# Consumer-Lending Discrimination in the FinTech Era*

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**Abstract**

U.S. fair-lending law prohibits lenders from making credit determinations that disparately impact minority borrowers if those determinations are based on characteristics unrelated to creditworthiness. Using an identification under this rule afforded by the GSEs' and FHA's pricing of mortgage credit risk, we show that risk-equivalent Latinx/African-American borrowers pay significantly higher interest rates on both GSE-securitized and FHA-insured loans, with particularly high rates being paid in high-minority-share neighborhoods. In total, we estimate that these rate differences cost minority borrowers over $450 million yearly. These rate disparities were substantially lower for FinTech lenders for loans issued between 2009 and 2015, but there is no significant difference between FinTech and other lenders for loans issued in 2018 and 2019.

JEL classification: G21, G28, G23, J14, K22, K23, R30.

Keywords: Discrimination; FinTech; GSE mortgages; credit scoring; algorithmic underwriting; big-data lending; platform loans; statistical discrimination; legitimate business necessity.

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# 1. Introduction

A long literature, going back at least to Black, Schweitzer, and Mandell (1978), has found differences between minority and non-minority borrowers in both mortgage approval probabilities and interest rates paid. However, almost all of this literature looks at mortgages issued prior to the 2008 financial crisis and much of it focuses on subprime loans. Most of the literature also suffers from an omitted-variable problem: lenders observe information that is unknown to researchers, so we cannot be sure whether an observed difference in rates paid by two groups of borrowers reflects discrimination or merely credit-risk differences between the groups that are observable to the lender but not to the researcher.

Lenders do not observe everything about borrowers' finances and may turn to proxies for what is unobserved. Under U.S. fair-lending law,[1] courts have ruled that lenders may use such proxy variables, even if they lead to worse outcomes for minorities, as long as the lender can show that these variables have a *legitimate business necessity.* While lenders might view many activities as being necessary for profit maximization, the courts have consistently limited the legitimate-business-necessity defense to the use of variables and practices to ascertain creditworthiness.[2] These decisions make clear that using variables for objectives other than determining creditworthiness, e.g., to earn higher profits by charging higher rates to applicants in financial deserts or with low shopping characteristics, cannot be justified as a legitimate business necessity, even if it is profit maximizing.[3]

To identify discrimination without omitted-variable concerns, we need a setting in which all legitimate-business-necessity variables are observed. In this paper, we investigate mortgage discrimination in just such a setting, made possible by the role of the Government Sponsored Enterprises (GSEs) — Fannie Mae and Freddie Mac — and of the Federal Housing Administration (FHA).

The GSEs determine credit-risk pricing adjustments via a fee that depends only on where the borrower sits in an 8 × 8 matrix of loan-to-value ratios (LTVs) and credit scores called

[1]We define U.S. fair-lending law as including the Fair Housing Act and the Equal Credit Opportunity Act (ECOA), together with all implementing regulations and judicial interpretations relating to them.

[2]See A.B. & S. Auto Service, Inc. v. South Shore Bank of Chicago, 962 F. Supp. 1056 (N.D. Ill. 1997) ("[In a disparate impact claim under the ECOA], once the plaintiff has made the prima facie case, the defendant-lender must demonstrate that any policy, procedure, or practice has a manifest relationship to the creditworthiness of the applicant...”). See also Lewis v. ACB Business Services, Inc., 135 F.3d 389, 406 (6th Cir. 1998) ("The [ECOA] was only intended to prohibit credit determinations based on 'characteristics unrelated to creditworthiness."'); Miller v. Countrywide Bank, NA, 571 F.Supp.2d 251, 258 (D. Mass 2008) (rejecting argument that discrimination in loan terms among African American and white borrowers was justified as the result of competitive "market forces," noting that prior courts had rejected the "market forces" argument insofar that it would allow the pricing of consumer loans to be "based on subjective criteria beyond creditworthiness.")

[3]See Bartlett, Morse, Stanton, and Wallace (2020) for further discussion.

Loan Level Price Adjustments (LLPAs). In return for paying the LLPA fees, lenders are guaranteed against credit risk. The critical point for our analysis is that even if the GSE pricing grid is not the optimal model for predicting default among all application variables,[4] it nevertheless completely determines the price that must be paid to the GSEs to absorb all credit risk. All legitimate-business-necessity variables are thus observed. Any interest-rate differences between loans within a given credit score/LTV grid cell cannot reflect differential credit risk, and may therefore reflect discrimination.

Similarly, FHA loans, which are insured against default by the FHA, have very little risk-based pricing. What little does exist is based on LTV and/or credit score, both of which are controlled for by the GSEs' LLPA grid.[5]

For our analysis, we construct a new data set by merging, for the first time, four mortgage data sources: i) loan-level McDash data compiled by Black Knight Financial Services; ii) property and loan-level data from ATTOM Data Solutions; iii) loan origination data from the Home Mortgage Disclosure Act (HMDA) data; and iv) loan performance data from Equifax that was pre-merged to the McDash data by Black Knight. Our data set includes never-before-linked loan-level information on income, race, ethnicity, loan-to-value ratios, debt-to-income ratios, presence of second liens, all contract terms apart from points and fees (such as coupon, loan amount, installment-payment structure, amortization, maturity, loan purpose, and mortgage-origination month), and indicators for whether the lender-of-record primarily used algorithmic scoring. We focus on two loan-origination vintages: i) about 5.7 million loans issued between 2009 and 2015 using the full merged data, of which 3.4 million are GSE loans and 2.3 million are FHA loans; and ii) 3.2 million loans originated in 2018 and 2019 using the recently expanded 2018–2019 HMDA data, of which 2.2 million are GSE loans and about 1 million are FHA loans.[6]

In addition to looking at the market overall, we also separately analyze FinTech lenders. Algorithmic decision-making can reduce face-to-face discrimination in markets prone to implicit and explicit biases, but the use of algorithms can also lead to inadvertent discrimination (Barocas and Selbst, 2016). The question of whether algorithmic decision-making promotes or inhibits impermissible discrimination is fundamentally an empirical one. For our definition of FinTech lenders, we follow the list of platform lenders in Buchak, Matvos, Piskorski,

[4]The actuarially fair GSE guarantee fee (or g-fee) is a central policy question in the determination of the future role of the GSEs in the U.S. mortgage markets (see Elenev, Landvoigt, and van Nieuwerburgh, 2016; Vickery and Wright, 2013). A standard g-fee is assessed on all mortgages as a percentage of the loan balance and is collected monthly (see Fuster, Goodman, Lucca, Madar, Molloy, and Willen, 2013).

[5]See Van Order and Yezer (2014), Gyourko, Lee, and Tracy (2015), Bhutta and Hizmo (2021), and Goodman (2015). Section 3 contains additional discussion.

[6]We cannot merge the 2018–2019 HMDA data with McDash, ATTOM and Equifax, but unlike the earlier data, the 2018–2019 data do include points and fees.

and Seru (2018).

For the 2009–2015 loan-origination data, we find that Latinx and African-American borrowers paid 4.7–4.9 basis points more in interest for GSE and FHA home-purchase loans and 1.5–1.6 basis points more for FHA and GSE refinance loans. Under our identification assumptions, this pattern would be deemed discrimination. Using the heuristic that 0.2% in rate $\approx$ 1 point (i.e., 1% of the loan amount), 2 bps corresponds to 0.1% of the loan amount, i.e., 20% of total average profit; 5 bps corresponds to 50% of total average profit."[7] For the 2018–2019 data, where we can control for points and total loan costs at origination, the differences are even larger. Latinx and African-American borrowers paid 5.4–7.7 basis points more interest for GSE and FHA home purchase loans, about 6.8 basis points more for GSE refinance loans, and about 1.9 basis points more for FHA refinance loans.

The rate differences that we find for minority borrowers also exist within the sample of loans issued by FinTech lenders between 2009 and 2015. For GSE loans, the magnitude of the rate disparities for minority borrowers are largely the same across FinTech and non-FinTech lenders; however, the rate disparities for FinTech lenders were 27% lower for FHA purchase loans and 37% lower for FHA refinance loans. We find similar results when we examine the 2018 and 2019 HMDA. In particular, we find no notable differences in the magnitude of rate disparities across FinTech and non-FinTech lenders for GSE purchase and refinance loans; however, the rate differential is not significantly different than zero for FHA refinance loans.

We find a strong geographical component to our results. In particular, we find that rate disparities for minority borrowers in high-minority-share census tracts are notably higher than our overall estimates for two reasons. First, the average level of mortgage rates is higher for *all* borrowers — both minority and non-minority — in high-minority-share census tracts; and second, in those same census tracts, minority borrowers also pay higher rates than non-minority borrowers. A minority borrower taking out a GSE purchase loan in a decile-10 minority-share census tract pays on average 13.8 basis points more than an otherwise-equivalent non-minority borrower in a decile-1 census tract; for FHA purchase loans, the difference is 16.2 basis points.

We perform a large number of additional robustness checks, looking at subsamples of the data and investigating whether there is heterogeneity in our results, to investigate alternative hypotheses, to shed light on the channels that drive these rate differentials, and to determine whether we should really think of them as being driven by discrimination. Specifically, we consider whether our results are related to put-back risk (i.e., forced originator buy-backs

[7]According to the Mortgage Bankers' Association, the average total mortgage profit is 50 basis points of the loan amount (see `https://www.mba.org/2020-press-releases/april/imb-production-volumes-and-profits-rise-in-2019`).

of securitized mortgages due to qualification defects), differences in default risk (and hence servicing costs), and possible mismeasurement of minority status. Our results are robust, regardless of how we split the data. The minority rate differential is higher for higher-LTV loans, and lower for higher incomes. This suggests that some of our results might be due to differential servicing costs; however, the fact that there is little relation between the rate differential and either credit score or realized default suggests that the income and LTV results might instead reflect something else, such as the correlation between income, financial sophistication, and a propensity to shop for rates.

