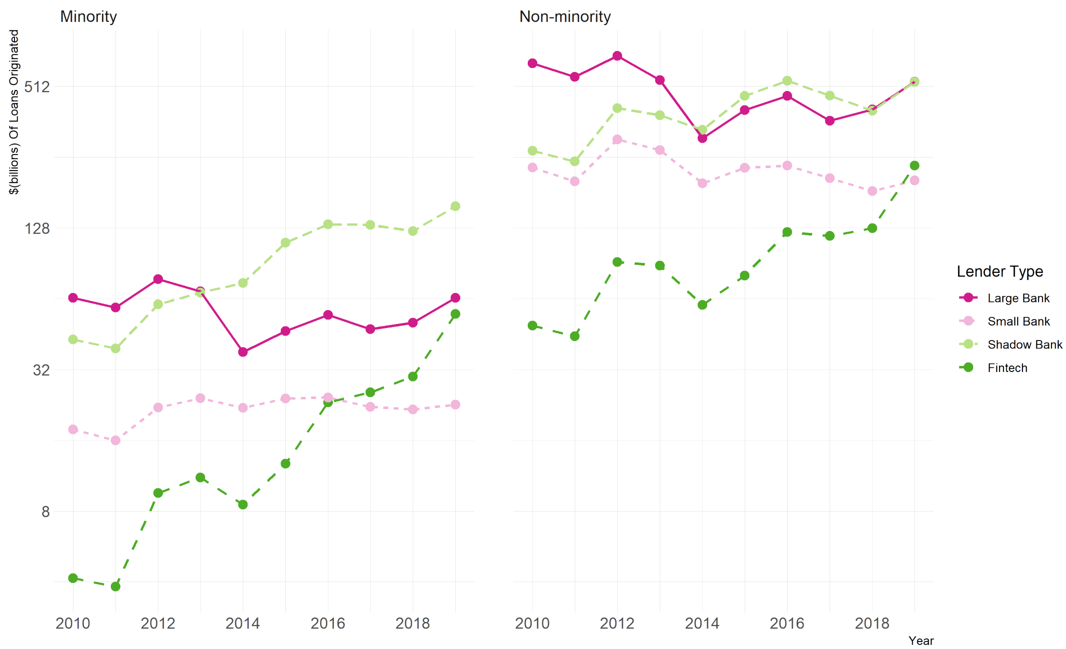
Figure 3 contains a heatmap of the fintech market share disparity within minority and non-minority borrowers across all counties. This figure suggests that there is a lot of heterogeneity in the type of borrower who accepts loans from a fintech lender.

4 Minority Credit Availability

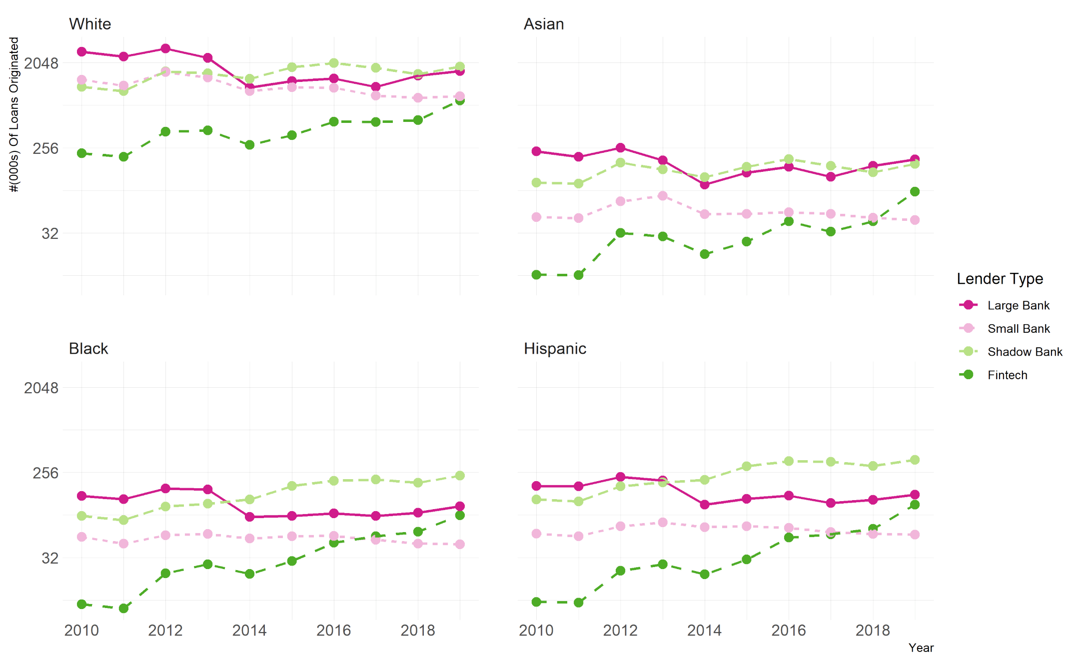
Having established our results for fintech's impact on expanding total mortgage lending to minority borrowers, our next analysis focuses on the costs of mortgages originated to minority borrowers. We focus on the difference in mortgage prices that are offered to minority and non-minority borrowers, as well as a more detailed breakdown in costs by race and ethnicity. We examine whether fintech lenders offer better pricing than non-fintech lenders in terms of both the interest rate (expressed as the rate spread of the interest rate changed over the prime mortgage market rate[7]) and non-interest costs, with non-interest costs broken down by origination charges, discount points, and total costs.

For identifying discrimination, our main identification strategy borrows from Bartlett et al. (2022), in that we rely on the institutional setting of the GSE mortgage market in underwriting credit risk. When a lender wants to sell a mortgage to a GSE such as Fannie Mae or Freddie Mac, they must submit the applicant data that will allow the GSE to evaluate the applicant's eligibility (credit score, income, LTV, DTI, etc.) to the GSE's automated underwriter system. The GSE charges the lender a guarantee fee (or g-fee) to cover project borrower default and operational costs. The g-fee charged for the loan is depicted in a loan-level pricing adjustment (LLPA) grid, varying across credit scores and LTV ratios. In essence, a lender are guaranteed against credit risk by the GSE by selling their loan to them, and the GSE charges the lender for this service. Lenders pass on the increase in costs to applicants that reflect the credit risk information given by the applicants' credit history and other relevant data.

[7]The prime mortgage market rate for each month is taken from Freddie Mac' Primary Mortgage Market Survey

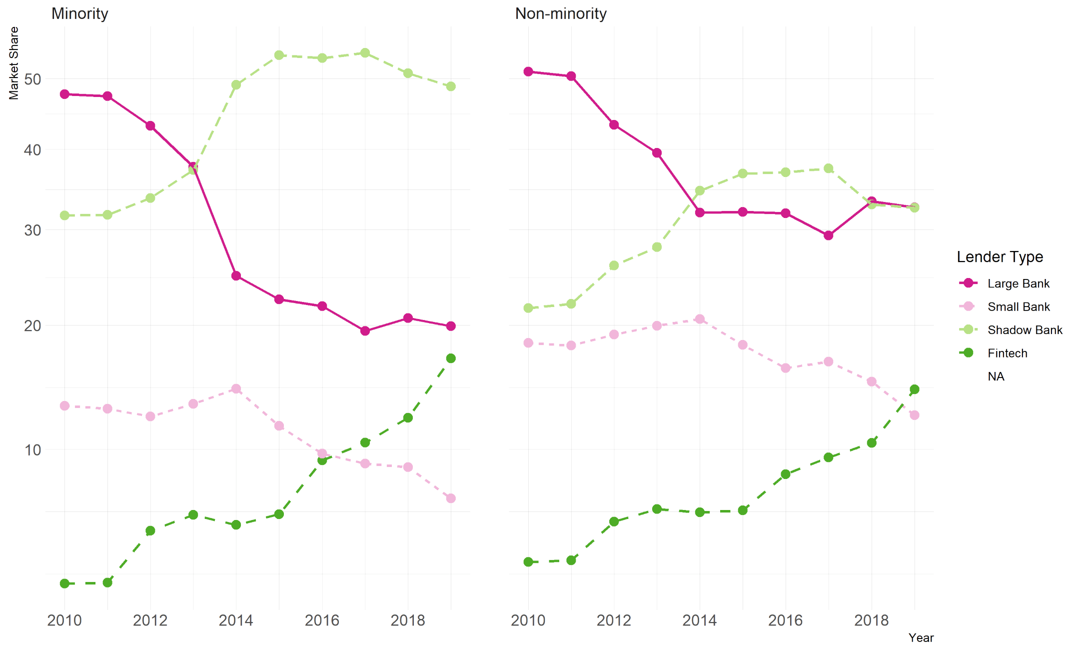


(a) By minority status



(b) By ethnicity status

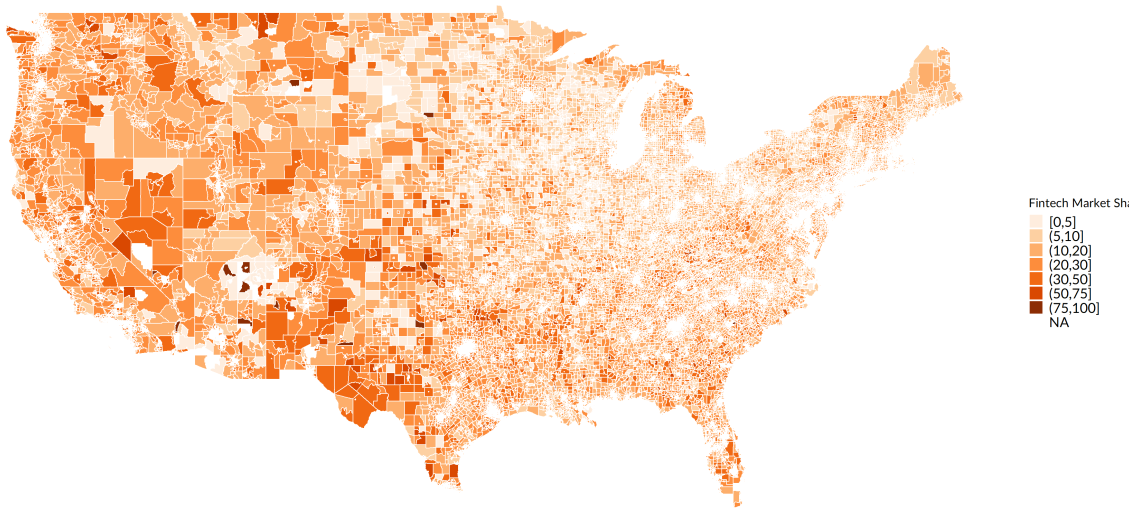
Figure 1: Aggregate Mortgage Lending by Minority Status and Ethnicity



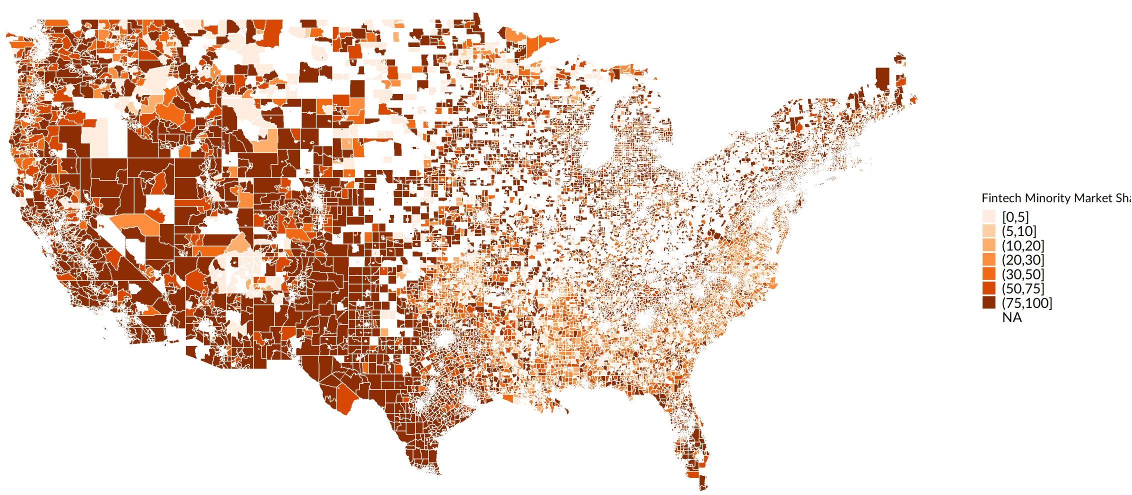
(a) By minority status

(b) By ethnicity status

Figure 2: Aggregate Mortgage Lending by Minority Status and Ethnicity



(a) All mortgages



(b) Minority mortgages

Figure 3: Geography of fintech penetration

Table 2: Fintech penetration and minority credit access

Panel A: All Mortgages

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.007 ***	0.007 ***	0.008 ***	0.004 ***	0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	413168	373987	310791	306860	230824
Adj. R^2	0.851	0.822	0.758	0.842	0.514

Panel B: Home Purchase

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.006 ***	0.007 ***	0.007 ***	0.004 ***	0.002 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	376049	321718	246528	260210	137312
Adj. R^2	0.806	0.786	0.734	0.802	0.546

Panel C: Refinancing

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.011 ***	0.01 ***	0.011 ***	0.008 ***	0.005 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	364454	292619	234145	218370	146125
Adj. R^2	0.795	0.777	0.715	0.809	0.516

This table displays the correlation between statewide Fintech penetration and the total lending to minority borrowers. The dependent variable is log dollar volume of mortgage loans originated for each demographic. Column (1)'s sample includes loans originated to borrowers who are not indicated as White or Asian in the HMDA dataset. Standard errors are clustered at the census tract level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 3: Fintech penetration and minority market share

Panel A: All Mortgages

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.059 ***	0.033 ***	0.042 ***	-0.014 ***	-0.001
	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	413168	373987	310791	306860	230824
Adj. R^2	0.91	0.916	0.897	0.901	0.606

Panel B: Home Purchase

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.015 ***	0.012 **	0.005	-0.037 ***	-0.012 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	376049	321718	246528	260210	137312
Adj. R^2	0.868	0.872	0.843	0.848	0.575

Panel C: Refinancing

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.053 ***	0.011 **	0.064 ***	-0.006	0.016 ***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	364454	292619	234145	218370	146125
Adj. R^2	0.85	0.858	0.829	0.836	0.522

This table displays the correlation between statewide Fintech penetration and the market share of minority borrowers. The dependent variable is log dollar volume of mortgage loans originated for each demographic. Column (1)'s sample includes loans originated to borrowers who are not indicated as White or Asian in the HMDA dataset. Standard errors are clustered at the census tract level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

We control for the credit risk of a borrower by forming credit score/LTV buckets similar to the cells displayed on a GSE LLPA pricing grid. The key idea behind this identification strategy is that the GSE pricing grid completely determines the price paid for the GSE to absorb all credit risk, and thus differences in pricing with a given credit score/LTV grid cell for interest rates and non-interest costs cannot reflect differential credit risk, but instead reflects discrimination in pricing.