It is possible that minority borrowers pay higher rates because they also pay lower up-front costs in the form of discount points. Starting with the 2018 data, HMDA began including information on loan-level points (both positive and negative), total loan costs at origination, loan-level information on the loan-to-value ratio, the type of refinance, and the interest rate on the loan, as well as all of the loan-level fields included in the earlier 2009–2015 HMDA data. We therefore use the 2018–2019 HMDA data to examine the importance of points. As with our other robustness checks, we find that the minority rate differential remains positive and significant across both GSE and FHA purchase loans and refinance loans.

Finally, we present some preliminary results on loan rejection rates. While not as well identified as our interest-rate results, we find that minority borrowers are more likely to be rejected than non-minority borrowers and the results are similar for the FinTech lenders. We cannot be completely sure that these differentials are not driven by differences in unobservable variables, but they are certainly large enough to suggest that further study is warranted.

## 2. Prior Literature

Early studies of discrimination in mortgage lending, such as Black et al. (1978), looked at the raw HMDA data and found that minority loan applicants were rejected much more often than white applicants, even with higher incomes; however, these papers did not control for variables not collected by HMDA, such as credit history. In a widely cited paper, Munnell, Browne, McEneaney, and Tootel (1996) combine HMDA data on loan applications in Boston in 1990 with additional borrower data collected via survey by the Federal Reserve Bank of Boston, and find that after controlling for borrower characteristics, especially credit history and loan-to-value ratio, white applicants with the same property and personal characteristics as minorities would have experienced a rejection rate of 20%, compared with the minority rejection rate of 28%. Courchane and Nickerson (1997) and Black, Boehm, and DeGennaro

(2003) find that black borrowers pay more in points, conditional on the loan interest rate.

Much of the more recent literature focuses on the pre-crisis period, often looking at subprime lending. Ghent, Hernández-Murillo, and Owyang (2014) examine subprime loans originated in 2005, and find that for 30-year, adjustable-rate mortgages, African-American and Latinx borrowers face interest rates 12 and 29 basis points, respectively, higher than other borrowers. Bayer, Ferreira, and Ross (2018) find that after conditioning on credit characteristics, African American and Hispanic borrowers were 103% and 78% more likely, respectively, than other borrowers to be in a high-cost mortgage between 2004 and 2007. Similar results were obtained by Reid, Bocian, Li, and Quercia (2017). Ambrose, Conklin, and Lopez (2021) look at loans approved and funded by a single large lender, New Century Financial Corporation, between 2003 and 2007, and find that minority borrowers pay significantly more in fees than similarly qualified non-minority borrowers, but the size of the effect depends on the race/ethnicity of both the borrower and the broker. In particular, black borrowers pay a premium when the broker is white, but not when the broker is also black.

Cheng, Lin, and Liu (2015) use data from the Survey of Consumer Finances to compare mortgage interest rates for minority and non-minority borrowers. They find that black borrowers on average pay about 29 basis points more than comparable white borrowers, with the difference larger for young borrowers with low education, subprime borrowers, and women. Focusing on the quality of consumer credit services, Begley and Purnanandam (2020) study the incidence of consumer complaints about financial institutions to the Consumer Financial Protection Bureau (CFPB). Even after controlling for income and education, they find that the level of complaints is significantly higher in markets with lower income and educational attainment, especially in areas with a higher share of minorities.

In one of the few experimental papers in this area, Hanson, Hawley, Martin, and Liu (2016) show that when potential borrowers (differing only in their name) ask for information about mortgages, loan officers are more likely to respond, and give more information, to white borrowers. Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2020) use post-crisis mortgage data from 2009–2019 and show that machine-learning techniques to evaluate credit quality may result in differential impact on loan provision to minority versus non-minority borrowers. Again, using post-crisis data, Bhutta and Hizmo (2021) analyze FHA loans originated in 2014 and 2015. Like us, they find that minority borrowers pay significantly higher interest rates. However, unlike us they conclude that the difference is insignificant because it is offset by differences in discount points. Finally, in a recent working paper using post-crisis data, Willen and Zhang (2021) point out some potential econometric problems with Bhutta and Hizmo (2021), and revisit their analysis, finding significant differences in rates for GSE loans but insignificant differences for FHA loans. We compare our results in detail with those of Bhutta and Hizmo (2021) in Section 6.1 below. Briefly, we find (using our larger sample) that the differences are significant for both GSE and FHA loans, even after conditioning on discount points.

There are also related results from other consumer-debt markets. For example, Dobbie, Liberman, Paravisini, and Pathania (2020) look at data from a high-cost lender in the UK and find significant bias against immigrant and older loan applicants when measured using long-run profits. However, they find no bias when using the (short-run) measure actually used to evaluate loan examiners, suggesting that the bias is due primarily to a misalignment of firm and examiner incentives. In a recent working paper, Butler, Mayer, and Weston (2020) find that, controlling for credit risk, Black and Hispanic applicants' auto loans are approved at a rate 1.5 percentage points lower than non-minority applicants. Moreover accepted minority borrowers both pay higher interest rates and default *less* than non-minority borrowers.

# 3. Lending and Pricing in GSE and FHA Markets

Our research design relies on the unique institutional setting that applies to the underwriting of credit risk in GSE and FHA mortgage markets. First, with respect to the GSE market, the GSEs' involvement in the mortgage process begins with the lender's submission of applicant data (credit score, income, liquid reserves, debt-to-income ratio, loan-to-value ratio, property value, etc.) into one of the two GSEs' automated underwriter systems (Desktop Underwriter for Fannie Mae; Loan Prospector for Freddie Mac). If the GSE underwriter system issues an approval on the application, and the lender decides to make an offer, the applicant gets a price quote and can decide to accept or not. If the mortgage is issued, the lender immediately sells it to the GSE. In return, the GSE compensates the lender with a cash transfer.[8] The GSE then packages the loan with a pool of similar mortgages into a mortgage-backed security (MBS), issues a default-risk guarantee on this product, and sells it to the MBS market.

Within this GSE process, the lender must decide about the price offered to the borrower. This interest rate quote structurally consists of three parts (see Fuster et al., 2013). First, all lenders face the same market price of capital, determined by the base mortgage rate, which reflects the primary market interest rate for loans to be securitized by the GSEs, in essence, the credit-risk-free rate. Second, when the lender sells the mortgage to the GSE, the lender

[8]If the originator is a large-volume lender, the lender transfers loans to the GSE in bulk and receives, instead of cash, a mortgage-backed security (MBS) backed primarily by the lender's mortgages and guaranteed against default by the GSE.

pays a guarantee fee (or g-fee) to cover projected borrower default and operational costs. Starting in March 2008 and adjusted a handful of times since then, this g-fee (for a given term and type of loan) varies only in an $8 \times 8$ matrix of LTVs and credit scores to reflect varying credit risk across the GSE grid.[9] Figure 1 depicts a typical GSE grid of Fannie Mae, also called the Loan Level Price Adjustments (LLPAs), for single-family loans with a maturity of 30 years.[10]

**Table 2: All Eligible Mortgages** **(Excluding MCM): LLPA by Credit Score/LTV**

| PRODUCT FEATURE | LLPAs by LTV Range | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ≤ 60.00% | 60.01 – 70.00% | 70.01 – 75.00% | 75.01 – 80.00% | 80.01 – 85.00% | 85.01 – 90.00% | 90.01 – 95.00% | 95.01 – 97.00% | SFC |
| Representative Credit Score | Applicable for all mortgages with greater than 15 year terms For whole loans purchased on or before March 31, 2011, or loans delivered into MBS pools with issue dates of March 1, 2011 or earlier | | | | | | | | |
| ≥ 740 | -0.250% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | N/A |
| 720 – 739 | -0.250% | 0.000% | 0.000% | 0.250% | 0.000% | 0.000% | 0.000% | 0.000% | N/A |
| 700 – 719 | -0.250% | 0.500% | 0.500% | 0.750% | 0.500% | 0.500% | 0.500% | 0.500% | N/A |
| 680 – 699 | 0.000% | 0.500% | 1.000% | 1.500% | 1.000% | 0.750% | 0.750% | 0.500% | N/A |
| 660 – 679 | 0.000% | 1.000% | 2.000% | 2.500% | 2.250% | 1.750% | 1.750% | 1.250% | N/A |
| 640 – 659 | 0.500% | 1.250% | 2.500% | 3.000% | 2.750% | 2.250% | 2.250% | 1.750% | N/A |
| 620 – 639 | 0.500% | 1.500% | 3.000% | 3.000% | 3.000% | 2.750% | 2.750% | 2.500% | N/A |
| < 620 (1) | 0.500% | 1.500% | 3.000% | 3.000% | 3.000% | 3.000% | 3.000% | 3.000% | N/A |

Figure 1: **An Example of the GSE Grid**. Presented is the LLPA (Loan-Level Price Adjustment) Grid of Fannie Mae for 2011. The figure is from the Fannie Mae Selling Guide, dated 12/23/2010. (MCMs, now retired, refers to "My Community Mortgages", a program of subsidized loans for low-income target areas.) The LLPA Grid has a parallel grid at Freddie Mac called the Credit Fees in Price chart. These grids provide the additional g-fee (guarantee fee) that lenders must pay the GSE for guaranteeing the mortgage, varying by LTV and credit score.

In practice, these one-time fees are commonly converted into monthly "flow" payments, which are added into the interest rate as rate pass-throughs to borrowers. The combination of these two costs results in a rate referred to as the par rate. The third component of pricing comes from lenders' discretion in quoting rates that deviate from the par rate (inclusive of any LLPA adjustments). Such deviations may reflect simple differences in overhead costs among lenders, or they may reflect strategic volume positioning or monopoly rent-taking. These pricing strategies may involve human discretion or could be machine-coded.

In return, lenders are guaranteed against credit risk. The critical point for our analysis is that even if this pricing grid is not the optimal model for predicting default among all application variables, it nevertheless completely determines the price lenders must pay the GSEs to absorb all credit risk.

[9] LLPAs are higher for cash-out refinances; we control for this in our regressions.

[10] See Federal Housing Finance Administration (2009, 2010, 2011, 2012, 2013) and Fuster and Willen (2010).

Similarly, FHA loans are insured against default by the Federal Housing Administration. While FHA lenders do not explicitly price using the same LTV $\times$ credit-score grids used in the GSE market, there is very little risk-based pricing in the FHA-loan market, and what does exist is based on LTV and/or credit score, both of which are controlled for by a loan's LLPA grid cell. Specifically, Van Order and Yezer (2014) and Gyourko et al. (2015) find that FHA insurance premia are almost constant, though Van Order and Yezer (2014) report that they are slightly higher for high-LTV loans. Bhutta and Hizmo (2021) look at rate sheets from several FHA lenders, which "confirm that there is only a modest amount of risk-based pricing, primarily for low FICO scores," and they conclude that "unobserved credit risk variables ... should not pose a serious threat to identification." Goodman (2015) notes that even long after the financial crisis, lenders still retain residual liability for originating FHA loans that fail to comply with HUD rules. However, she describes lenders' response to this as being to make it harder to obtain a loan at all, rather than increasing prices.[11] Our analysis looks at interest rates conditional on a loan being originated in the first place.

These institutional features of the GSE and FHA market inform our empirical research design. Specifically, for GSE loans within a given GSE grid cell of credit score and LTV and otherwise having the same duration and issue date, any mortgage interest rate differences between them cannot reflect differential credit risk, but must instead reflect strategic pricing decisions on the part of lenders. For similar reasons, any rate differentials between FHA loans having the same duration, issue date, credit score and LTV must likewise reflect strategic pricing decisions by a lender that are unrelated to a borrower's creditworthiness. In other words, the GSE and FHA markets provide us with a setting where all legitimate business necessity variables are observable. Consequently, any interest rates differentials across race or ethnicity that persist after controlling for these observable variables should be unrelated to creditworthiness and could reflect discrimination.

# 4. Data

## *4.1. Base Sample, 2009–2015*

A key obstacle for prior studies of mortgage discrimination has been a reliance on the HMDA data. The HMDA compliance surveys cover 90% of mortgage originations in the U.S.

[11] For example, she notes that "According to CoreLogic servicing data, the share of borrowers with credit scores below 640 has gone from 45 percent in 2001 to 55 percent in 2007, 7 percent in 2011, and 6 percent in 2014."

(see Engel and McCoy, 2011)[12] and are the only data source with loan-level information on applicant race and ethnicity. What HMDA lacks during this period is information on the contracting structure of the loan (exact date, interest rate, maturity, loan-to-value ratio), on the type of loan (fixed, ARM), on the property characteristics (e.g., address), on loan performance, and on the applicant's credit data used by the GSEs and other lenders (credit score, debt-to-income ratio, etc.).[13] We overcome the lack of a direct way to link the HMDA data and other data sets that contain this missing data with a multi-year project of linking loan-level data across the following data providers:

- HMDA data include information on applicant income, race, ethnicity, loan amount, and lender name, as well as the census tract of the property.
- ATTOM data provide transaction and assessor information, including lien-holder name, loan-performance data (i.e., prepayment and default), borrower and lender names and exact property location, but very little information on mortgage contract terms other than the loan amount, the origination date, the purpose of the loan, and whether it is a fixed or floating contract.
- McDash data provide loan-level data compiled by Black Knight Financial Services and include detailed mortgage terms (including interest rates, loan amount, loan-to-value ratio, and zip code of the mortgaged property) and month-by-month mortgage performance information.
- Equifax data that is pre-merged to the McDash data and provide information on other consumer financing balances that are held by borrowers in addition to their mortgages.

We exploit overlapping variables within HMDA, ATTOM, and the McDash/Equifax data sets to construct a merged data set of candidate loans with performance information, contract terms, the mortgage lender, and borrower information. To standardize our loan-pricing analysis, we focus on candidate loans in each data set that are first-lien, fixed-rate, owner-occupied 30-year single-family residential loans, securitized by the GSEs or insured by the FHA over the period 2009–2015. We exclude manufactured housing, investment properties, condos, duplexes, triplexes, quadraplexes, and loans with outstanding second liens at origination. We also impose minimum and maximum loan-to-value ratios and minimal credit scores, among other filters discussed in the Internet Appendix. Our overall merge rate for

[12] HMDA reporting is not required for institutions with assets (of the entity and its parent corporation) below an (annually updated) threshold on the preceding December 31. This threshold was $10 million in 2010 and increased to $47 million by 2020 — see `http://www.ffiec.gov/hmda/pdf/2010guide.pdf` and `http://www.ffiec.gov/hmda/pdf/2020guide.pdf`.

[13] The HMDA data have improved from 2018 on, though they still do not include information about loan performance.

candidate loans is 73.99% and the final filtered data set includes loans from all states.[14]

The HMDA data include information on both ethnicity and race. For our purposes, we define a minority applicant to be one with either Latinx ethnicity or African-American race. We combine to a single minority category in order to keep the minority pool consistent throughout the paper, even when implementing fine-grid geography and lender fixed effects. HMDA has missing values on race and ethnicity (Buchak et al., 2018). We therefore augment the HMDA race/ethnicity indicator variable with additional race/ethnicity data obtained from processing the borrower name field from ATTOM data, using a race and ethnic-name categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008). We also report a robustness check for the consistency of our results when excluding these fixes.

Panels (a) and (b) of Table 1 report summary statistics for the 2009–2015 core data set. The mortgage interest rate is the primary dependent variable in the pricing analysis. The mean interest rate for the GSE securitized mortgages is 4.42% with a standard deviation of 55 basis points; the mean interest rate for the FHA mortgages is 4.40% with a standard deviation of 68 basis points. The mean loan amount is $239,979 for the GSE loans with a standard deviation of $121,976, while the mean loan amount is $176,710 for the FHA loans with a standard deviation of $91,615. The average origination loan-to-value ratio for GSE securitized loans is 74.0%. The average GSE borrower has a 10% probability of being Latinx or African-American and has an average income of $101,981 and an average credit score of 757.6. The average origination loan-to-value ratio for FHA loans is 93.6%. The average FHA borrower has a 24.6% probability of being Latinx or African-American and an average income of $66,455 and an average credit score of 697.3. Finally, among the GSE mortgages, 8.2% of the refinanced mortgages were for the purpose of extracting cash, whereas only 2.1% of the FHA refinance mortgages were cash-outs.

Table 1 also reports summary information concerning the types of lending institutions that received the loan applications in our sample. Using the list of firms identified as FinTech in Buchak et al. (2018), we find that FinTech lenders originated approximately 3.1% of

[14]Section I1 of the Internet Appendix describes our merging algorithm, which is governed by compliance with IRB standards and is anonymized. The merge rate for candidate loans between HMDA (51,482,961 loans) and ATTOM (58,540,894 loans) is 76.82%, and 77.79% of the candidate loans in the McDash/Equifax data set (20,022,570 loans) are successfully merged to ATTOM. The final four-way merge rate is 73.79%, leaving us with a final merged data set of 11,493,172 candidate loans. We apply exclusions to further standardize these data (e.g., filtering for outliers, such as by imposing minimum and maximum LTVs, minimal credit scores, and other filters described in the Internet Appendix), leaving a final analysis data set, as shown in Table 1, of 5,650,044 loans. The composition of our data set is is comparable to the similarly filtered raw McDash data, which is composed of: 67.85% GSE loans (our data set has 59.76% GSE loans); 32.15% FHA loans (our data set has 40.24% FHA loans); 43.72% refinance loans (our data set has 42.00% refinance loans); and 56.28% purchase loans (our data set has 58.00% purchase loans). This is discussed in more detail in the Internet Appendix.

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Cash-out refinance | 3,376,600 | .0822052 | .2746771 | 0 | 1 |
| CRA census tract | 3,375,949 | .0926474 | .2899378 | 0 | 1 |
| Credit score | 2,950,931 | 757.6442 | 43.06677 | 620 | 850 |
| FinTech | 3,376,600 | .0312394 | .1739641 | 0 | 1 |
| Income | 3,252,686 | 101.9811 | 81.34873 | 20 | 9755 |
| Loan amount | 3,376,600 | 239.9792 | 121.9767 | 40 | 729 |
| Loan interest rate | 3,376,600 | .0442447 | .0054665 | .0275 | .07875 |
| Loan-to-value ratio | 3,376,600 | .7397208 | .1488221 | .3 | .95 |
| Minority borrower | 3,376,600 | .1001579 | .3002104 | 0 | 1 |
| Refinance | 3,376,600 | .5309895 | .4990388 | 0 | 1 |
| Top-25 lender | 3,376,600 | .4095857 | .4917574 | 0 | 1 |
| *N* | 3,376,600 | | | | |

(a) GSE loans

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Cash-out refinance | 2,273,444 | .0212822 | .1443237 | 0 | 1 |
| CRA census tract | 2,273,365 | .1781905 | .3826731 | 0 | 1 |
| Credit score | 1,994,340 | 697.3241 | 49.53322 | 580 | 850 |
| FinTech | 2,273,444 | .0160492 | .1256648 | 0 | 1 |
| Income | 1,999,753 | 66.4546 | 45.83809 | 20 | 7424 |
| Loan amount | 2,273,444 | 176.71 | 91.61529 | 40 | 729 |
| Loan interest rate | 2,273,444 | .0440192 | .0068095 | .0275 | .0775 |
| Loan-to-value ratio | 2,273,444 | .9358196 | .0674404 | .3 | .9825 |
| Minority borrower | 2,273,444 | .2461666 | .4307768 | 0 | 1 |
| Refinance | 2,273,444 | .2619699 | .4397065 | 0 | 1 |
| Top-25 lender | 2,273,444 | .2854264 | .4516174 | 0 | 1 |
| *N* | 2,273,444 | | | | |

(b) FHA loans

Table 1: **Summary Statistics: core sample.** Data are fixed-rate mortgage originations obtained from a loan-level merge of HMDA, ATTOM, McDash, and Equifax data. Loan amount, applicant income and Latinx-/African-American are from HMDA. Interest rate, LTV, and credit score are from McDash-Equifax. Top-25-volume lender is calculated annually from volume of loans by lender. FinTech is a platform identifier from Buchak et al. (2018).

the GSE securitized loans and were responsible for 1.6% of the FHA loans. Table 1 also highlights the dominance of the largest originators in the mortgage-lending industry. The top 25 originators (by origination volume in their respective loan-origination year) accounted for 41.0% of GSE lending and 28.5% of FHA loans.[15] In all of our analyses, we divide the market between purchase and refinance loans. Purchase loans represent 59.5% of the loans in the pricing analysis, while 40.5% are refis.