Our suggest that fintech lenders are less discriminatory to minority borrowers in terms of costs for refinancing mortgages, but not home purchase loans. For mortgages originated by fintech lenders, the difference in interest rates for minority borrowers for mortgages compared to non-minority borrowers is eliminated entirely for refinancing mortgages, but is unchanged for home purchase mortgages. In terms of non-interest costs, for refinancing mortgages, the differences between minority and non-minority prices are reduced by 43% for origination charges, 30% for discount points, and 49% for total non-interest costs. However, similar to our findings for interest rates, these results apply only for refinancing mortgages, rather than home purchase mortgages.

We further explore the demographics and characteristics of minority borrowers that benefit the most from fintech, as well as how discrimination and lending costs for both fintech and non-fintech lenders change as fintech becomes more dominant in an area.

4.1 Fintech vs. Non-fintech Lenders

We first examine the average difference in mortgage costs charged by fintech and non-fintech lenders to minority and non-minority borrowers. Figure 4 shows average mortgage lending costs by lender type and minority status for all matched mortgages in our sample.

In general, the pattern we find across every measure of mortgage costs and across each sector of the mortgage market are that minority borrowers are charged higher costs than non-minority borrowers for each type of lender.[8] The rate spread for non-minorities in the home purchase market ranges from 0.224% to 0.335%, and for minorities ranges from 0.313% to 0.446%. A similar pattern holds for refinancing (0.211% to 0.373% for non-minorities, and 0.323% to 0.471% for minorities), and for individual non-interest cost categories as well. Furthermore, the pattern holds across lender type, with each type of

[8] Small bank lenders are defined as banks with less than $10 billion in total assets, while large bank lenders have more than that amount in total assets. Shadow bank lenders are defined as non-depository lenders that do not fit the definition of fintech lenders.

lender charging minority borrowers more than non-minority borrowers, including fintech lenders. This finding alone doesn't prove racial or ethnic discrimination, as lenders could be charging minority borrowers higher costs due to credit risk or other factors that make lending to minority borrowers a legitimately riskier business decision. Nevertheless, we can see that in raw numbers, fintech lenders do not give minority borrowers better prices in terms of interest rates and non-interest costs.

When we take a deeper look at costs by lender type, we find that small banks charge the lowest amounts in terms of interest rates and non-interest costs in general[9], while fintech lenders have the highest non-interest costs across all three measures and for each market. Compared to non-fintech shadow bank lenders, fintech lenders Since fintech lenders tend to have higher rates of securitization compared to other lenders (Buchak et al. (2018), Law and Mislang (2022)), it fits the business model of fintech lenders to pass on higher non-interest costs to borrowers rather than higher interest rates, as fintech lenders will profit from any up-front non-interest costs, but not from long-term payments on interest that will instead be given to investors purchasing mortgage-backed securities from Fannie Mae and Freddie Mac.

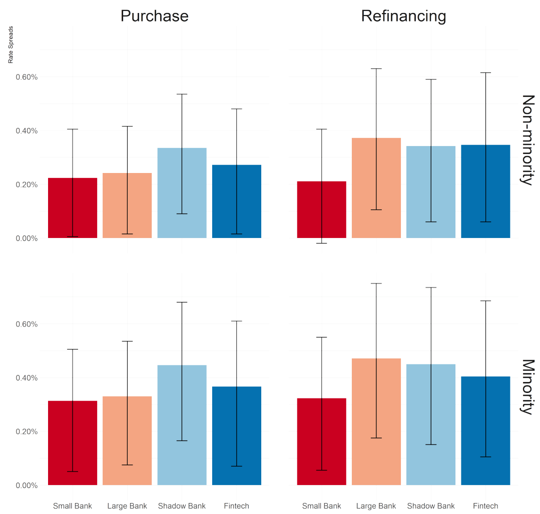
Figure A.1 breaks down costs even further by race and ethnicity. The general patterns previously described across lenders and minority groups still hold when breaking costs down by individual groups. Of note is that Asian borrowers, which we do not include as part of minority borrowers, consistently get the lowest mortgage prices even in comparison to white borrowers.

For Table 4, our empirical specification regresses different cost measures of a mortgage on an indicator for the borrower being a minority applicant, an indicator for the lender being a fintech lender, and the interaction between the two lenders, while controlling for risk and lender and time variation, to determine whether fintech lenders reduce discrimination in mortgage pricing. For Panel A of Table 4, we run the following regression,

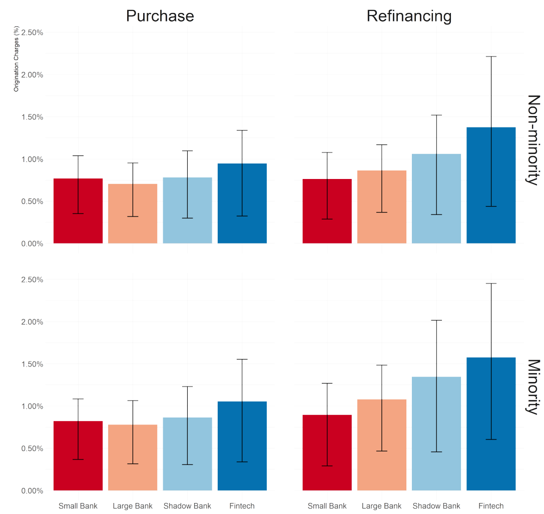
$$y_{i,l,t} = \beta_1 \text{Minority}_{i,t} + \beta_2 \text{Fintech}_{l,t} + \beta_3 \text{Minority}_{i,t} \times \text{Fintech}_{l,t} + X_{i,t} + \mu_{l,t(y)} + \delta_{i,t} + \varepsilon_{i,l,t} \tag{1}$$

$y_{i,l,t}$ equals a specific mortgage cost for a loan originated by lender l to borrower i at time t. The measures of costs we use include the interest rate spread, origination charges,

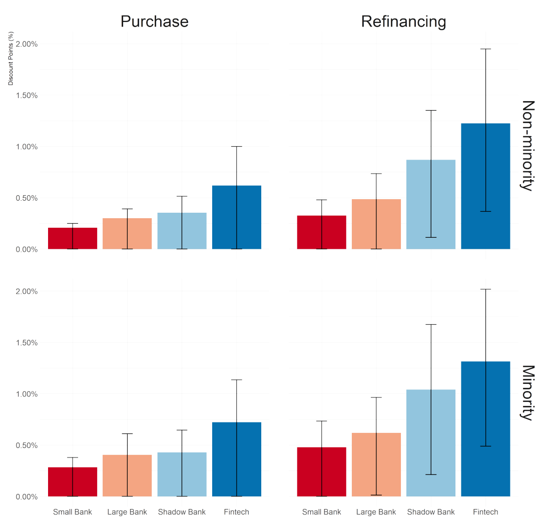
[9]For origination charges and total non-interest costs, small bank costs edge out large bank costs in the home purchase market, but are smaller than large bank costs again in the refinancing market.



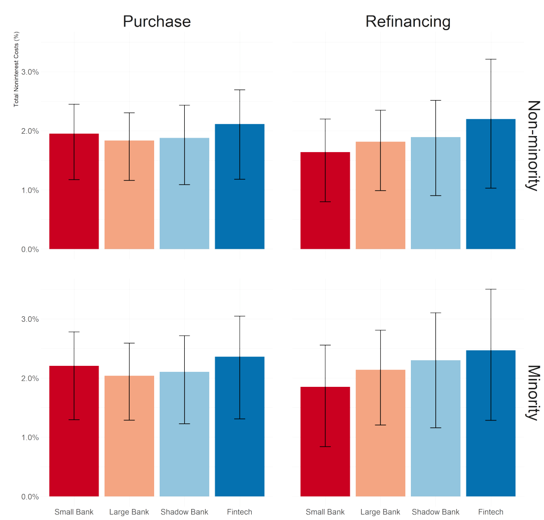
(a) Rate Spreads



(b) Origination Charges



(c) Discount Points



(d) Total Non-interest Costs

Figure 4: Mortgage Lending Costs by Minority Status

discount points, and total non-interest costs.[10] $\text{Minority}_{i,t}$ indicates whether borrower i is a minority applicant, and $\text{Fintech}_{l,t}$ indicates whether lender l is a fintech lender. $X_{i,t}$ are controls for the mortgage, including owner occupancy, sex, log loan amount, log income, and number of borrowers. $\mu_{l,t(y)}$ are lender by year fixed effects, which capture differential pricing by lenders over time. $\delta_{i,t}$ are the GSE LLPA credit score/LTV grid by year/month fixed effects, which allow us to capture pricing effects with each grid, while also allowing us to capture pricing fluctuations over time. We run Equation 1 for each mortgage cost category, and for home purchase and refi mortgages separately, to examine the heterogeneity in the impact of fintech on discriminatory outcomes for different sectors of the mortgage market.

Our main coefficients of interest are β_1, which measures the average difference in costs that minorities pay compared to non-minority borrowers, and β_3, which measures the difference in the minority differential between fintech lenders and non-fintech lenders. Based on the previous literature (Bartlett et al. (2022), Black, Schweitzer, and Mandell (1978)), we expect β_1 to be positive and significant, indicating significant minority discrimination in the mortgage market. If fintech lenders are significantly less discriminatory than non-fintech lenders, β_3 should be negative and significant, reflecting the removal of discrimination in mortgage pricing decisions by the algorithms underlying fintech lending decisions.

Panel A of Table 4 displays the results of Equation 1. For both GSE-purchase and refi mortgages, we find that even after controlling for risk, lender, and time variation, minorities pay significantly higher mortgage costs than non-minority borrowers across all measures of cost. Minority borrowers pay 1.25-4.19 bps more interest rates and 6-17 bps more in non-interest costs than non-minority borrowers. For interest rates, as minorities pay a premium in costs in both interest rates and discount points, we can see that on average, the minority premium in interest rates is not being offset by smaller payments for discount points in comparison to non-minorities. As such, we can conclude that significant discrimination in credit availability exists for minority borrowers in the mortgage market. [11]

[10] Non-interest costs are expressed as a percentage compared to the mortgage principal.

[11] In comparison to the previous literature, our interest rate differential estimates are closely in line with those found in Bartlett et al. (2022), which finds a 4.67 bps and 1.63 bps interest rate difference for home purchase and refi mortgages, respectively, between minorities and non-minorities. Bartlett et al. (2022) matches HMDA data with the proprietary Optimal Blue dataset, while our paper matches HMDA with public data provided by Fannie Mae and Freddie Mac. Despite the difference in data used, we still find very similar results in terms interest rate differentials. However, Bartlett et al. (2022) estimates that there are no differences in interest rate disparities for minorities for GSE mortgages between fintech and non-

For fintech lenders' impact on minority discrimination, we find significant differences between home purchase and refi mortgages. For home purchase mortgages, fintech lenders do not significant charge minorities lenders less than non-fintech lenders for any measure we use in our model. However, for refinancing mortgages, fintech lenders charge minority borrowers significantly less than non-fintech lenders across all mortgage cost measures. Fintech lenders charge minority borrowers 1.33 bps less in interest rates and 8.53 bps less in total non-interest costs. For interest rates, minority discrimination in terms of interest rates is absent for fintech refi mortgages. In terms of non-interest costs, fintech lenders reduce minority discrimination by 49% in terms of total non-interest costs. Thus, even though fintech lenders charge minority borrowers higher costs on average, when controlling for risk, they charge significantly lower costs compared to non-fintech lenders.