## *4.2. HMDA Data, 2018–2019*

The 2009–2015 HMDA data used for our core sample do not include information on points or other costs at loan origination. However, in October 2015 the Consumer Financial Protection Bureau (CFPB) amended the requirements under HMDA to require the reporting of this information, commencing with data collected after January 1, 2018. To examine whether our results are robust to the payment of points, we therefore repeat our analysis using recently released HMDA data for 2018 and 2019, which include points paid (both positive and negative). In addition, due to concerns that HMDA lenders may be reporting or classifying their overall up-front points (both positive and negative) in different ways, we also redo our analysis using the new 2018–2019 HMDA variable *Total Loan Cost*, which includes both points and other costs. Total loan cost is likely to be a better control for cases where some lenders charge higher points than others but their other fees are lower. In such cases, borrowers might be indifferent between lenders, even though they have a very different distribution of points paid.

A limitation of the 2018–2019 HMDA data is that they do not include loan-level information on the credit score at origination. Additionally, an insufficient period of time has elapsed since the issue date to acquire this data from a merge with our other data sets. We proxy for the unobserved loan-level credit scores in the HMDA 2018–2019 loan-level data using credit score averages by census tract, by loan type (GSE versus FHA), and by minority status (Latinx/African American versus White/Asian) using the ATTOM/HMDA/McDash/Equifax loan-level data from 2009–2015.

Table 2 presents summary statistics for the 2018–2019 HMDA data used in our pricing analysis, controlling for points and loan-origination costs. To keep the data for the 2009–2015 and 2018–2019 analyses comparable, we only consider first-lien, fixed-rate, 30-year single-family residential mortgages securitized by the GSEs or insured by the FHA. We also apply the same filters to the loan-to-value ratio, income, and loan amount. Similarly we exclude manufactured housing, investment properties, loans on condos, duplexes, triplexes,

[15] We identify the top 25 mortgage originators per year by matching HMDA lender names with mortgage-origination statistics obtained from Inside Mortgage Finance.

and quadraplexes.

As shown in Table 2, the share of refinance mortgages in the 2018–2019 HMDA data is lower for the GSE loans compared to those reported in the 2009–2015 data with 39.1% comprising refinance loans in the GSE data whereas slightly more of the FHA loans, 30.3%, are refinances. The interest rates are similar to the earlier vintage mortgages with an average interest rate of 4.44% for the GSE loans and 4.48% for the FHA loans. The average loan amount for the GSE mortgages is $263,619 with a loan-to-value ratio of 76.1%, and the average loan amount for the FHA loans is $232,006 with a loan-to-value ratio of 89.7%. Average borrower income for the GSE loans is $100,707, which is slightly lower than the 2009–2015 data, and the proxy for the credit score is 747.9, which is somewhat lower than in the 2009–2015 data. For the FHA loans the average income of $78,645 is higher than in the 2009–2015 vintage sample; the proxy average credit score of 730.1 is also higher.

In the 2018–2019 analysis, we lack the borrower's actual name (contained in the ATTOM data); therefore, we use the HMDA measure for race and ethnicity rather than the updated minority measure that is used in the 2009–2015 vintage analysis. As shown in Table 2, 4.5% of the GSE loans are to minority borrowers in the 2018–2019 data, compared with 14.8% of the FHA loans. The two new variables measuring borrower fees at origination are points (both positive and negative) and total loan costs. Both of these are measured as a fraction of the origination loan balance. For the GSE loans, points represent .17% on average of the origination loan balance with a standard deviation of .67% and total loan costs represent 1.8% on average of the loan balance with a standard deviation of 1.1%. Average points for the FHA loans represent 0.17% of the origination loan balance with a standard deviation of 0.72% and the average total loan costs represents 3.7% of the loan balance with a standard deviation of 1.2%.

# 5. Estimation

As described above, the GSEs' and FHA's role in guaranteeing loans provides a setting (in the largest consumer-loan market in the United States) in which we can fully see the price of credit risk by observing a borrower's LTV and credit score. This feature of the GSE and FHA market allows us to decompose a borrower's interest rate into (a) a base mortgage rate (captured by time fixed effects), (b) credit risk (captured by a borrower's LTV and credit score) and (c) a residual that reflects a lender's strategic pricing. While "grid pricing" formally applies only to GSE loans, doing no risk pricing (or perhaps charging slightly more for high-LTV loans) is equivalent to using the GSE grid and then setting the same interest rate in every cell (or perhaps charging a slightly higher rate in high-LTV cells). Thus, for

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Credit score | 2,212,246 | 747.86608 | 14.674482 | 620 | 829 |
| FinTech | 2,212,246 | .13038062 | .33672179 | 0 | 1 |
| Income | 2,184,873 | 100.70703 | 63.440554 | 20 | 635 |
| Loan amount | 2,212,246 | 263.61896 | 129.73451 | 45 | 725 |
| Loan interest rate | 2,212,246 | .04441362 | .00538968 | .0275 | .079 |
| Loan-to-value ratio | 2,212,246 | .76053186 | .14402249 | .3003096 | .94957983 |
| Minority borrower | 2,212,246 | .04495567 | .20720685 | 0 | 1 |
| Points | 2,164,245 | .00169405 | .0066614 | -.01922169 | .02753803 |
| Refinance | 2,185,338 | .39142412 | .48806904 | 0 | 1 |
| Total loan costs | 2,192,384 | .01818049 | .01120778 | 0 | .07018133 |
| $N$ | 2,212,246 | | | | |

(a) GSE loans

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Credit score | 953,192 | 730.0895 | 18.10742 | 580.125 | 826 |
| FinTech | 953,192 | .0912523 | .2879678 | 0 | 1 |
| Income | 910,670 | 78.64494 | 41.06824 | 20 | 635 |
| Loan amount | 953,192 | 232.0056 | 105.3531 | 45 | 725 |
| Loan interest rate | 953,192 | .0448173 | .006458 | .0275 | .07875 |
| Loan-to-value ratio | 953,192 | .8967726 | .0928592 | .300813 | .9823009 |
| Minority borrower | 953,192 | .1483636 | .3554602 | 0 | 1 |
| Points | 920,361 | .0016903 | .0072352 | -.0192209 | .0275377 |
| Refinance | 943,124 | .3030906 | .4595943 | 0 | 1 |
| Total loan costs | 901,869 | .0366662 | .0117278 | 0 | .0701836 |
| $N$ | 953,192 | | | | |

(b) FHA loans

Table 2: **Summary Statistics: 2018/19 HMDA data.** Data are fixed-rate mortgage originations obtained from the 2018–2019 HMDA data. The credit scores are measured as average credit scores at the loan's census tract for originated mortgages in the ATTOM/McDASH data. The borrower minority status is constructed from the HMDA measure for ethnicity and race in the 2018–2019 HMDA data.

consistency in presentation, we apply this decomposition model to both GSE and FHA loans.

Figures 2 and 3 visualize this identification strategy. Figure 2 shows histograms of raw mortgage interest rates by minority status for 30-year fixed-rate mortgages in our sample. The histograms reveal a wide distribution of rates for both minority and non-minority-status loans, as one might expect given the length of our sample period and the variation in creditworthiness in the sample. However, when we consider interest rates within the grid by subtracting out the month-year-grid means, Figure 3 shows a dramatic reduction in the distribution of interest rates for both groups of borrowers. Nonetheless, residual variation in rates remains. Our interest is in whether this residual variation is correlated with a borrower's race or ethnicity.

Based on these results, our base empirical specification regresses the mortgage interest rate on an indicator for the applicant being Latinx or African-American plus dummies for the 64 GSE grid levels interacted with year/month and whether the loan is a cash-out refinance; and for lender interacted with year. This allows us to capture pricing in the grid, the fact that there is a different pricing grid for cash-out refinances, differential pricing by lender, and fluctuations over time. In addition, because many of the costs of issuing a loan are fixed, mortgage interest rates are well-known to be negatively correlated with loan amount (controlling for other loan and borrower characteristics);[16] therefore, we also include fixed effects for loan-size deciles. Overall, the regression run is

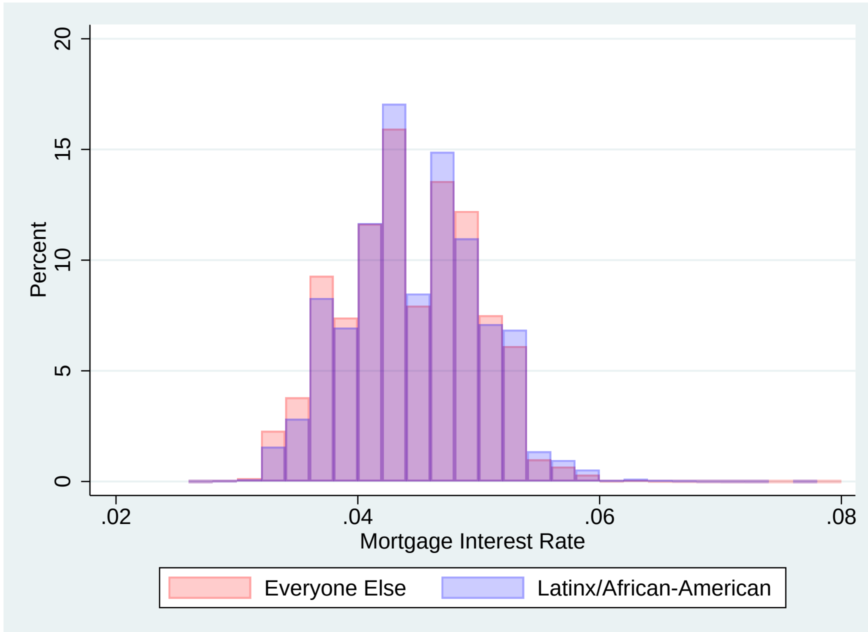
$$\text{interest rate}_{it} = \alpha I(\text{Latinx or African-American})_i + \mu_{\text{Cash-out} \times \text{GSE-grid} \times \text{year/month}} + \mu_{\text{Lender} \times \text{year/month}} + \mu_{\text{Amount decile}} + \epsilon_{it}. \quad (1)$$

## 5.1. *Baseline Estimates*

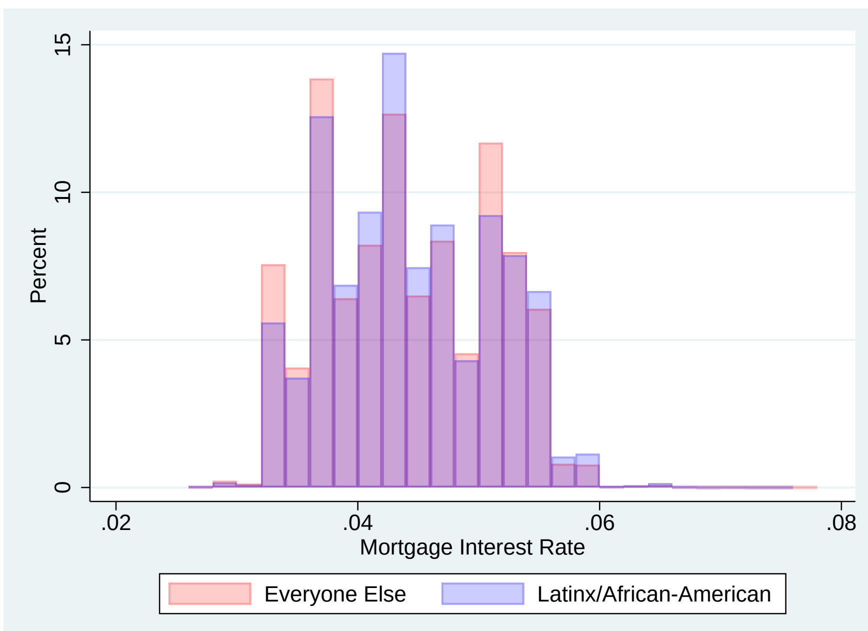
Table 3 presents the results of running Regression (1) for the loans in our sample. The first two columns present estimates for GSE loans, while the second two columns present estimates for FHA loans. Because lenders' pricing strategies may vary by mortgage type, we present estimates for purchase mortgages (columns 1 and 3) separately from refinance mortgages (columns 2 and 4).

The overall mean difference in the purchase-mortgage interest rate between Latinx/African-American and non-minority borrowers is between about 2 and 5 basis points (0.02%–0.05%), ranging from 1.63 basis points for GSE refis to 4.67 basis points for GSE purchase loans. The range for FHA loans is 4.87 basis points for purchase loans and 1.53 basis points for refis. According to the Mortgage Bankers' Association, the average *total* mortgage profit per

[16] See `https://www.zillowhomeloans.com/resources/factors-influencing-interest-rate/`.

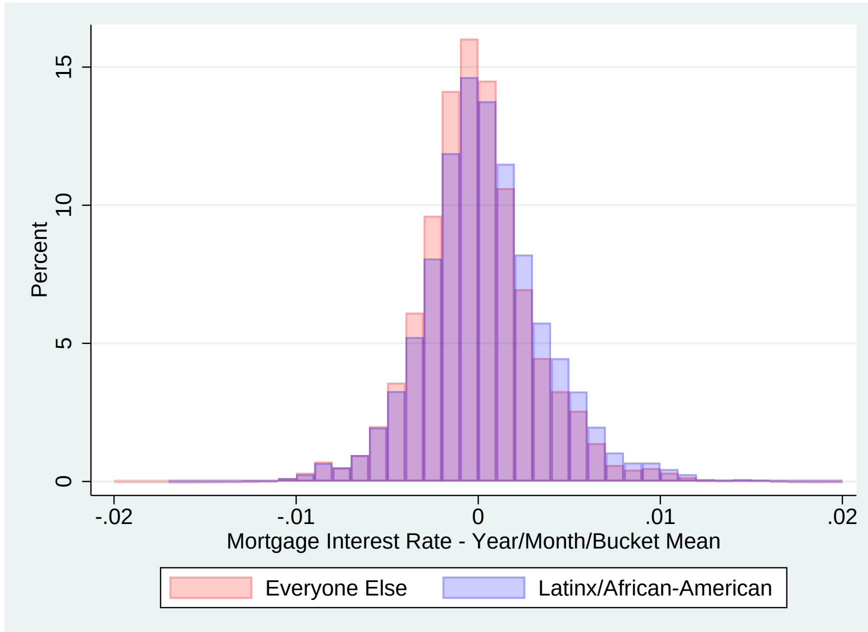



(a) GSE loans

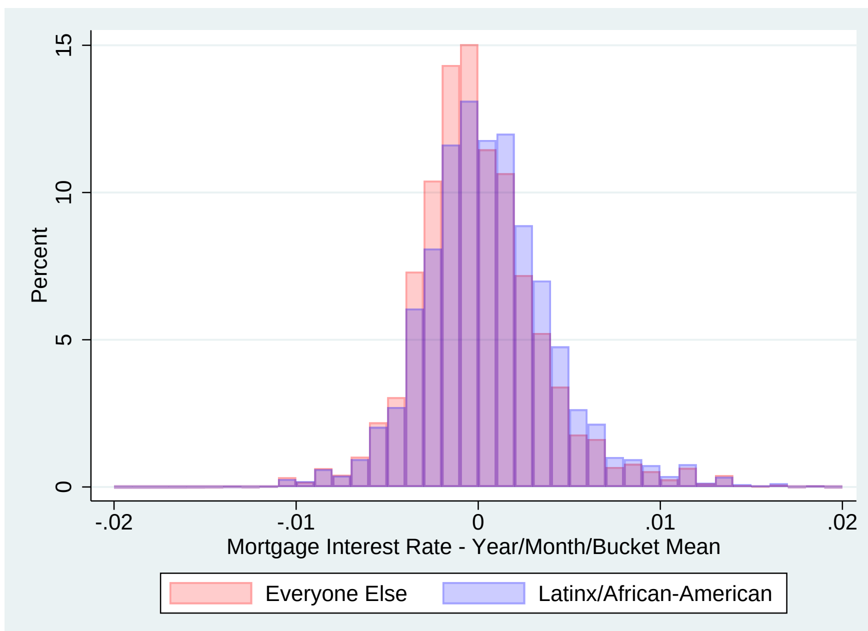



(b) FHA loans

Figure 2: **Raw Interest Rates by Race/Ethnicity.** Presented are histograms of raw interest rates originated on 30-year fixed-rate mortgages, 2009–2015. The histograms are plotted for Latinx and African-Americans and for everyone else.




(a) GSE loans




(b) FHA loans

Figure 3: **De-meaned Interest Rate Histograms by Race/Ethnicity: The Role of the GSE Grid.** The figure shows loan interest rates for 30-year mortgages from 2009 to 2015, de-meaned to the GSE grid for the relevant month and year (calculated separately for purchase and refinance loans and for GSE vs. FHA loans). The histogram is plotted for Latinx and African-American borrowers and for everyone else.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 4.674*** | 1.632*** | 4.866*** | 1.527*** |
| | (0.255) | (0.227) | (0.333) | (0.253) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: **Interest-rate differentials.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

loan between 2008 and 2019 was 50 basis points of a loan's principal,[17] so using the heuristic that 0.2% in rate $\approx$ 1 point, 2 bps corresponds to 20% of total average profit.

Also of interest in Table 3 is the ability of the model to explain between 77% and 87% of the variation in interest rates within our sample of loans. The unexplained variation ($1 - R^2$ = 13–23%) might reflect strategic pricing, either on borrowers' location (perhaps due to collusion or to opportunistic pricing in financial deserts) or on borrowers' behavioral characteristics (perhaps reflecting profiling using variables or soft information that correlate with a lack of shopping). The disparity between purchase and refinance mortgage discrimination suggests that borrower sophistication and hurriedness matter. Refinancing borrowers are, by definition, experienced and may be in less of a hurry to re-contract than the average purchase-mortgage borrower (who may also be time-constrained to bid on a house on the market).

## *5.2. FinTech Lenders*

Using data from Optimal Blue, Bhutta, Fuster, and Hizmo (2020) find a 54 basis-point gap between the 10th and 90th percentile mortgage rates paid for identical loans with the

[17] See `https://www.mba.org/2020-press-releases/april/imb-production-volumes-and-profits-rise-in-2019`.

same number of points by borrowers with the same characteristics in the same market on the same day. Even after controlling for the individual loan officer within a branch, the 10th–90th percentile spread is still 26 basis points. In other words, even after approval by the GSEs or FHA, lenders exercise substantial control over what rate actually gets paid by a given borrower on a given day.

This control is exerted by individual loan-officers at traditional lenders, and increasingly by computer algorithms at FinTech lenders. Supporting the notion that the rate-setting process may be different at the two types of lenders, Buchak et al. (2018) find that "Relative to non-fintech shadow banks, fintech lenders . . . appear to use different information in setting interest rates, consistent with a big data component of technology." Fuster et al. (2020), in finding that FinTech lenders have gained market share in recent years, likewise note the possibility that these lenders price risk differently.

Fuster, Plosser, Schnabl, and Vickery (2019) study FinTech lenders in detail, and conclude that the main difference between them and other lenders is efficiency: FinTech lenders process mortgage applications 20% faster. However, they also find that "FinTech default rates are about 25% lower than those for traditional lenders, even when controlling for detailed loan characteristics." While they interpret this as evidence that FinTech lenders are not more lax in their screening than traditional lenders, it may also indicate the use of more sophisticated credit-screening or pricing algorithms.[18] Survey evidence shows that industry participants believe that more sophisticated models, including the use of AI, will play an ever-increasing role in the lending process, including evaluation of creditworthiness.[19]

Given these changes in the market, we here examine whether FinTech originators perform any better than traditional lenders in avoiding discrimination. Although face-to-face lenders provide loan officers with personal contact with applicants, which can induce racism and in-group bias in decision-making, platforms may have equal opportunity to cause inadvertent discrimination. Algorithmic pricing of loans applies estimation techniques over large sets of data to enable profit-maximizing pricing strategies. An algorithm could naturally discover that higher prices could be quoted to profiles of borrowers or geographies associated with low-shopping tendencies.[20] As described earlier, if such pricing induces higher

[18]It may also indicate the presence of selection — e.g., perhaps the borrowers who seek out FinTech lenders are relatively sophisticated and thus less likely to default. However, Fuster et al. (2019) conclude that this explanation is unlikely to be correct. As they state, "We also find no robust evidence that FinTech penetration leads to slower processing speeds or higher defaults for other lenders, as would be expected if the pool of unobservably 'fast' or low-default borrowers had simply migrated away to FinTech. Furthermore, we show that FinTech has grown most quickly in regions where mortgage processing times were previously unusually slow, again at odds with an explanation that FinTech lenders target 'fast' borrowers."