Panel B of Table 4 looks at the impact of fintech on discrimination by looking at race and ethnicity.[12] For Panel B, we rerun Equation 1, replacing $\text{Minority}_{i,t}$ with indicators for indicators for Black, Asian, Hispanic, and other non-white descent. Again, we find significant increases in mortgage costs for minority groups, with the effect of fintech on minority discrimination being insignificant for home purchase mortgages, and negative and significant for refi mortgages. Amongst minority groups, we find that Hispanic borrowers benefit the most from fintech lenders in terms of cost, as across all minority groups, Hispanic borrowers are the only minority group to have a negative and significant β_3 coefficient across all measures of mortgage costs for refi mortgages. By comparison, Black borrowers benefit from fintech lenders in terms of mortgage pricing only for total non-interest costs for refi mortgages. Even then, Black borrowers benefit less than Hispanic borrowers - fintech lenders charge Black borrowers 4.82 bps less total non-interest costs, but charge Hispanic borrowers 17.14 bps less total non-interest costs.

4.2 Discount points and interest rate trade-offs

When a borrower chooses to approach a lender for a mortgage, a lender may present a borrower a "menu" with different combinations of interest rates and discount points to choose from. A borrower can choose to pay discount point, with each point equal to 1% of

fintech lenders, and only 27% and 36% lower for FHA home purchase and refi mortgages respectively. In comparison, we find that fintech lenders eliminate interest rate disparities for minority borrowers, as well as significantly lower disparities for non-interest costs, for GSE refi mortgages.

[12] Although we do not include Asian as falling under the heading of a minority borrower in line with the literature, we still include an indicator for Asian descent in our model, as Asian borrowers have significantly different mortgage costs than White borrowers.

Table 4: Mortgage costs and minority status

	Panel A: Minority Status							
	Rate Spreads		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority	4.194 ***	1.25 ***	6.267 ***	12.382 ***	5.63 ***	5.928 ***	17.138 ***	17.246 ***
	(0.371)	(0.299)	(0.769)	(1.293)	(0.679)	(0.617)	(1.522)	(2.244)
Fintech	-0.826	2.153	-7.144 *	-1.982	-9.784 ***	-7.351	-1.12	-4.275
	(1.587)	(2.611)	(4.27)	(9.43)	(4.034)	(23.092)	(2.925)	(12.097)
Minority * Fintech	-0.366	-1.326 *	1.257	-5.354 **	0.707	-1.798 **	-0.688	-8.526 ***
	(1.049)	(0.775)	(1.477)	(1.522)	(0.931)	(0.824)	(2.514)	(2.238)
Lender X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.575	0.598	0.282	0.402	0.256	0.394	0.468	0.599
Observations	968522	725400	584872	261852	377124	156522	637181	368445

	Panel B: Ethnicity							
	Rate Spreads		Origination Charges		Discount Points		Total Non-interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	3.342 ***	1.524 ***	6.842 ***	15.02 ***	8.341 ***	10.722 ***	14.665 ***	19.472 ***
	(0.304)	(0.308)	(0.827)	(1.723)	(0.659)	(1.426)	(1.604)	(2.52)
Asian	-2.062 ***	-0.922 *	5.702 ***	-1.219	5.734 ***	1.052	11.136 ***	-2.126
	(0.438)	(0.491)	(1.185)	(2.334)	(1.26)	(1.532)	(2.095)	(2.322)
Hispanic	4.567 ***	1.156 ***	7.378 ***	11.207 ***	5.615 ***	2.949 ***	21.471 ***	16.557 ***
	(0.402)	(0.374)	(1.046)	(1.27)	(0.935)	(0.802)	(1.833)	(2.385)
Other	1.461 ***	0.097	2.982 **	9.781 ***	2.515 **	10.766 ***	6.115 ***	11.456 ***
	(0.552)	(0.539)	(1.439)	(2.049)	(1.178)	(2.845)	(2.321)	(1.872)
Fintech	-0.77	2.518	-5.711	-0.286	-8.107 **	-6.609	0.582	-2.464
	(1.591)	(2.634)	(3.897)	(9.593)	(3.355)	(23.222)	(2.957)	(12.55)
Black * Fintech	-0.197	-0.917	2.869	0.874	0.473	-0.437	2.908	-4.82 *
	(1.136)	(0.99)	(2.601)	(2.733)	(1.305)	(1.68)	(3.33)	(2.468)
Asian * Fintech	-0.699	-4.43 **	-9.905	-23.545 *	-12.013	-12.669 ***	-11.254	-24.842 *
	(0.901)	(1.815)	(7.702)	(12.445)	(10.196)	(4.39)	(10.125)	(13.398)
Hispanic * Fintech	-0.594	-2.301 **	-2.4	-14.531 ***	-1.844	-5.734 ***	-5.591 **	-17.142 ***
	(1.181)	(0.98)	(2.219)	(3.398)	(2.505)	(1.773)	(2.376)	(3.673)
Other * Fintech	0.441	-0.921	9.233 ***	4.272 *	5.892 ***	-1.185	8.796 *	5.417 *
	(0.977)	(0.708)	(2.309)	(2.352)	(2.012)	(3.666)	(4.498)	(2.932)
Lender X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.575	0.599	0.283	0.404	0.257	0.395	0.469	0.6
Observations	968338	725272	584756	261837	377045	156512	637056	368424

The dependent variable are mortgage costs in terms of basis points. For Columns (3) through (8), costs are expressed as a ratio of dollar costs to the mortgage principal. The independent variables are indicator variables for the minority status and whether the lender was a fintech lender, along with the interaction between the fintech lender status and borrower demographic. Controls include the log mortgage amount, log income, owner occupancy status, sex, and number of borrowers. Fixed effects are included for GSE-grid bucket by year/month and lender by year. Standard errors are clustered at the lender level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

the mortgage balance, in exchange for a lower interest rate.[13] The menus that are offered, and thus the trade-off between interest rates and non-interest costs, vary from lender to lender, and thus can reflect price discrimination. Though the borrower can choose any combination of discount points and interest rates from the menu presented by the lender, the options that are presented are set by the lender, and thus the options a borrower is presented with by a lender can reflect discrimination if options that are offered to a minority borrower are less favorable than options offered to a non-minority borrower. Conversely, fintech lenders could also reduce discrimination if the options that are offered to a minority applicant to a fintech lender are more favorable than options offered by a non-fintech lender.

Taking a closer look at the trade-off between interest rates and discount points, and how fintech lenders compare to non-fintech lenders, we borrow from Bhutta and Hizmo (2020) and compare the interest rates offered for differing amounts of discount points bought, conditional on lender fintech status and borrower race and ethnicity. Figure 5 plots the average amount of discount points paid versus the interest rate spread offered by lender status and race and ethnicity. For larger rate spreads, fintech lenders offer better deals than non-fintech lenders on average. However, as the rate spread decreases, the gap between fintech lenders and non-fintech lenders shrinks, suggesting that fintech lenders lower interest rates by a lesser amount than non-fintech lenders for one discount point. Furthermore, Asian and Hispanic borrowers benefit more than white and Black borrowers from fintech lenders in terms of the discount point-interest rate trade-off. For every rate spread amount on Figure 5, Asian and Hispanic borrowers pay a less discount points to a fintech lender than to a non-fintech lender. The effect is more ambiguous for Black and White borrowers, who pay less discount points at higher rate spread amounts, but more discount points at lower rate spread amounts, to fintech lenders than to non-fintech lenders. For these borrowers in general, paying more discount points for lower interest rates is not a good deal when receiving a mortgage from a fintech lender, which is in line with papers such as Agarwal, Ben-David, and Yao (2017), which finds paying for discount points to not be a worthwhile investment for most mortgage borrowers.

[13]Lender credits represent the opposite of discount points, where a borrower can receive more up-front cash/pay lower upfront fees in return for a higher interest rate.

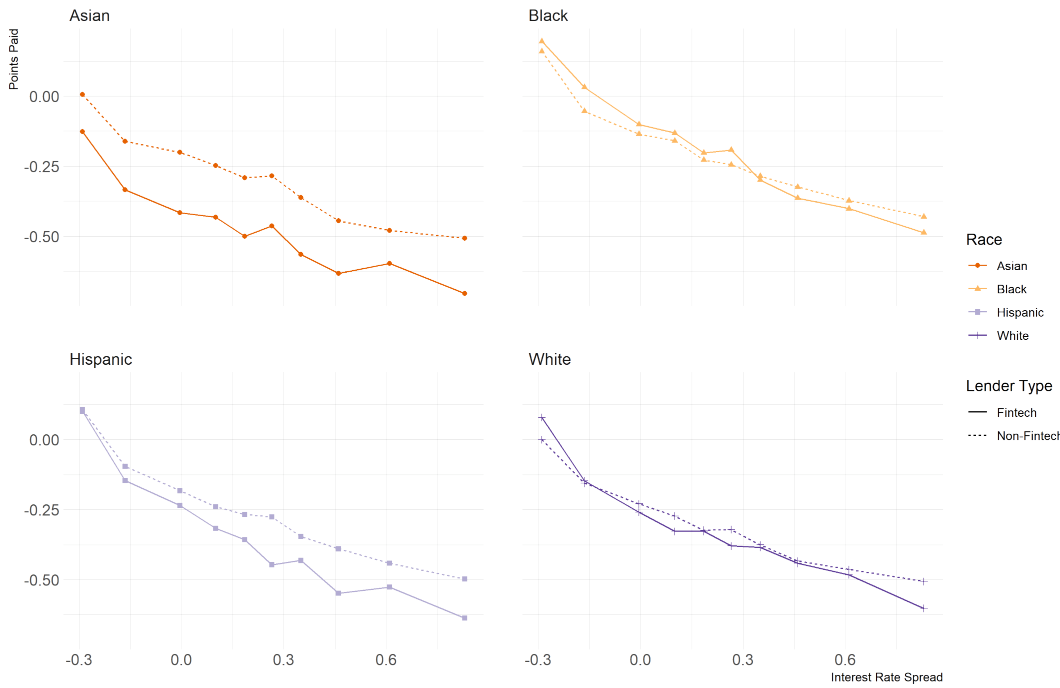


Figure 5: Trade-off between discount points and interest rates by race and fintech status
This figure plots coefficients from regression of discount points on interest rate spread deciles interacted with race and ethnicity indicators and a fintech lender indicator. Only white, Black, Asian, and Hispanic borrowers with interest spreads over -50 bps and under 110 bps are included in the regression. Controls include lender by year fixed effects, GSE grid buckets by year/month fixed effects, log loan amount, log income, owner occupancy, sex, and number of borrowers.

4.3 High quality borrowers

Though Panel B of Table 4 breaks down the benefits of fintech lending to minorities by race and ethnicity, another question that can be raised is whether the gains in credit availability by fintech lenders are going to more credit worthy or less credit worthy borrowers. Much of the literature on fintech (Di Maggio and Yao (2020), Erel and Liebersohn (2020), Tang (2019), Law and Mislang (2022)) looks at how fintech complements or substitutes for more traditional lenders, particularly if fintech lenders ”bottom-fish” or ”cream-skim” from other lenders.[14] We rerun Equation 1 for borrowers with credit scores of at least 720 and LTV ratios at most 70%, focusing only on high quality borrowers.[15]

For Panel A of Table 5, β_1 is smaller for each column (save for Columns (5) and (6)) compared to its counterpart in Table 4, suggesting that minority price discrimination amongst higher quality borrowers is smaller on average. Furthermore, for both Panels A and B, β_3 is either less significant or more positive for every column, suggesting that for high quality minority borrowers in general, fintech lenders offer no advantage in costs for either home purchase or refi mortgages. Asian borrowers are the only high quality borrowers that benefit in terms of interest rate, while both Asian and Hispanic high quality borrowers benefit less from fintech lenders in terms of non-interest costs compared to lower quality borrowers. Taken together, these results suggest that the benefits of fintech on credit availability to minority borrowers have mainly accrued to borrowers that, at least on paper, are of comparatively lower quality and carry higher credit risk for lenders.

4.4 Fintech expansion

Though the previous sections suggest that fintech lenders charge minority borrowers significantly lower costs than non-fintech lenders when accounting for risk, the question is raised as to whether they continue to do so once they become more dominant in a market. Di Maggio and Yao (2020) establishes that fintech lenders shift lending towards more creditworthy borrowers as they become more entrenched in a market, which raises the

[14]”Bottom-fishing” refers to taking lower quality borrowers away from non-fintech lenders, whereas ”cream-skimming” refers to taking higher quality borrowers away.

[15]We also run another regression for even higher quality borrowers with credit scores of at least 740 and LTV ratios below 60%, focusing on borrowers in the highest quality grid of the GSE LLPA matrix. We are forced to replace the GSE bucket times month fixed effects with only month fixed effects, as according to the identification strategy, all borrowers remaining in our sample have the same level of credit risk. Our results from Table 5 are not qualitatively affected.