[19]See, for example, ForbesInsights, "Key Takeaways on the Rise of AI in the Mortgage Industry," 2020, `https://forbesinfo.forbes.com/the-rise-of-AI-in-the-Mortgage-Industry`.

[20]An alternative possible explanation for the mechanism inducing minority borrowers to pay higher rates

mark-ups for minorities, the lender must have a *legitimate-business-necessity* defense for this form of algorithmic profiling. However, as noted, courts have consistently limited the legitimate-business-necessity defense to a lender's use of variables and practices to ascertain creditworthiness. In the case of mortgage lending in the GSE or FHA systems, no residual creditworthiness assessment is needed within the GSE grid to price credit risk; therefore, pricing strategies that cause higher mark-ups for minorities within a given grid cell using this strategy would constitute impermissible discrimination according to these court cases. (We note below that face-to-face lenders may also seek to charge higher rates to borrowers having a lower propensity to shop around by preparing different rate sheets by branch or geography, a practice that has led to several fair-lending enforcement actions.)

Table 4 shows discrimination results for loans issued by FinTech lenders. All of the coefficients are still significantly greater than zero. The differences between the baseline estimates reported in Table 3 and those in Table 4 are negligible for GSE loans or FHA refinance loans. However, they are 27% lower for FHA purchase loans and 36% lower for FHA refinance loans. As shown in Table 4, the FHA purchase loans have a statistically significant 132 basis point minority pricing differential between the FinTech and non-FinTech lenders, whereas the GSE loans and FHA refi differentials are not statistically significant.

Of course, who goes to a FinTech lender is not random, so we cannot be sure to what extent these results can be extrapolated to the whole population of borrowers. However, as discussed above, Fuster et al. (2019) conclude that selection is unlikely to be a major issue.

## 5.3. *Time Pattern*

Woodward and Hall (2012) discuss the importance of shopping behavior for equal treatment in mortgage outcomes. It might be that the existence of FinTech and algorithmic lending creates an environment that is more conducive to shopping for the best rate or more competitive because of FinTech entrants. Additionally, for loans issued after 2011, post-crisis reforms to Regulation Z sought to reduce the incentive of brokers to place borrowers into high-cost loans by prohibiting loan originators from receiving compensation that is based on the interest rate or other loan term.[21]

is that initial quotes are the same for everybody (conditional on observables), but minority borrowers may be less likely to negotiate for a lower rate (e.g., with a competing offer). Even under this alternative interpretation, however, it is important to note that the resulting disparities would remain unrelated to a borrower's creditworthiness. For this reason, courts have consistently rejected attempts to dismiss disparate impact claims in lending where defendants have argued that disparate loan pricing is simply the result of customers "negotiating in the shadow of market forces." (See Miller v. Countrywide Bank, NA, 571 F.Supp.2d 251, 258 (D. Mass 2008)).

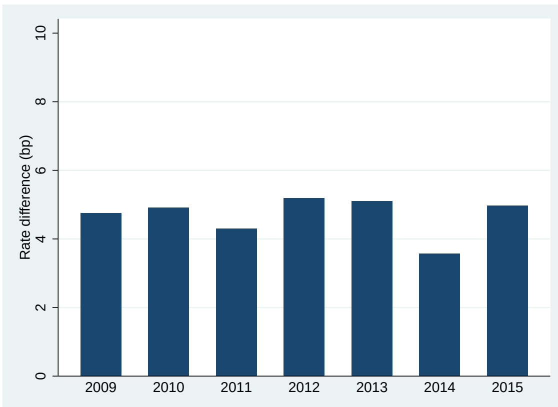
[21]See Regulation Z, 75 Fed. Reg. 58,509 (Sept. 24, 2010). This rule was subsequently tightened by the CFPB in 2013. See Loan Originator Compensation Requirements Under the Truth in Lending Act

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Non-FinTech × Minority | 4.666*** | 1.631*** | 4.877*** | 1.548*** |
| | (0.256) | (0.238) | (0.336) | (0.262) |
| FinTech × Minority | 5.081*** | 1.565*** | 3.550*** | 0.969** |
| | (0.124) | (0.271) | (0.373) | (0.385) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| p-value for test of equality | 0.1172 | 0.8570 | 0.0084 | 0.2204 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| FinTech FE | Y | Y | Y | Y |

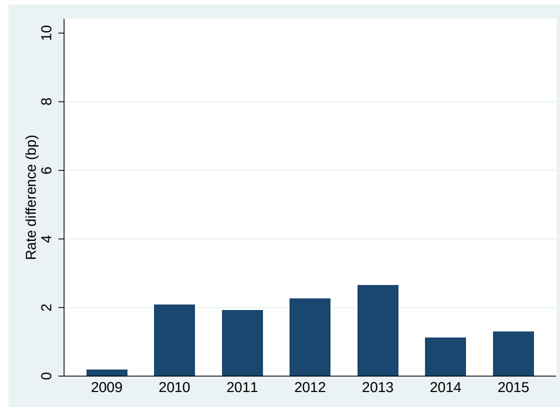
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: **Interest-rate differentials: FinTech vs. non-FinTech lenders.** The table reports interest-rate differentials as in Table 3, split by FinTech vs. non-FinTech lenders (as defined by Buchak et al., 2018). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

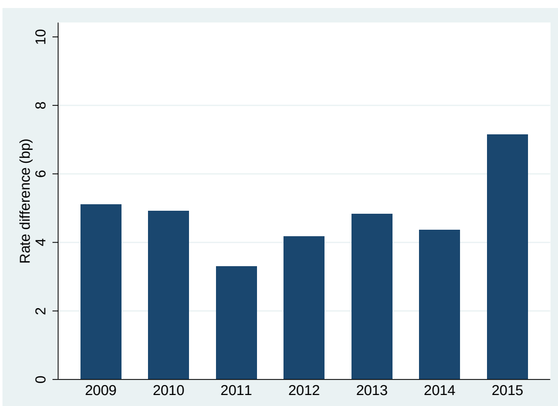
Figure 4 shows the pricing-differential coefficient by loan-issue year from 2009 to 2015. For all four groups of loans, the coefficient has been fairly stable over the period, with no obvious patterns, suggesting that neither the introduction of FinTech lending nor post-crisis changes to Regulation Z has so far had any notable impact on outcomes.



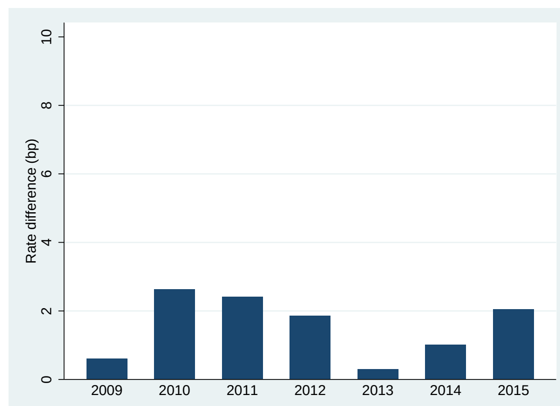

(a) GSE purchase loans




(b) GSE refi loans




(c) FHA purchase loans




(d) FHA refinance loans

Figure 4: **Interest-rate differentials by year.** The figure plots interest-rate differentials as in Table 3, estimated year by year. The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile.

(Regulation Z), 78 Fed. Reg. 11280 (Feb. 15, 2013).

## 5.4. Geography

This section investigates geographical variation in mortgage rates, shedding light on an important channel driving rate differentials between minority and non-minority borrowers. First, Table 5 repeats the baseline regressions in Table 3 with the addition of census-tract $\times$ year fixed effects and without firm fixed effects. As before, Latinx and African-American borrowers pay significantly higher rates than non-minority borrowers, though the differences are smaller than in Table 3: rate effects for minority borrowers are 2.003 and 1.926 basis points for purchase mortgages, and 0.768 and .499 basis points for refinance mortgages (GSE and FHA, respectively). This change in coefficient estimates suggests a geographical component to our results, which we now investigate further.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 2.003*** | 0.768*** | 1.926*** | 0.499*** |
| | (0.186) | (0.207) | (0.213) | (0.183) |
| Observations | 1,320,534 | 1,489,748 | 1,476,865 | 367,377 |
| R-squared | 0.827 | 0.788 | 0.870 | 0.894 |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Census tract $\times$ year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: **Interest-rate differentials with census-tract controls.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, loan-amount decile, and census-tract $\times$ year/month. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

### 5.4.1. Census-tract minority share

Figure 5 presents our point estimates for the minority rate differential using the same regressions as Table 5, but this time with the minority indicator interacted with deciles of the share of minority residents within each census tract.[22] One could easily imagine that

[22]Table I2 in the internet appendix presents the coefficient estimates that correspond to this figure.