Table 5: Mortgage costs and minority status - high quality borrowers

Panel A: Minority Status

	Rate Spreads		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority	2.437 ***	1.282 ***	6.912 ***	11.255 ***	7.197 ***	5.776 ***	18.49 ***	16.395 ***
	(0.304)	(0.32)	(1.299)	(1.464)	(1.185)	(0.953)	(1.936)	(2.475)
Fintech	1.527	4.089	-24.194 ***	10.065	-15.092 ***	4.637	-19.142 *	13.46
	(2.227)	(3.44)	(5.128)	(6.564)	(4.938)	(16.817)	(10.478)	(9.036)
Minority * Fintech	-0.714	-0.671	6.391	0.569	8.773 ***	2.192	1.627	-3.511
	(0.684)	(0.54)	(3.937)	(2.668)	(2.888)	(1.506)	(4.972)	(4.197)
Lender X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.538	0.59	0.303	0.41	0.233	0.404	0.468	0.594
Observations	109045	217151	70611	74073	46777	43206	71151	74317

Panel B: Ethnicity

	Rate Spreads		Origination Charges		Discount Points		Total Non-interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.568	2.115 ***	5.939 ***	13.077 ***	9.604 ***	10.443 ***	14.581 ***	19.443 ***
	(0.522)	(0.308)	(2.255)	(1.732)	(2.025)	(1.576)	(3.526)	(2.45)
Asian	-1.628 ***	-0.623	7.249 ***	-1.405	7.007 ***	1.165	15.984 ***	-2.643
	(0.418)	(0.513)	(1.46)	(2.491)	(1.579)	(2.258)	(2.354)	(3.004)
Hispanic	3.169 ***	1.193 ***	8.45 ***	10.162 ***	7.431 ***	2.64 **	23.397 ***	14.972 ***
	(0.326)	(0.365)	(1.618)	(1.598)	(1.367)	(1.238)	(2.462)	(2.728)
Other	-0.208	-0.883 *	6.554 **	12.108 ***	4.634	16.925 ***	11.093 ***	14.724 ***
	(1.014)	(0.474)	(3.111)	(2.969)	(3.735)	(3.159)	(3.517)	(3.493)
Fintech	1.34	4.569	-22.116 ***	12.483 *	-12.948 **	5.422	-16.776	15.764 *
	(2.271)	(3.45)	(4.77)	(6.376)	(3.355)	(16.365)	(11.187)	(9.287)
Black * Fintech	0.068	-0.256	11.022 ***	0.874	15.576 **	4.618 *	11.357	2.952
	(1.897)	(0.818)	(8.135)	(3.724)	(7.101)	(2.209)	(9.146)	(5.294)
Asian * Fintech	0.868	-4.775 *	-12.724	-31.701 **	-13.94	-20.792 ***	-14.124	-30.959 *
	(0.893)	(2.547)	(10.357)	(15.814)	(10.471)	(5.868)	(10.426)	(17.436)
Hispanic * Fintech	-0.649	-1.615	-0.023	-13.145 ***	5.131 *	-3.833 *	-4.636	-15.833 ***
	(0.893)	(1.066)	(3.197)	(3.085)	(2.983)	(2.042)	(3.556)	(3.438)
Other * Fintech	-1.357	-0.672	15.544	12.834 **	1.747	0.44	11.716	14.869 **
	(2.129)	(1.095)	(10.662)	(5.46)	(7.205)	(5.168)	(16.269)	(6.359)
Lender X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.538	0.59	0.303	0.413	0.235	0.395	0.505	0.596
Observations	109024	217110	70596	74069	46768	43202	71136	74313

The dependent variable are mortgage costs in terms of basis points. For Columns (3) through (8), costs are expressed as a ratio of dollar costs to the mortgage principal. The independent variables are indicator variables for the minority status and whether the lender was a fintech lender, along with the interaction between the fintech lender status and borrower demographic. Controls include the log mortgage amount, log income, owner occupancy status, sex, and number of borrowers. Fixed effects are included for GSE-grid bucket by year/month and lender by year. Standard errors are clustered at the lender level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

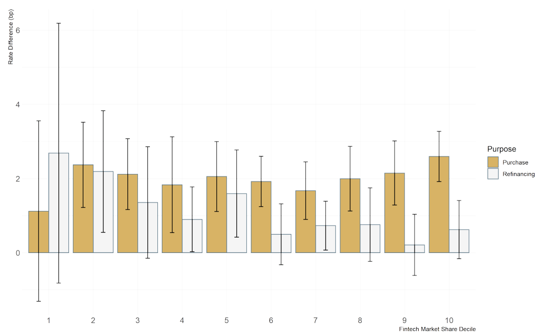
question if a similar pattern occurs in terms of lending costs. Do fintech lenders initially offer minority borrowers competitive interest rates and fees, only to raise their prices once they are more established and less worried about competition from non-fintech lenders? If so, any policy proposals aimed at promoting the growth of fintech to benefit minority borrowers may backfire if fintech lenders become more discriminatory as they gain market share.

First, we examine the correlation between overall discrimination and fintech penetration in a market. Figure 6 plots the difference in minority and non-minority costs against fintech market share across all mortgages in our sample. For home purchase mortgages, we see no pattern of change in price discrimination as fintech becomes more dominant in an area. For refi mortgages, however, we see a significant change in average price differentials with increasing fintech penetration of a market. Greater fintech market share is correlated with smaller rate spread differentials, and higher origination charges and total non-interest cost differentials between minorities and non-minorities. By itself, these facts do not indicate whether it is the growth of fintech that is driving these changes, or whether the change in average price differentials are due to the relative distribution of mortgage originations shifting towards fintech lenders or due to non-fintech lenders changing their pricing behavior for minority borrowers.

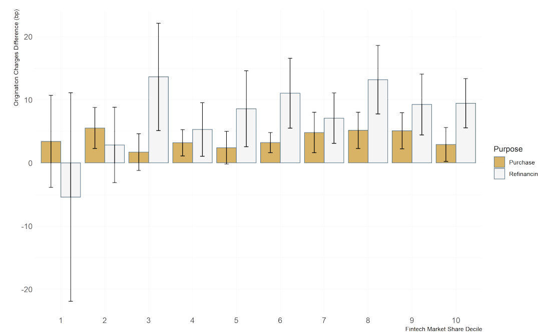
Tables 6 and 7 looks directly at the changes in mortgage pricing by fintech and non-fintech lenders as fintech becomes more dominant in a market. We run the following fixed-effects model to estimate the impact of fintech dominance on mortgage prices:

$$
\begin{aligned}
y_{i,l,c,t} = & \beta_1 \text{Minority}_{i,t} + \beta_2 \text{Fintech}_{l,t} + \beta_3 \text{Minority}_{i,t} \times \text{Fintech}_{l,t} \\
& + \beta_4 \text{Fintech Market Share}_{c,t} + \beta_5 \text{Minority}_{i,t} \times \text{Fintech Market Share}_{c,t} \\
& + \beta_6 \text{Minority}_{i,t} \times \text{Fintech Market Share}_{c,t} \times \text{Fintech}_{l,t} \\
& + X_{i,t} + \gamma_{c,t(y)} + \delta_{i,t} + \varepsilon_{i,l,t}
\end{aligned} \tag{2}
$$

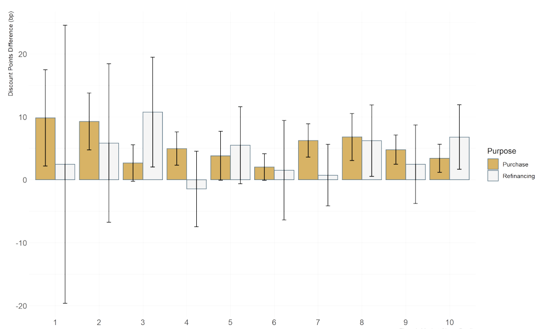
$y_{i,l,c,t}$ equals a specific mortgage cost for a loan originated by lender l to borrower i located in census tract c at time t. Fintech Market Share$_{c,t}$ equals the market share of fintech in census tract c at time t. $\gamma_{c,t(y)}$ are census tract by year fixed effects, which capture geographic and temporal variation in mortgage pricing. Other indicator variables, controls and fixed effects are the same as in Equation 1. Similar to Equation 1, we run Equation 2 for each mortgage cost category, and for home purchase and refi mortgages separately. Our main coefficients of interest are β_5, which measures average changes in



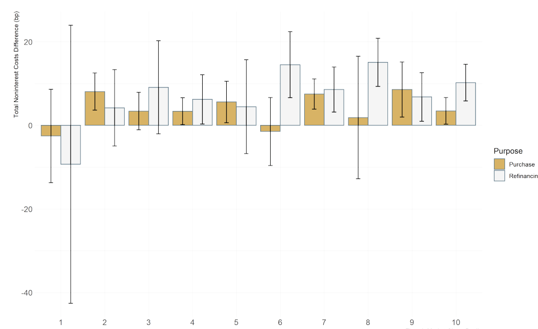
(a) Rate Spreads



(b) Origination Charges



(c) Discount Points



(d) Total Noninterest Costs

Figure 6: Fintech Penetration and Minority Premiums

This figure displays the correlation between fintech penetration of a market and the minority discrimination in mortgage prices. We regress mortgage costs by fintech market share decile and an indicator for a borrower's minority status, with controls for log loan amount, log income, owner occupancy status, sex, number of borrowers, census tract by year fixed effects, and GSE bucket by month fixed effect. Standard errors are clustered by lender. Solid bars display the estimated coefficient, and errors bars display the 95% confidence interval.

minority lending costs with increasing fintech penetration, for mortgages originated by all lender types, and β_6, which measures changes in minority lending costs for fintech originated mortgages specifically.

Table 6 displays the results of Equation 2, showing the changes in minority mortgage pricing with increasing fintech market penetration. For every column, β_5 is statistically insignificant, suggesting that non-fintech lenders do not significantly change relative minority lending costs in areas with greater fintech market share. As such, we can conclude that the changes in pricing discrimination amongst refinancing loans observed in Figure 6 are driven mainly by a shift towards fintech lenders in markets with greater fintech penetration. For prices from fintech loans specifically, β_6 is positive and significant in Columns (1) and (8), which suggest that a 1% increase in fintech market share is associated with a 0.4 bps increase in fintech home purchase mortgage interest rates, and a 3.2 bps increase in fintech refi non-interest costs.

One way to interpret the increase in fintech lending costs to minorities as fintech becomes more dominant in a market is to suggest that fintech cost reduction for minorities observed in Subsection 4.1 is used to established a foothold amongst minority borrowers in a market by offering better prices initially, and then gradually raising prices for mortgages as they gain market share. A similar story can be found in Di Maggio and Yao (2020), which finds fintech lenders in the consumer credit market initially lending to less creditworthy borrowers, and then increase market share by extending credit to higher quality borrowers later. However, in terms of interest rates, we see the rise in the fintech price differential for minorities amongst home purchase mortgages rather than amongst refi mortgages where fintech lenders are less discriminatory, suggesting against this interpretation.

Another interpretation is that the changes in minority fintech cost premiums are related to the business model of fintech lenders. Section 5 finds that amongst minority borrowers looking for a home purchase mortgage, fintech lenders originate to less creditworthy borrowers on average. As such, it is possible that fintech lenders are willing to offer comparatively better rates initially to attract market share amongst purchasing mortgages, and then gradually raise rates as they become more established, as the borrowers they attract for home purchase mortgages have less options to switch to different lenders due to lower credit ratings. Similarly, for refinancing mortgages, comparatively lower interest rates attract borrowers looking to refinance their original mortgages. As fintech lenders become more established, they are more likely to raise non-interest costs, partly to retain competitive advantage against non-fintech lenders in terms of interest rates, and also due to only being able to collect up-front non-interest fees from securitization.

Table 6: Fintech penetration and Mortgage Costs - Minority Status

	Rate Spreads		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority	0.955	1.065 **	1.489	12.977 *	4.791 *	11.717 *	4.915	18.08 **
	(0.673)	(0.507)	(2.781)	(6.785)	(2.679)	(6.922)	(3.419)	(8.076)
Fintech	3.298	12.428 ***	38.521 ***	68.449 ***	28.761 **	56.092 ***	46.203 ***	66.2 ***
	(2.935)	(3.924)	(13.501)	(15.166)	(11.756)	(16.356)	(14.652)	(15.289)
Minority * Fintech	-4.478 *	-4.17 ***	1.071	-29.861 ***	-3.249	-11.69	-10.248	-53.566 ***
	(2.403)	(1.491)	(6.608)	(0.6)	(4.257)	(11.306)	(9.278)	(10.65)
Fintech Market Share	0.007	0.342	0.38	0.007	0.399	-0.791	0.395	1.026
	(0.181)	(0.333)	(0.44)	(1.203)	(0.543)	(2.035)	(0.628)	(1.213)
Minority * Fintech Market Share	0.084	0.014	0.127	-0.199	-0.038	-0.322	-0.021	-0.42
	(0.067)	(0.058)	(0.185)	(0.346)	(0.174)	(0.401)	(0.254)	(0.439)
Minority * Fintech Market Share * Fintech	0.365 *	0.196	0.094	1.853	0.487 **	0.334	0.754	3.192 ***
	(0.22)	(0.13)	(0.524)	(0.6)	(0.248)	(0.602)	(0.744)	(0.63)
Census Tract X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.579	0.599	0.317	0.379	0.311	0.333	0.517	0.582
Observations	920048	667191	536037	201685	357270	131351	538709	202457

The dependent variable are mortgage costs in terms of basis points. For Columns (3) through (8), costs are expressed as a ratio of dollar costs to the mortgage principal. The independent variables are indicator variables for the borrower's minority status and whether the lender was a fintech lender, along with the interaction between the fintech lender status and borrower demographic. Controls include the log mortgage amount, log income, owner occupancy status, sex, and number of borrowers. Fixed effects are included for GSE-grid bucket by year/month and census tract by year. Standard errors are clustered at the lender level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 7 breaks down changes in minority mortgage pricing with fintech penetration even further by race and ethnicity, replacing $Minority_{i,t}$ in Equation 2 with race and ethnicity indicators similar to Panel B in Table 4. When we look at individual race and ethnicity categories, we see similar changes in costs for fintech minority mortgages in Columns (1) and (8) as in Table 6, but also increases in origination charges amongst fintech refi mortgages for minority borrowers as fintech market share grows. For all minority borrower categories (Black, Hispanic, and Other), a 1% increase in fintech market share is associated with a 1.8-1.9 bps increase in origination charges, and a 3-3.6 bps increase in total non-interest costs for refi mortgages.

5 Fintech and Borrower Quality

In this section, we examine the quality of minority borrowers that are targeted by fintech lenders in terms of income and credit worthiness, as well as the quality of borrowers of non-fintech lenders as fintech gains more market share. In doing so, we can gain a better understanding of whether fintech lenders substitute or complement non-fintech lenders for minority lending, and where the gains in consumer welfare by the growth of fintech lending are heading to for minority borrowers.

5.1 Who borrows from fintech lenders?

To examine the quality of fintech minority borrowers, we run the following regression:

$$\begin{aligned}\mathbb{1}(\text{Fintech})_{i,c,t} = &\beta_1 \text{Loan Amount}_{i,t} + \beta_2 \text{Income}_{i,t} + \beta_3 \text{Credit Score}_{i,t} \\ &+ \beta_4 \text{LTV}_{i,t} + \beta_5 \text{DTI}_{i,t} + \beta_6 \text{Age}_{i,t} + X_{i,t} + \mu_c + \delta_t + \varepsilon_{i,c,t}\end{aligned} \tag{3}$$

$\mathbb{1}(\text{Fintech})_{i,c,t}$ is an indicator variable for whether a borrower i located in county c at time t received a mortgage originated from a fintech lender. The main measures of borrower quality in our regression are Credit $\text{Score}_{i,t}$, $\text{LTV}_{i,t}$, and $\text{DTI}_{i,t}$. Negative βs for the former measure and positive βs for the latter two measures suggest lower borrower quality for fintech lenders. $\text{Age}_{i,t}$ are dummy variables for borrower age categories in

Table 7: Fintech penetration and Mortgage Costs - Race & Ethnicity

	Rate Spread		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	1.229	2.106 ***	1.088	13.773 *	6.34 *	8.866	8.248	18.339 **
	(0.941)	(0.609)	(3.59)	(7.416)	(3.648)	(9.314)	(5.106)	(7.493)
Asian	0.463	-1.368	8.134 ***	11.242	8.674 **	14.389	10.36 **	13.904
	(0.533)	(1.2)	(2.861)	(7.963)	(3.465)	(11.576)	(4.089)	(9.876)
Hispanic	1.366 **	0.032	3.418	10.755	4.132	12.083 **	5.473	16.335 *
	(0.618)	(0.644)	(3.262)	(7.235)	(3.451)	(5.756)	(4.459)	(8.998)
Other	-0.525	0.932	-0.356	24.291	9.652 *	28.462	-2.596	26.575
	(1.048)	(1.356)	(6.642)	(15.165)	(4.703)	(21.288)	(8.508)	(16.325)
Fintech	3.049	12.584 ***	40.622 ***	69.378 ***	31.585 **	58.805 ***	49.375 ***	68.158 ***
	(2.932)	(3.975)	(14.043)	(15.707)	(13.133)	(17.261)	(15.417)	(15.714)
Black * Fintech	-0.02	-3.859 **	-2.263	-24.112 **	-1.402	1.193	-13.034	-54.05 ***
	(2.967)	(1.526)	(12.298)	(11.995)	(9.563)	(13.152)	(13.003)	(12.361)
Asian * Fintech	0.172	-3.754	-22.801 **	-39.005 **	-31.747 *	-48.455 *	-34.279 **	-54.391 ***
	(1.825)	(2.931)	(9.84)	(16.667)	(16.962)	(28.646)	(13.991)	(19.001)
Hispanic * Fintech	-6.8 ***	-4.291 **	-2.052	-40.445 ***	-8.573	-20.671	-14.643	-61.602 ***
	(2.619)	(1.942)	(7.207)	(12.221)	(5.334)	(14.085)	(11.02)	(12.393)
Other * Fintech	-0.986	-6.141 ***	6.998	-23.107	1.376	-45.916	0.647	-47.926 **
	(3.592)	(2.405)	(18.139)	(19.707)	(16.878)	(28.536)	(28.413)	(21.446)
Fintech Market Share	0.049	0.345	0.417	0.012	0.426	-0.747	0.445	1.051
	(0.184)	(0.33)	(0.438)	(1.211)	(0.519)	(2.03)	(0.633)	(1.221)
Black * Fintech Market Share	0.039	-0.062	0.258	0.003	0.03	0.302	-0.067	-0.194
	(0.086)	(0.073)	(0.243)	(0.505)	(0.267)	(0.671)	(0.334)	(0.509)
Asian * Fintech Market Share	-0.264 ***	-0.198 **	-0.307 *	-0.969 **	-0.278	-1.379 *	-0.526 *	-1.367 **
	(0.06)	(0.096)	(0.175)	(0.453)	(0.252)	(0.756)	(0.27)	(0.58)
Hispanic * Fintech Market Share	0.026	0.0325	0.014	-0.222	0.019	-0.677 *	-0.094	-0.493
	(0.061)	(0.083)	(0.203)	(0.404)	(0.228)	(0.383)	(0.325)	(0.522)
Other * Fintech Market Share	0.067	0.038	0.177	-0.956	-0.63	-1.324	0.423	-1.085
	(0.089)	(0.157)	(0.491)	(0.786)	(0.44)	(1.107)	(0.716)	(0.919)
Black * Fintech Market Share * Fintech	-0.021	0.134	0.555	1.862 ***	0.474	-0.319	1.154	3.508 ***
	(0.235)	(0.147)	(0.736)	(0.716)	(0.655)	(0.728)	(0.746)	(0.8)
Asian * Fintech Market Share * Fintech	-0.404 *	0.052	0.665	0.74	0.868	2.194	1.339 *	1.843 *
	(0.237)	(0.257)	(0.737)	(0.739)	(1.031)	(1.894)	(0.757)	(1.004)
Hispanic * Fintech Market Share * Fintech	0.486 **	0.191	-0.064	1.803 ***	0.452	0.53	0.691	3.031 ***
	(0.226)	(0.167)	(0.562)	(0.687)	(0.299)	(0.882)	(0.866)	(0.713)
Other * Fintech Market Share * Fintech	0.117	0.33	0.073	1.895 *	0.601	2.828	-0.253	3.629 ***
	(0.289)	(0.204)	(1.412)	(1.106)	(1.282)	(1.861)	(2.018)	(1.237)
Census Tract X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.579	0.599	0.318	0.381	0.313	0.334	0.517	0.584
Observations	919878	667067	535935	201674	357198	131343	539607	202446

The dependent variable are mortgage costs in terms of basis points. For Columns (3) through (8), costs are expressed as a ratio of dollar costs to the mortgage principal. The independent variables are indicator variables for the borrower's ethnicity and whether the lender was a fintech lender, along with the interaction between the fintech lender status and borrower demographic. Controls include the log mortgage amount, log income, owner occupancy status, sex, and number of borrowers. Fixed effects are included for GSE-grid bucket by year/month and census tract by year. Standard errors are clustered at the lender level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

HMDA,[16] and are used as a rough proxy of borrower sophistication, as papers such as Campbell (2006) and Calvet, Campbell, and Sodini (2009) show older borrowers (above age 65) to be less financial sophisticated and more likely to make financial mistakes. $X_{i,t}$ are the same county-level controls as in Section 3, and μ_c and δ_t are county and month fixed effects respectively. We run the regression separately for home purchase mortgages and refi mortgages separately, as well as for minorities and for non-minorities as a comparison group.

The results are shown in Table 8. For home purchase mortgages, minority borrowers who approach fintech lenders are relatively higher income, yet also lower quality compared to other minority borrowers in the home purchase market. The same holds true for non-minorities in the home purchase market. We also find no significant differences in age between fintech and non-fintech borrowers amongst home purchase mortgages.

For refi mortgages, minority borrowers who approach fintech lenders have relatively higher incomes, and relatively lower credit scores and higher LTV ratios, but also lower DTI ratios as well. Furthermore, they tend to be significantly older than other minority borrowers in the refi mortgage market. The general pattern also holds for non-minority borrowers in the refi market.

Table A.5 breaks fintech borrower quality down even further by race and ethnicity. The general pattern previously described for both home purchase mortgages and refi mortgages holds when looking at individual racial and ethnic groups - fintech borrowers tend to be of lower quality in the home purchase market, but relatively similar in quality to non-fintech borrowers in the refinancing market. For the refi market, white and Black borrowers who get a mortgage from fintech lenders tend to be older borrowers from their respective groups, but this pattern does not hold for other racial ethnic groups.

5.2 What is left for non-fintech lenders?

Next, we examine the impact of fintech on the borrower quality distribution of minority borrowers for non-fintech lenders. We run the following regression, using county-year data, borrowing from Tang (2019),

[16]Borrower age categories were only recorded from 2018 onwards. Borrower age is categorized into "¡25", "25-34", "35-44", "45-54", "55-64", "65-74", and "¿74".

Table 8: Fintech borrower composition by minority status

	Purchase		Refinancing	
	Minorities	Non-Minorities	Minorities	Non-Minorities
	(1)	(2)	(3)	(4)
Loan Amount (Log)	-0.0187 ***	0.0065 ***	0.0273 ***	0.0319 ***
	(0.0039)	(0.0017)	(0.008)	(0.0035)
Income (Log)	0.0185 ***	0.01 ***	0.0222 ***	-0.0025
	(0.0029)	(0.0123)	(0.0068)	(0.0029)
Credit Score	-0.0001 ***	-0.0001 ***	-0.0002 ***	-0.0003 ***
	(0)	(0)	(0.0001)	(0)
LTV	0.0012 ***	0.0004 ***	0.0011 ***	0.0015 ***
	(0.0001)	(0)	(0.0002)	(0.0001)
DTI	0.0007 ***	0.0007 ***	-0.0015 ***	-0.0008 ***
	(0.0001)	(0)	(0.0003)	(0.0001)
Age				
25-34	-0.0194 ***	0.0013	0.0042	0.0617 ***
	(0.0073)	(0.0026)	(0.0313)	(0.0121)
35-44	-0.0214 ***	0.0101 ***	0.0219	0.0958 ***
	(0.0074)	(0.0027)	(0.0312)	(0.012)
45-54	-0.0193 **	0.0076 ***	0.0638 **	0.1237 ***
	(0.0075)	(0.0028)	(0.0313)	(0.012)
55-64	-0.0137 *	0.0155 ***	0.1022 ***	0.1662 ***
	(0.0081)	(0.003)	(0.0314)	(0.0121)
65-74	-0.0116	0.0112 ***	0.125 ***	0.1602 ***
	(0.01)	(0.0036)	(0.0323)	(0.0124)
>74	-0.0084	0.0033	0.0888 ***	0.1517 ***
	(0.0171)	(0.0055)	(0.0343)	(0.0134)
Loan Controls	X	X	X	X
County Controls	X	X	X	X
Month FE	X	X	X	X
Adj. R^2	0.012	0.01	0.023	0.02
Observations	101401	551470	33835	174709

The dependent variable is whether the loan was originated by a fintech lender. Loan-level controls include sex, owner occupancy status, and number of borrowers. The sample for columns (1) and (2) include only home purchase mortgages, and columns (3) and (4) include only refi mortgages. County-level controls include population density, median income, house price, house price growth, homeownership rates, poverty rates, minority population percentage, and educational controls. Month of origination fixed effects are also included. Standard errors are clustered at the census tract level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

$$y_{k,c,t} = \beta_1 \text{Fintech Market Share}_{c,t} + X_{c,t} + \mu_c + \delta_t + \varepsilon_{c,t} \tag{4}$$

$y_{k,c,t}$ is a measure of minority borrower quality, and we measure the impact of fintech for each $k \in \{5, 10, ..., 95\}$ percentile for county c at year t. Fintech Market Share$_{c,t}$ is the market share of fintech lenders in percentage points of total dollar volume lending, and $X_{c,t}$ are the same county-level controls as before. μ_c and δ_t are county and year fixed effects. If fintech lenders act as substitutes for non-fintech lenders amongst minority borrowers

The results of Equation 4 are shown in Table 9. For home purchase mortgages, fintech expansion has no significant effect on minority borrower quality for non-fintech lenders. For refinancing mortgages, however, in terms of both credit score and LTV ratios, fintech market share is associated with a significant drop in minority borrower quality for non-fintech lenders. A 1% increase in fintech market share is correlated with a 1.17 reduction in mean credit score and a 0.873% increase in mean LTV ratios for non-fintech minority borrowers. Furthermore, we see a drop in credit score and LTV for every percentile for non-fintech lenders, suggesting that fintech lenders are substituting for non-fintech lenders along the entire distribution of minority refi borrowers.

Taken together, the evidence suggests that fintech lenders act as complements to non-fintech lenders in the home purchase market and substitutes in the refinancing market for minority borrowers. Fintech lenders target relatively more marginal borrowers in terms of credit-worthiness for home purchase loans, but target higher quality borrowers for refinancing mortgages.