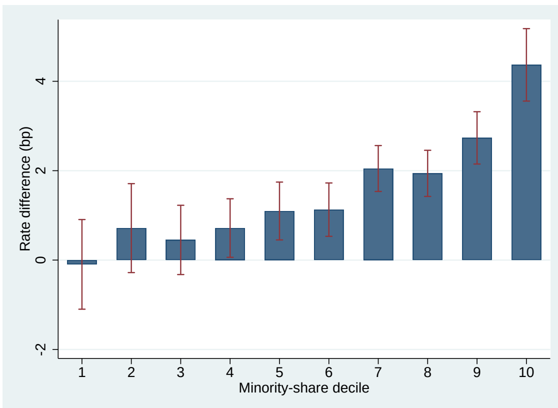
bias might be stronger where there is less opportunity to encounter minority individuals who could dispel negative stereotypes. However, we find the opposite. The treatment coefficient is *increasing* in the minority share, especially for purchase loans. For the highest minority-share decile, it is between 1.1 and 4.1 bp (for FHA refinance and GSE purchase loans, respectively), and it is statistically indistinguishable from zero for many of the lowest-minority-share areas (at least for GSE loans and FHA refinance loans).[23]

To examine this in more detail, Figure 6 shows binned scatter plots (see Cattaneo, Crump, Farrell, and Feng, 2019a,b) of the census-tract $\times$ year fixed effects from the regression in Figure 5 plotted against census-tract minority share, with the data in ten equal bins. The fixed effects are sharply increasing in the census-tract minority share, with the average rate for *all* borrowers in decile-10 minority-share census tracts higher than that for equivalent borrowers in decile-1 census tracts by 9.7–14.3 bp for purchase loans (GSE and FHA, respectively) and 3.1–5.8 bp for refinance loans (GSE and FHA, respectively).

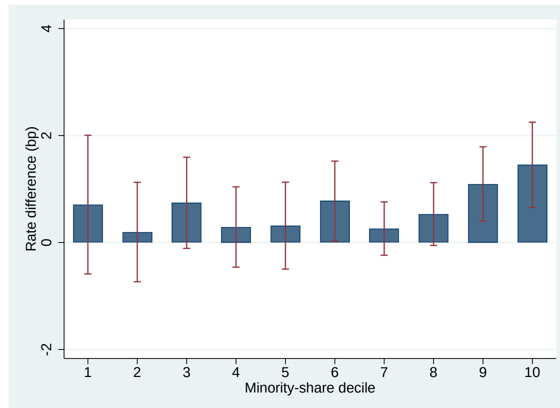
Thus, average rate disparities for minority borrowers in high-minority-share census tracts are higher than our overall estimates for two reasons. First, the average level of mortgage rates is higher for *all* borrowers — both minority and non-minority — in high-minority-share census tracts; and second, in those same census tracts, minority borrowers also pay higher rates than non-minority borrowers. Thus, a minority borrower taking out a GSE purchase loan in a decile-10 minority-share census tract pays on average $9.7 + 4.1 = 13.8$ basis points more than an otherwise-equivalent non-minority borrower in a decile-1 census tract. For FHA purchase loans, the difference is even larger: $14.3 + 1.9 = 16.2$ basis points.

While these differences are striking, could they perhaps just reflect different costs in different areas, such as differential default risk? Table I3 in the Internet Appendix reruns the regressions shown in Figure 5 and Table I2, but this time also including as controls three dummy variables for whether each loan subsequently went into foreclosure/REO, 60-days-plus delinquent, or 90-days-plus delinquent. Of course, these ex-post default realizations would not have been available to lenders at the time the loans were initially issued, regardless of how much data they had to analyze, but even conditioning on all three measures makes very little difference to our estimates, so differential default risk does not explain our results. However, there are also other costs associated with issuing and servicing loans, e.g., prepayment risk, state foreclosure laws (which affect the cost of foreclosure), and rent levels. Looking again at Figure 6, we see that for both GSE and FHA loans, the rate spread between high- and low-minority-share census tracts is substantially higher for purchase loans than for

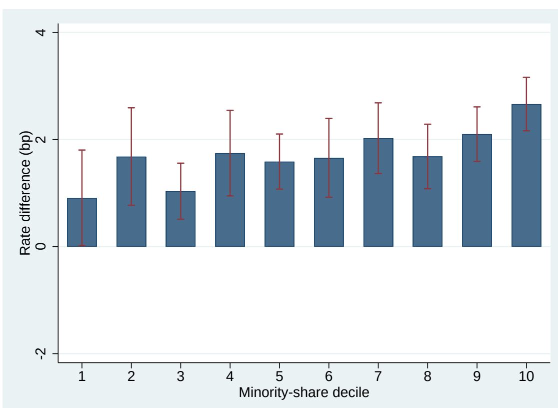
[23]The lack of significance for lower deciles is in part due to the small proportion of minority borrowers in those census tracts. For example, for FHA refinance loans, 63.5% of loans in decile-10 census tracts are taken out by minority borrowers, compared with only 2.1% for decile 1.



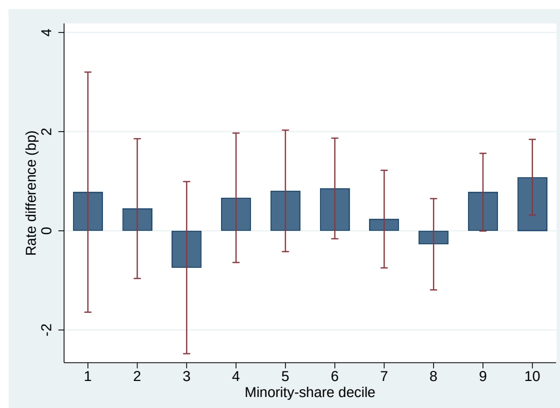

(a) GSE purchase loans




(b) GSE refi loans

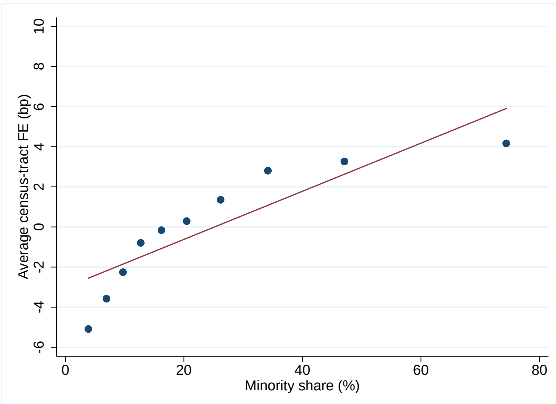



(c) FHA purchase loans

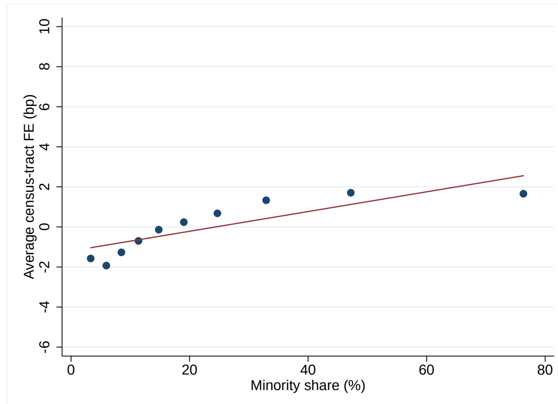



(d) FHA refinance loans

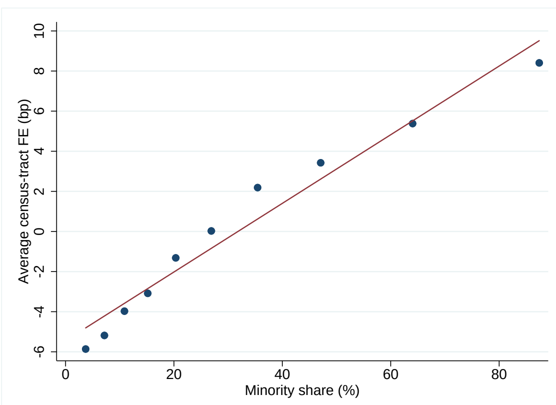
Figure 5: **Interest-rate differentials with census-tract controls by minority-share decile** (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for minority-share decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, loan-amount decile, and census-tract × year. Standard errors are clustered at the lender level.



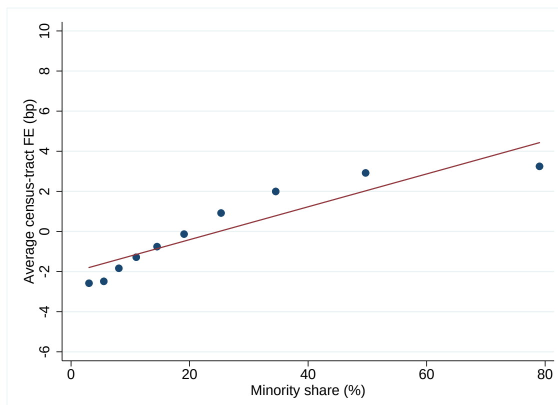

(a) GSE purchase loans




(b) GSE refi loans



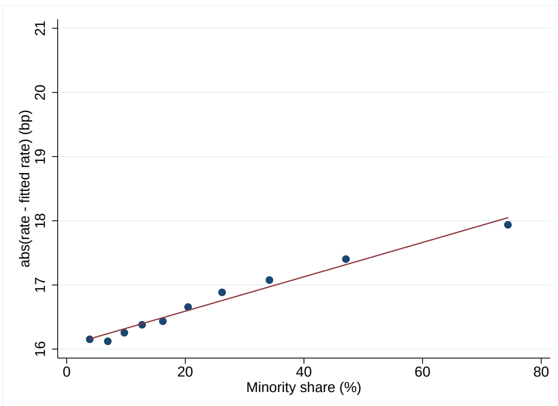

(c) FHA purchase loans



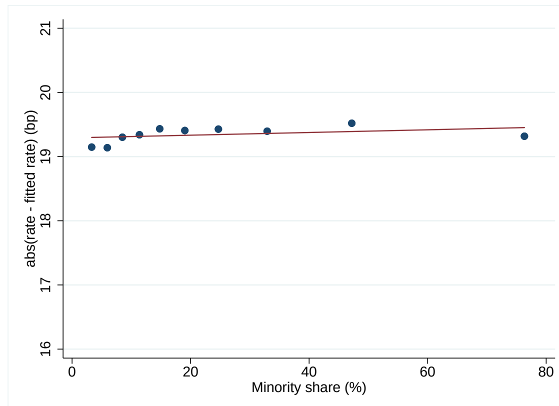

(d) FHA refinance loans

Figure 6: **Average interest-rate levels by minority-share decile.** The figure shows binned scatter plots of the census-tract $\times$ year fixed effects from the regression in Table 5 versus the census-tract minority share, with the data in ten equal bins.