As a point of comparison, we run Equation 4 for non-minority borrowers to see if fintech complementary or substitution with non-fintech lenders differs for non-minority borrowers. Table A.4 details the results. For refinancing mortgages, the result is similar to our results for minority borrowers as greater fintech market share is correlated with decreasing borrower quality for non-fintech lenders, although to a lesser extent. For home purchase mortgages, however, the effect is more ambiguous - increasing fintech market share is associated with lower LTV ratios for the 5th, 15th, and 45th percentiles, but higher LTV and DTI ratios at the 65th-95th percentiles for non-fintech non-minority borrowers. For non-minority home purchase mortgages, fintech lenders act more as complements to non-fintech lenders at the lower end of the borrower quality distribution, but more as substitutes on the higher end of borrower quality.

Table 9: Impact of fintech on minority borrower composition for non-fintech lenders

Panel A: Home Purchase

	Percentile										
	5th (1)	15th (2)	25th (3)	35th (4)	45th (5)	55th (6)	65th (7)	75th (8)	85th (9)	95th (10)	Mean (11)
	Credit Score										
Fintech Market Share	**0.736** *	0.569	0.456	0.292	0.209	0.079	-0.082	-0.216	-0.37	-0.548	0.097
	(0.379)	(0.35)	(0.337)	(0.325)	(0.319)	(0.318)	(0.32)	(0.323)	(0.328)	(0.335)	-0.304
Adj. R^2	0.365	0.277	0.224	0.194	0.185	0.197	0.232	0.28	0.337	0.391	0.202
	LTV										
Fintech Market Share	-0.053	-0.022	-0.026	-0.955	-0.084	-0.079	-0.069	-0.059	-0.067	-0.061	-0.054
	(0.114)	(0.094)	(0.084)	(0.082)	(0.082)	(0.078)	(0.076)	(0.075)	(0.076)	(0.078)	-0.075
Adj. R^2	0.345	0.221	0.199	0.195	0.205	0.238	0.284	0.316	0.336	0.345	0.22
	DTI										
Fintech Market Share	0.024	-0.013	-0.027	0.004	0.009	-0.008	-0.013	-0.039	-0.057	-0.081	-0.019
	(0.071)	(0.064)	(0.061)	(0.058)	(0.056)	(0.054)	(0.054)	(0.055)	(0.057)	(0.061)	-0.053
Adj. R^2	0.288	0.197	0.164	0.164	0.189	0.228	0.275	0.32	0.367	0.418	0.201
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7158	7158	7158	7158	7158	7158	7158	7158	7158	7158	7158

Panel B: Refinancing

	Percentile										
	5th (1)	15th (2)	25th (3)	35th (4)	45th (5)	55th (6)	65th (7)	75th (8)	85th (9)	95th (10)	Mean (11)
	Credit Score										
Fintech Market Share	**-1.181** ***	**-1.246** ***	**-1.156** ***	**-1.18** ***	**-1.212** ***	**-1.266** ***	**-1.223** ***	**-1.169** ***	**-1.192** ***	**-1.263** ***	**-1.166** ***
	(0.472)	(0.426)	(0.407)	(0.393)	(0.386)	(0.381)	(0.383)	(0.389)	(0.397)	(0.411)	(0.364)
Adj. R^2	0.296	0.214	0.172	0.15	0.149	0.168	0.199	0.243	0.295	0.35	0.159
	LTV										
Fintech Market Share	**0.418** ***	**0.497** ***	**0.577** ***	**0.669** ***	**0.767** ***	**0.86** ***	**0.966** ***	**1.095** ***	**1.241** ***	**1.492** ***	**0.873** ***
	(0.156)	(0.144)	(0.138)	(0.138)	(0.139)	(0.144)	(0.152)	(0.164)	(0.179)	(0.203)	(0.142)
Adj. R^2	0.378	0.293	0.256	0.249	0.26	0.286	0.315	0.351	0.389	0.429	0.3
	DTI										
Fintech Market Share	0.155	0.095	0.051	0.028	0.019	-0.007	-0.033	-0.054	-0.081	-0.093	0.009
	(0.098)	(0.088)	(0.084)	(0.08)	(0.078)	(0.077)	(0.077)	(0.078)	(0.08)	(0.083)	(0.076)
Adj. R^2	0.288	0.22	0.186	0.177	0.187	0.215	0.249	0.284	0.317	0.358	0.199
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6541	6541	6541	6541	6541	6541	6541	6541	6541	6541	6541

6 Conclusion

In this paper, we examine the impact of fintech on consumer welfare for minorities in the mortgage market, in terms of both total volume and cost of mortgages. We examine how minority borrowers have benefited from the growth of fintech lenders that rely on algorithms rather than human judgement to make lending decisions. The growth of fintech lending has correlated with an expansion in total mortgage lending to minorities in both home purchase and refinancing mortgages, but more so in the latter market. Fintech lenders also charge minority refi borrowers significantly less than non-fintech lenders in terms of both interest rates and non-interest costs, particularly for lower quality borrowers. On average, fintech lenders save minority borrowers \$209 in non-interest costs, and \$32.5 in annual interest rate payments. The gains in consumer welfare from fintech lending have mainly to accrued to lower quality borrowers, but not to underserved communities located in CRA tracts. However, the reduction in costs to minority borrowers diminishes as fintech lenders gain market share.

We also find that minority borrowers who get a loan originated by a fintech lender are relatively lower quality in terms of credit-worthiness for home purchase mortgages, but less so for refinancing mortgages. Fintech lenders also act as a complement to non-fintech lenders in the home purchase market, but as substitutes in the refinancing market.

The mechanism behind the changes in minority credit access and availability is still unknown at the moment. It is possible that the algorithms powering fintech lending are less discriminatory towards minorities, but it is also possible that they are simply efficient at reducing costs. It is also possible that borrowers that approach fintech lenders are more likely to shop around between lenders in order to get a better deal, and that different minority groups are more likely to engage in price shopping than others. Further research into the mechanism behind fintech lending for minorities would help clarify what is driving the differences in consumer outcomes, how exactly fintech lenders benefit minority communities, and policy implications for the future of the mortgage market.

References

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder (Nov. 2021). “The Effects of the 1930s HOLC ”Redlining” Maps”. In: *American Economic Journal: Economic*

Policy 13(4), pp. 355–92. DOI: 10.1257/pol.20190414. URL: https://www.aeaweb.org/articles?id=10.1257/pol.20190414.
Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao (2017). "Systematic mistakes in the mortgage market and lack of financial sophistication". In: *Journal of Financial Economics* 123(1), pp. 42–58. ISSN: 0304-405X. DOI: https://doi.org/10.1016/j.jfineco.2016.01.028. URL: https://www.sciencedirect.com/science/article/pii/S0304405X16301258.
Ambrose, Brent W, James N Conklin, and Luis A Lopez (Aug. 2020). "Does Borrower and Broker Race Affect the Cost of Mortgage Credit?" In: *The Review of Financial Studies* 34(2), pp. 790–826. ISSN: 0893-9454. DOI: 10.1093/rfs/hhaa087. eprint: https://academic.oup.com/rfs/article-pdf/34/2/790/36090415/hhaa087.pdf. URL: https://doi.org/10.1093/rfs/hhaa087.
Appel, Ian and Jordan Nickerson (2010 2016). "Pockets of Poverty: The Long-Term Effects of Redlining". In: URL: https://dx.doi.org/10.2139/ssrn.2852856.
Barocas, Solon and Andrew D. Selbst (2016). "Big Data's Disparate Impact". In: *California Law Review* 104(3), pp. 671–732. ISSN: 00081221. URL: http://www.jstor.org/stable/24758720 (visited on 05/24/2022).
Bartlett, Robert et al. (2022). "Consumer-lending discrimination in the FinTech Era". In: *Journal of Financial Economics* 143(1), pp. 30–56. ISSN: 0304-405X. DOI: https://doi.org/10.1016/j.jfineco.2021.05.047. URL: https://www.sciencedirect.com/science/article/pii/S0304405X21002403.
Bayer, Patrick, Fernando Ferreira, and Stephen L. Ross (Feb. 2016). "The Vulnerability of Minority Homeowners in the Housing Boom and Bust". In: *American Economic Journal: Economic Policy* 8(1), pp. 1–27. DOI: 10.1257/pol.20140074. URL: https://www.aeaweb.org/articles?id=10.1257/pol.20140074.
Becker, Gary (1957). *The Economics of Discrimination*. 1st ed. University of Chicago Press.
Bhutta, Neil and Aurel Hizmo (Apr. 2020). "Do Minorities Pay More for Mortgages?" In: *The Review of Financial Studies* 34(2), pp. 763–789. ISSN: 0893-9454. DOI: 10.1093/rfs/hhaa047. eprint: https://academic.oup.com/rfs/article-pdf/34/2/763/36090360/hhaa047.pdf. URL: https://doi.org/10.1093/rfs/hhaa047.
Black, Harold, Robert L. Schweitzer, and Lewis Mandell (1978). "Discrimination in Mortgage Lending". In: *The American Economic Review* 68(2), pp. 186–191. ISSN: 00028282. URL: http://www.jstor.org/stable/1816686 (visited on 05/24/2022).
Broady, Kristen (2021). "How Fintech Companies Can Mitigate the Racial Wealth Gap". In.
Buchak, Greg et al. (2018). "Fintech, regulatory arbitrage, and the rise of shadow banks". In: *Journal of Financial Economics* 130(3), pp. 453–483. ISSN: 0304-405X. DOI:

https://doi.org/10.1016/j.jfineco.2018.03.011. URL: https://www.sciencedirect.com/science/article/pii/S0304405X1830237X.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini (May 2009). "Measuring the Financial Sophistication of Households". In: *American Economic Review* 99(2), pp. 393–98. DOI: 10.1257/aer.99.2.393. URL: https://www.aeaweb.org/articles?id=10.1257/aer.99.2.393.

Campbell, John Y. (2006). "Household Finance". In: *The Journal of Finance* 61(4), pp. 1553–1604. DOI: https://doi.org/10.1111/j.1540-6261.2006.00883.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2006.00883.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2006.00883.x.

Charles, Kerwin Kofi and Erik Hurst (2002). "The Transition To Home Ownership And The Black-White Wealth Gap". In: *The Review of Economics and Statistics* 84(2), pp. 281–297. URL: https://EconPapers.repec.org/RePEc:tpr:restat:v:84:y:2002:i:2:p:281-297.

Cloud, Cathy and George Galster (1993). "What do we know about Racial Discrimination in Mortgage Markets?" In: *The Review of Black Political Economy* 22(1), pp. 101–120. DOI: 10.1007/BF02689922. eprint: https://doi.org/10.1007/BF02689922. URL: https://doi.org/10.1007/BF02689922.

Cohen, Gregory et al. (2018). "The US syndicated loan market: Matching data". In: *Federal Reserve Bank of Kansas City Working Paper*(18-09).

Di Maggio, Marco and Vincent Yao (Dec. 2020). "Fintech Borrowers: Lax Screening or Cream-Skimming?" In: *The Review of Financial Studies* 34(10), pp. 4565–4618. ISSN: 0893-9454. DOI: 10.1093/rfs/hhaa142. eprint: https://academic.oup.com/rfs/article-pdf/34/10/4565/40406703/hhaa142.pdf. URL: https://doi.org/10.1093/rfs/hhaa142.

Erel, Isil and Jack Liebersohn (Aug. 2020). *Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program*. Working Paper 27659. National Bureau of Economic Research. DOI: 10.3386/w27659. URL: http://www.nber.org/papers/w27659.

Favaretto, Maddalena, Eva De Clercq, and Bernice Simone Elger (2019). "Big Data and discrimination: perils, promises and solutions. A systematic review". In: *Journal of Big Data* 6(1), p. 12. DOI: 10.1186/s40537-019-0177-4. URL: https://doi.org/10.1186/s40537-019-0177-4.

Fei, Celine Yue and Keer Yang (Oct. 2021). "Fintech and Racial Barriers in Small Business Lending". In: DOI: 10.2139/ssrn.3949148. URL: https://ssrn.com/abstract=3949148.

Fuster, Andreas et al. (Apr. 2019). "The Role of Technology in Mortgage Lending". In: *The Review of Financial Studies* 32(5), pp. 1854–1899. ISSN: 0893-9454. DOI: 10.1093/rfs/hhz018. eprint: https://academic.oup.com/rfs/article-pdf/32/5/1854/28275247/hhz018.pdf. URL: https://doi.org/10.1093/rfs/hhz018.

Fuster, Andreas et al. (May 2021a). *How Resilient Is Mortgage Credit Supply? Evidence from the COVID-19 Pandemic*. Working Paper 28843. National Bureau of Economic Research. DOI: 10.3386/w28843. URL: http://www.nber.org/papers/w28843.

Fuster, Andreas et al. (2021b). "Predictably Unequal? The Effects of Machine Learning on Credit Markets". In: *The Journal of Finance* n/a(n/a). DOI: https://doi.org/10.1111/jofi.13090. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.13090. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13090.

Glantz, Aaron and Emmanuel Martinez (Feb. 15, 2018). "For people of color, banks are shutting the door to homeownership". In: *Reveal*. URL: https://revealnews.org/article/for-people-of-color-banks-are-shutting-the-door-to-homeownership/ (visited on 05/28/2022).

Haupert, Tyler (2022). "The Racial Landscape of Fintech Mortgage Lending". In: *Housing Policy Debate* 32(2), pp. 337–368. DOI: 10.1080/10511482.2020.1825010. eprint: https://doi.org/10.1080/10511482.2020.1825010. URL: https://doi.org/10.1080/10511482.2020.1825010.

Howell, Sabrina et al. (Oct. 2021). "Racial Disparities in Access to Small Business Credit: Evidence from the Paycheck Protection Program". In: Working Paper Series(29364). URL: https://www.nber.org/system/files/working_papers/w29364/w29364.pdf.

Law, Kody and Nathan Mislang (Feb. 2022). "The Heterogeneity of Bank Responses to the Fintech Challenge". In: DOI: http://dx.doi.org/10.2139/ssrn.4069077. URL: https://ssrn.com/abstract=4069077.

Louis Lee Woods, II (2012). "The Federal Home Loan Bank Board, Redlining, and the National Proliferation of Racial Lending Discrimination, 1921–1950". In: *Journal of Urban History* 38(6), pp. 1036–1059. DOI: 10.1177/0096144211435126. eprint: https://doi.org/10.1177/0096144211435126. URL: https://doi.org/10.1177/0096144211435126.

Philippon, Thomas (Sept. 2019). *On Fintech and Financial Inclusion*. Working Paper 26330. National Bureau of Economic Research. DOI: 10.3386/w26330. URL: http://www.nber.org/papers/w26330.

Quillian, Lincoln, John J. Lee, and Brandon Honoré (2020). "Racial Discrimination in the U.S. Housing and Mortgage Lending Markets: A Quantitative Review of Trends,

1976–2016”. In: *Race and Social Problems* 12(1), pp. 13–28. DOI: 10.1007/s12552-019-09276-x. URL: https://doi.org/10.1007/s12552-019-09276-x.
Reid, Carolina K. et al. (2017). “Revisiting the subprime crisis: The dual mortgage market and mortgage defaults by race and ethnicity”. In: *Journal of Urban Affairs* 39(4), pp. 469–487. DOI: 10.1080/07352166.2016.1255529. eprint: https://doi.org/10.1080/07352166.2016.1255529. URL: https://doi.org/10.1080/07352166.2016.1255529.
Tang, Huan (Apr. 2019). “Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?” In: *The Review of Financial Studies* 32(5), pp. 1900–1938. ISSN: 0893-9454. DOI: 10.1093/rfs/hhy137. eprint: https://academic.oup.com/rfs/article-pdf/32/5/1900/28275194/hhy137_supp.pdf. URL: https://doi.org/10.1093/rfs/hhy137.
Taylor, Keeanga-Yamahtta (2019). *Race for Profit: How Banks and the Real Estate Industry Undermined Black Homeownership*. University of North Carolina Press. ISBN: 9781469653662. URL: http://www.jstor.org/stable/10.5149/9781469653686_taylor (visited on 05/28/2022).
Woodward, Susan E. (2008). “A Study of Closing Costs for FHA Mortgages”. In: *U.S. Department of Housing and Urban Development*.
Woodward, Susan E. and Robert E. Hall (Dec. 2012). “Diagnosing Consumer Confusion and Sub-optimal Shopping Effort: Theory and Mortgage-Market Evidence”. In: *American Economic Review* 102(7), pp. 3249–76. DOI: 10.1257/aer.102.7.3249. URL: https://www.aeaweb.org/articles?id=10.1257/aer.102.7.3249.
Zenou, Yves and Nicolas Boccard (2000). “Racial Discrimination and Redlining in Cities”. In: *Journal of Urban Economics* 48(2), pp. 260–285. ISSN: 0094-1190. DOI: https://doi.org/10.1006/juec.1999.2166. URL: https://www.sciencedirect.com/science/article/pii/S0094119099921666.

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 is a lot of overlapping variables between these datasets which can be leveraged to create a mapping file for merging them. 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. (2018). 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.

Using the lender name match, we move on to the second stage of loan matching. This begins with preprocessing variables in each dataset 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 Statewide mortgage regulations

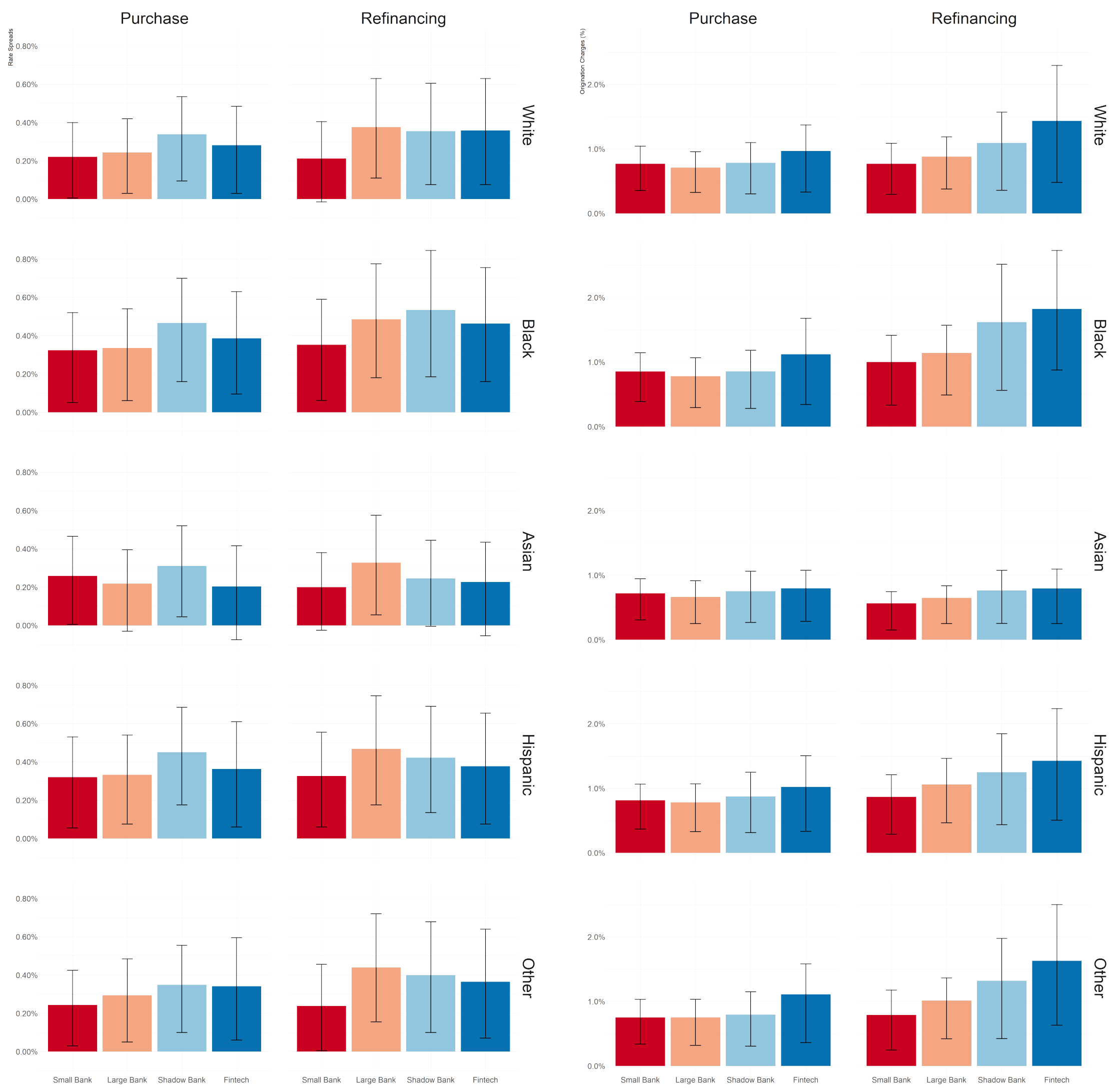
We collect data on a year-by-year basis from the Nationwide Multistate Licensing System Registry (NMLS) and by hand on the following statewide mortgage regulations:

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.

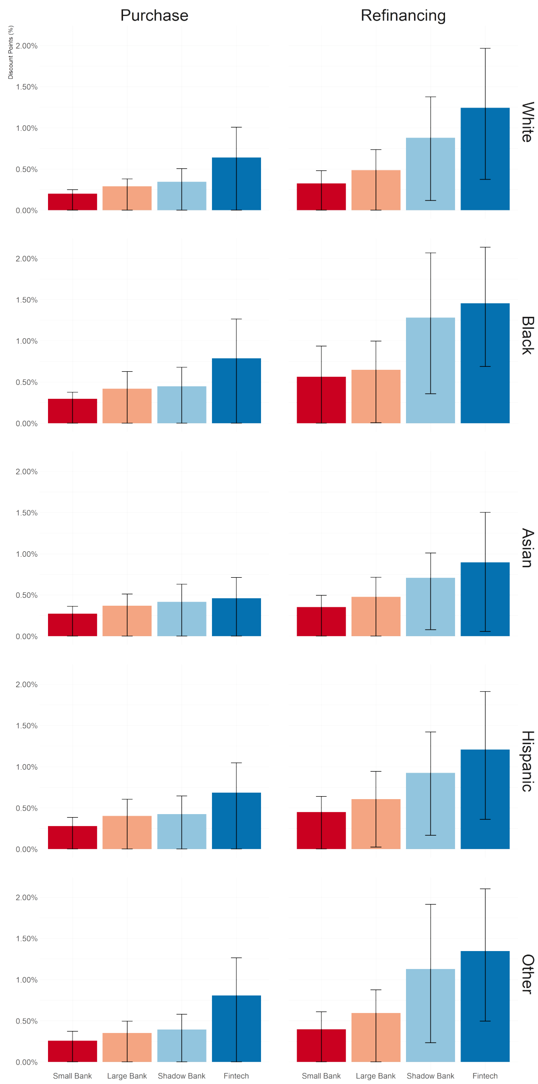
Recording Tax: Several states charge a tax for a home purchaser to record a mortgage. The amount of the recording tax is based on the principal of the mortgage, and can range from 0.1% in Alabama to 1.925% in New York. These taxes are levied upon the borrower, not the lender, but the additional taxation 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.

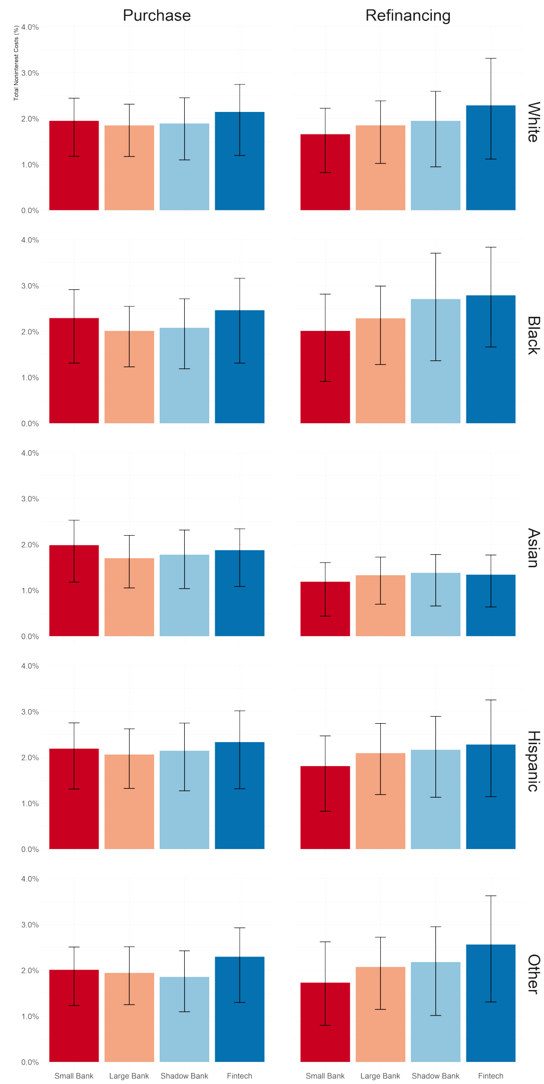
Annual Auditing Requirements: Some states require any lender operating in that state to submit annual audited financial statements. We use an indicator variable to record whether a state that has any annual auditing requirements. Some states require lenders to only submit an annual unaudited financial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



(a) Rate Spreads **(b)** Origination Charges



(c) Discount Points



(d) Total Noninterest Costs

Figure A.1: Mortgage Lending Costs by Race

Table A.1: Fintech penetration and minority credit access - CRA Tracts

Panel A: All Mortgages

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	-0.003	0.004	0.004	0.003	-0.006
	(0.002)	(0.003)	(0.004)	(0.006)	(0.004)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	13510	9693	7344	4441	6580
Adj. R^2	0.698	0.645	0.648	0.426	0.495

Panel B: Home Purchase

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0	0.002	0.002	0.006	-0.004
	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	11320	7300	5831	3045	4136
Adj. R^2	0.651	0.653	0.524	0.461	0.521

Panel C: Refinancing

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.002	-0.002	-0.001	0.005	0
	(0.002)	(0.003)	(0.003)	(0.007)	(0.004)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	10312	5646	5231	1955	3694
Adj. R^2	0.557	0.59	0.482	0.376	0.405

This table displays the correlation between statewide Fintech penetration and total fintech lending to minority borrowers. The dependent variable is log dollar volume of mortgage loans originated for each demographic. Column (1)'s sample includes loans originated to borrowers who are not indicated as White or Asian in the HMDA dataset. Standard errors are clustered at the census tract level. ***,

Table A.2: Fintech penetration and minority market share - CRA Tracts

Panel A: All Mortgages

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.055 ***	0.022 *	0.071 ***	0.015	0.001
	(0.017)	(0.013)	(0.025)	(0.015)	(0.013)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	13510	9693	7344	4441	6580
Adj. R^2	0.821	0.896	0.739	0.549	0.675

Panel B: Home Purchase

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	-0.013	-0.012	-0.005	0.004	-0.003
	(0.022)	(0.022)	(0.032)	(0.02)	(0.025)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	11320	7300	5831	3045	4136
Adj. R^2	0.704	0.805	0.565	0.524	0.558

Panel C: Refinancing

	Minorities	Hispanic	Black	Asian	Other
	(1)	(2)	(3)	(4)	(5)
Fintech Market Share	0.048 **	0.022	0.049	0.039	0.018
	(0.023)	(0.032)	(0.036)	(0.047)	(0.036)
Census Tract Controls	X	X	X	X	X
Census Tract FE	X	X	X	X	X
State FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	10312	5646	5231	1955	3694
Adj. R^2	0.652	0.768	0.503	0.504	0.464

This table displays the correlation between statewide Fintech penetration and the market shar eof minority borrowers. The dependent variable is log dollar volume of mortgage loans originated for each demographic. Column (1)'s sample includes loans originated to borrowers who are not indicated as White or Asian in the HMDA dataset. Standard errors are clustered at the census tract level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table A.3: Mortgage costs and minority status - geographic variation

Panel A: Minority Status								
	Rate Spread		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority	2.036 ***	1.327 ***	3.617 ***	10.788 ***	4.353 ***	5.636 **	5.017 ***	13.405 ***
	(0.331)	(0.439)	(0.773)	(2.339)	(0.685)	(2.623)	(1.163)	(3.228)
Fintech	-1.791	0.361	21.8 *	37.051 **	27.911 *	50.659 ***	28.912 **	39.903 ***
	(1.574)	(2.293)	(11.569)	(15.732)	(14.339)	(16.878)	(11.921)	(15.02)
Minority * Fintech	-0.01	-2.886 **	1.745	-2.612	3.148	-3.096	0.55	-9.096
	(1.76)	(1.205)	(2.335)	(4.443)	(2.065)	(4.704)	(3.351)	(5.813)
Census Tract X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.575	0.584	0.312	0.373	0.313	0.324	0.524	0.588
Observations	968522	725400	584872	261852	377124	156522	637181	368445

Panel A: Minority Status								
	Rate Spread		Origination Charges		Discount Points		Total Non-Interest Costs	
	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	1.865 ***	1.659 ***	4.69 ***	13.961 ***	6.689 ***	12.944 **	7.605 ***	17.161 ***
	(0.492)	(0.587)	(0.926)	(4.223)	(0.8)	(5.384)	(1.506)	(5.131)
Asian	-2.672 ***	-3.042 ***	3.598 ***	-2.114	4.954 ***	-3.124	1.834	-3.73
	(0.615)	(0.569)	(1.366)	(3.058)	(1.183)	(1.999)	(2.417)	(3.833)
Hispanic	1.732 ***	0.52	4.118 ***	8.441 ***	4.443 ***	0.359	4.54 ***	10.501 ***
	(0.384)	(0.556)	(1.001)	(2.326)	(0.857)	(2.217)	(1.464)	(3.271)
Other	0.344	1.131 **	2.113	12.726 **	1.863	13.516	2.839	13.234 **
	(0.5)	(0.494)	(2.06)	(5.72)	(2.056)	(9.108)	(2.453)	(6.06)
Fintech	-1.13	0.726	23.769 *	39.917 **	30.587 **	51.52 ***	31.427 **	44.022 ***
	(1.309)	(2.32)	(12.312)	(16.28)	(15.293)	(16.841)	(12.685)	(15.107)
Black * Fintech	-0.438	-3.345 **	4.831	6.019	5.042 *	-0.858	2.707	-6.493
	(1.682)	(1.592)	(3.504)	(6.11)	(2.69)	(8.079)	(3.87)	(7.289)
Asian * Fintech	-5.145 **	-4.202 ***	-14.458	-29.034 ***	-20.355 *	-16.452 ***	-17.114	-38.412 ***
	(2.503)	(1.497)	(8.824)	(9.594)	(11.211)	(4.727)	(11.777)	(10.354)
Hispanic * Fintech	-0.796	-3.328 **	-3.627	-13.852 **	-2.523	-7.242 *	-5.136	-19.593 ***
	(01.754)	(1.332)	(2.486)	(5.507)	(2.34)	(4.192)	(3.711)	(6.236)
Other * Fintech	0.105	-2.808 ***	7.256 *	4.445	8.78 **	-6.666	5.383	-1.327
	(1.044)	(1.041)	(4.144)	(6.541)	(4.069)	(8.936)	(5.825)	(7.232)
Census Tract X Year FE	X	X	X	X	X	X	X	X
GSE Bucket x Month FE	X	X	X	X	X	X	X	X
Adj. R^2	0.576	0.585	0.313	0.375	0.315	0.326	0.525	0.59
Observations	968338	725272	584756	261837	377045	156512	637056	368424

The dependent variable are mortgage costs in terms of basis points. For Columns (3) through (8), costs are expressed as a ratio of dollar costs to the mortgage principal. The independent variables are indicator variables for the minority status and whether the lender was a fintech lender, along with the interaction between the fintech lender status and borrower demographic. Controls include the log mortgage amount, log income, owner occupancy status, sex, and number of borrowers. Fixed effects are included for GSE-grid bucket interacted with year/month and census tract interacted with year. Standard errors are clustered at the lender level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table A.4: Fintech penetration and non-minority borrower composition for non-fintech lenders

Panel A: Home Purchase

	Percentile										
	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Credit Score					
Fintech Market Share	**-0.42 ***	-0.182	-0.049	0.049	0.088	0.122	0.14	0.153	0.158	0.142	-0.005
	(0.215)	(0.186)	(0.17)	(0.159)	(0.153)	(0.148)	(0.145)	(0.146)	(0.149)	(0.155)	(0.136)
Adj. R^2	0.372	0.267	0.214	0.189	0.178	0.189	0.219	0.251	0.285	0.336	0.176
						LTV					
Fintech Market Share	**-0.295 *****	**-0.187 *****	0.023	-0.017	**-0.105 *****	-0.109	-0.056	**0.104 *****	**0.091 ****	**0.087 ****	**-0.068 ****
	(0.08)	(0.058)	(0.035)	(0.039)	(0.04)	(0.04)	(0.039)	(0.032)	(0.038)	(0.038)	(0.036)
Adj. R^2	0.419	0.29	0.189	0.19	0.216	0.28	0.354	0.316	0.362	0.32	0.281
						DTI					
Fintech Market Share	-0.024	-0.002	-0.053	**0.059 ***	**0.07 ****	**0.091 *****	**0.101 *****	0.015	**0.093 *****	**0.091 ****	**0.055 ***
	(0.042)	(0.037)	(0.044)	(0.033)	(0.033)	(0.032)	(0.032)	(0.038)	(0.033)	(0.036)	(0.028)
Adj. R^2	0.321	0.223	0.22	0.187	0.203	0.233	0.27	0.388	0.364	0.425	0.206
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	13099	13099	13099	13099	13099	13099	13099	13099	13099	13099	13099

Panel B: Refinancing

	Percentile										
	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Credit Score					
Fintech Market Share	**-0.557 ***	**-0.627 *****	**-0.555 *****	**-0.446 ****	-0.303	-0.198	-0.139	-0.118	-0.147	-0.136	**-0.34 ****
	(0.284)	(0.235)	(0.213)	(0.198)	(0.187)	(0.179)	(0.171)	(0.167)	(0.166)	(0.169)	(0.165)
Adj. R^2	0.283	0.18	0.146	0.147	0.17	0.207	0.252	0.305	0.358	0.416	0.157
						LTV					
Fintech Market Share	-0.033	0.052	0.076	**0.111 ***	**0.164 ****	**0.22 *****	**0.332 *****	**0.416 *****	**0.412 *****	**0.521 *****	**0.223 *****
	(0.086)	(0.074)	(0.067)	(0.064)	(0.064)	(0.066)	(0.071)	(0.078)	(0.089)	(0.109)	(0.066)
Adj. R^2	0.468	0.352	0.289	0.258	0.251	0.261	0.286	0.33	0.379	0.444	0.307
						DTI					
Fintech Market Share	-0.042	-0.05	-0.031	-0.017	0.002	-0.006	-0.019	-0.026	-0.043	-0.053	-0.03
	(0.045)	(0.04)	(0.037)	(0.036)	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)	(0.039)	(0.031)
Adj. R^2	0.392	0.302	0.246	0.207	0.19	0.198	0.225	0.267	0.32	0.389	0.195
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	12881	12881	12881	12881	12881	12881	12881	12881	12881	12881	12881

Table A.5: Fintech borrower composition by race & ethnicity

	Purchase					Refinancing				
	White	Asian	Black	Hispanic	Other	White	Asian	Black	Hispanic	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Loan Amount (Log)	0.0062 ***	0.009	-0.0123 *	-0.025 ***	-0.0234	0.0306 ***	0.038 ***	0.0513 ***	0.0127	-0.0022
	(0.0018)	(0.0055)	(0.0064)	(0.0051)	(0.0156)	(0.0036)	(0.0138)	(0.0124)	(0.0112)	(0.0332)
Income (Log)	0.0065 ***	0.0353 ***	0.0047	0.0263 ***	0.0031	-0.0054 *	0.0361 ***	-0.0273 **	0.0515 ***	0.0285
	(0.0013)	(0.0033)	(0.0055)	(0.0037)	(0.0106)	(0.003)	(0.01)	(0.011)	(0.0093)	(0.0261)
Credit Score	-0.0001 ***	0.0001 **	-0.0002 ***	0	-0.0004 ***	-0.0003 ***	-0.0001	-0.0001	-0.0002 ***	-0.0004 *
	(0)	(0)	(0)	(0)	(0.0001)	(0)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
LTV	0.0004 ***	0.0001	0.0015 ***	0.0007 ***	0.0019 ***	0.0015 ***	0.0015 ***	0.0008 **	0.0011 ***	0.001
	(0)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0008)
DTI	0.0007 ***	0.0004 **	0.0009 ***	0.0007 ***	0.0009	-0.0007 ***	-0.0018 ***	-0.0019 ***	-0.0015 ***	0.0018
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0006)	(0.0001)	(0.0005)	(0.0005)	(0.0004)	(0.0013)
Age										
25-34	0.0017	-0.0066	-0.0463 ***	-0.0098	-0.0529	0.0673 ***	-0.0294	0.0806	-0.0147	-0.0033
	(0.0026)	(0.0101)	(0.0174)	(0.0081)	(0.0378)	(0.0122)	(0.0559)	(0.0631)	(0.0364)	(0.1412)
35-44	0.0096 ***	0.0011	-0.0435 **	-0.0128	-0.0636	0.102 ***	-0.0098	0.1307 **	-0.0156	0.0272
	(0.0028)	(0.0101)	(0.0174)	(0.0083)	(0.0381)	(0.012)	(0.0555)	(0.0623)	(0.0362)	(0.1405)
45-54	0.0094 ***	-0.0054	-0.0305 *	-0.0194 **	-0.028	0.1348 ***	-0.0098	0.1778 **	0.02	0.1093
	(0.0029)	(0.0106)	(0.0177)	(0.0085)	(0.0399)	(0.012)	(0.0556)	(0.0624)	(0.0363)	(0.1411)
55-64	0.0188 ***	-0.0086	-0.0225	-0.0143	-0.0635	0.1784 ***	0.0038	0.2101 ***	0.0505	0.1464
	(0.0031)	(0.0119)	(0.0181)	(0.0094)	(0.0409)	(0.0122)	(0.0564)	(0.0624)	(0.037)	(0.1412)
65-74	0.0136 ***	-0.0226	-0.0235	-0.0108	-0.0648	0.1715 ***	-0.0304	0.2227 ***	0.0816 **	0.1115
	(0.0037)	(0.0164)	(0.0202)	(0.0129)	(0.0451)	(0.0124)	(0.0583)	(0.0631)	(0.039)	(0.1436)
>74	0.0057	-0.0666 ***	-0.0394	0.0063	-0.0174	0.1589 ***	0.1037	0.1509 **	0.0517	0.2378
	(0.0056)	(0.0239)	(0.0298)	(0.0223)	(0.0681)	(0.0134)	(0.071)	(0.0645)	(0.0447)	(0.155)
County FE	X	X	X	X	X	X	X	X	X	X
Adj. R^2	0.01	0.014	0.016	0.012	0.014	0.022	0.026	0.023	0.022	0.036
Observations	456278	56453	32931	61860	5236	162509	12443	13018	18345	2219

The dependent variable is whether the loan was originated by a fintech lender. Loan-level controls include sex, owner occupancy status, and number of borrowers. County-level controls include population density, median income, house price, house price growth, homeownership rates, poverty rates, minority population percentage, and educational controls. Month of origination fixed effects are also included. Standard errors are clustered at the census tract level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.