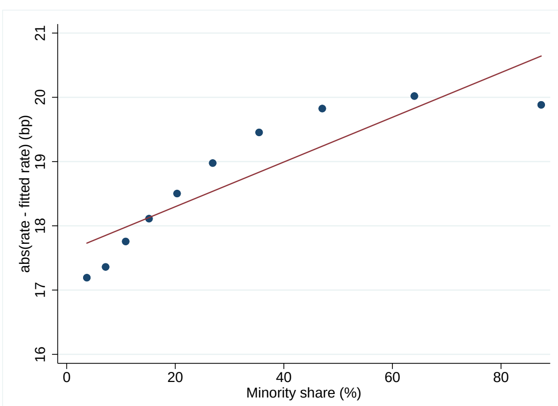
refinance loans, something that is hard to reconcile with a differential-cost story. Moreover, while higher costs in a given area could explain higher mean mortgage rates, they would not imply any change in other moments of mortgage rates, such as standard deviation or skewness. Figure 7 shows binned scatter plots of the absolute residuals from the regressions used for Table 5 against minority share. There is a substantially higher spread in mortgage rates, at least for purchase loans, in high-minority-share census tracts. All of these points argue against our results being driven by differential costs.



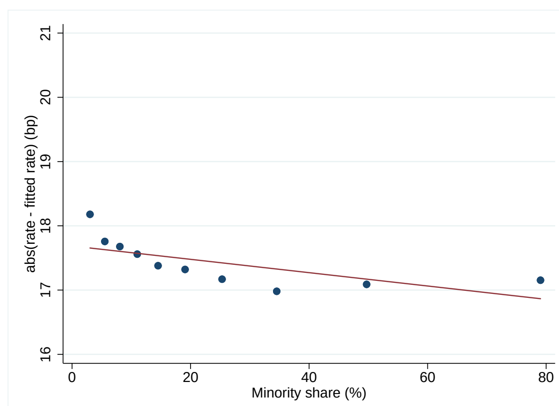

(a) GSE purchase loans




(b) GSE refi loans




(c) FHA purchase loans

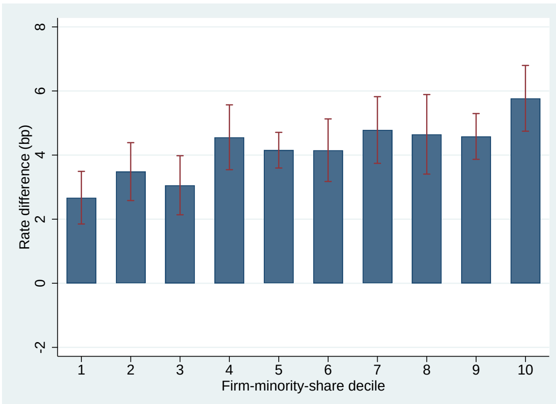



(d) FHA refinance loans

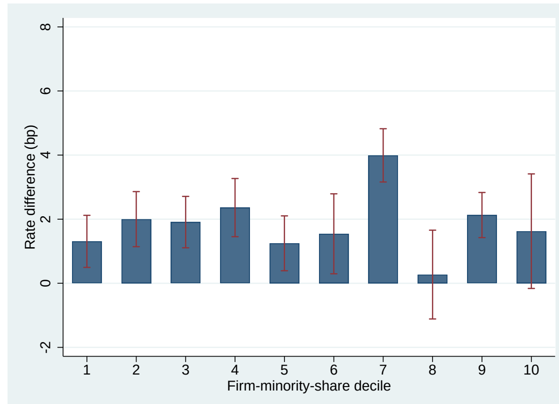
Figure 7: **Binned scatter plots of absolute residuals from Table 5 against minority share.**

### *5.4.2. Firm minority share*

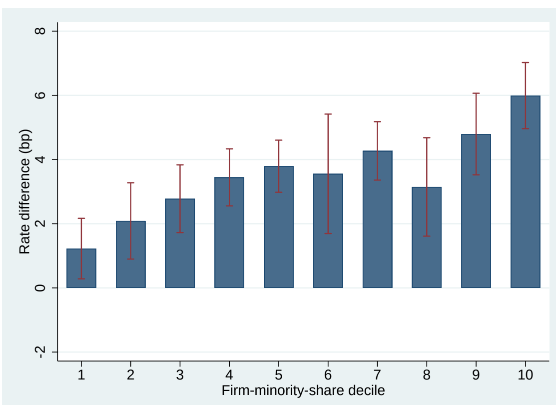
We see similar patterns in Figure 8, which shows how the minority coefficient varies with the lender's proportion of loans issued to minorities.[24] Again, the coefficient gets larger as the proportion of loans issued to minority borrowers increases.



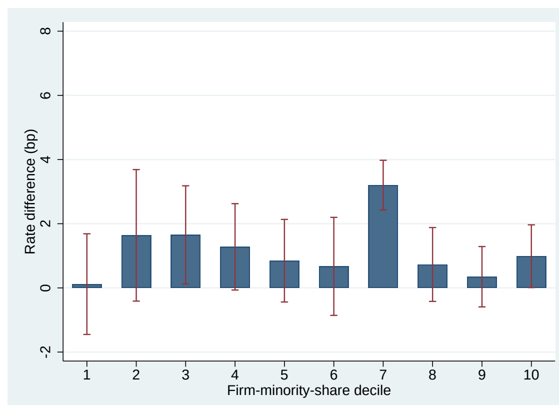

(a) GSE purchase loans




(b) GSE refi loans




(c) FHA purchase loans




(d) FHA refinance loans

Figure 8: **Interest-rate differentials by firm-minority-share decile** (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for firm-minority-share decile. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, loan-amount decile, and firm-minority-share decile. Standard errors are clustered at the lender level.

[24] To avoid multicollinearity, these regressions do not include lender fixed effects.

#### 5.4.3. CRA

Table 6 shows the treatment coefficient for CRA versus non-CRA census tracts. We see

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Non-CRA tract × Minority | 4.043*** | 1.411*** | 4.555*** | 1.334*** |
| | (0.248) | (0.194) | (0.338) | (0.225) |
| CRA tract × Minority | 6.431*** | 1.856*** | 5.397*** | 1.223*** |
| | (0.334) | (0.474) | (0.328) | (0.365) |
| Observations | 1,371,437 | 1,540,614 | 1,533,484 | 436,401 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| p-value for test of equality | 0.0000 | 0.2188 | 0.0000 | 0.6579 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| CRA FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Interest-rate differentials by CRA status.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for CRA status. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

that the rate differential is significantly greater than zero for both CRA and non-CRA census tracts. In CRA census tracts, minority purchase borrowers pay 6.43 (5.39) basis points more for GSE (FHA) loans, respectively, and refi borrowers pay 1.41 for GSE loans. However, FHA refi borrowers pay a somewhat lower differential of 1.22 basis points.

### 5.5. Additional Robustness Tests

This section performs some additional robustness tests, exploring the issues of put-back risk, servicing-cost risk, and HMDA ethnicity/race designations. Section 6 explores the impact of discount points.

*5.5.1. Put-back risk*

Our identification relies on the lender not being exposed to repayment risk. Once a mortgage is placed into the hands of the GSE the only repayment risk faced by the originating lender is put-back risk. Put-backs can occur when the documentation on income (tax returns, pay stubs, etc.), credit score, loan purpose (residential vs. non-occupancy) or property value (the appraisal) is falsified or missing. Put-backs from mortgages issued prior to and through the 2008 mortgage crisis were very material.[25] However, after the crisis, because of the repercussions for misrepresentation, lenders ceased no-documentation GSE loans and adjusted their policies to lessen the potential for falsified documentation. As a result, the magnitudes of put-backs on post-2008 GSE originations have become a trickle compared with early-2000s issuances (see, for example, Goodman, Parrott, and Zhu, 2015).

Of course, realized put-backs being low does not necessarily imply that they had a negligible ex-ante probability.[26] To address the issue of put-backs in more detail, we perform three analyses:

1. **Loans from 2013 on:** Panel (a) of Table 7 repeats the regressions of Table 3, but only for loans issued in or after 2013, when put-back risk was no longer a significant issue, certainly for GSE loans.[27] The treatment coefficients are of similar magnitude to the base coefficients in Table 3.
2. **High-quality borrowers:** Put-back risk cannot be a significant issue for the highest-quality loans. Panel (b) of Table 7 repeats the base regressions including only high-quality loans: for GSE loans, we define this as loans with a borrower credit score of at least 740 and an LTV of 0.6 or below; for FHA loans, we define this as loans with a borrower credit score of at least 700 and an LTV of 0.75 or below. Not surprisingly, these filters result in a substantial reduction in the number of observations of FHA loans. Nonetheless, the point estimates of the treatment coefficients are slightly smaller than, but similar to, the baseline coefficients for GSE purchase and refinance loans as well as for FHA purchase loans, though the coefficient for FHA refinance loans is not statistically distinguishable from zero.
3. **Banks vs. non-banks:** Finally, if put-back risk is an issue, it ought to be less relevant for nonbank lenders than for banks, who have more franchise value at stake. Panel (c) of

[25] The GSEs put back $4.2 billion of pre-crisis loans in 2010 alone (American Banker, July 14, 2016).

[26] Indeed, as late as November 2012, lenders' fear of put-backs was cited in a speech by Ben Bernanke as a reason for tight lending standards (see `https://www.federalreserve.gov/newsevents/speech/bernanke20121115a.htm`).

[27] See, for example, Clea Benson, "Mortgage Putback Threat Reduced for Lenders Under New Rules," Bloomberg News, September 11, 2012. Goodman (2015) notes, however, that residual liability for originating FHA loans that failed to comply with HUD rules remained a concern for FHA loans originated even after 2012.

Table 7 shows treatment coefficients for banks and non-banks separately. For both groups of lenders, the coefficients are similar to the base values. (The larger nonbank coefficients are statistically different from the bank minority coefficients for purchase mortgages but not for refi mortgages.)

All of these results together imply that the coefficient on the treatment variable is not caused by put-back risk.

*5.5.2. Servicing costs*

Not all default costs are borne by the GSE (or FHA) that insures the loan. There are also significant costs borne by the servicer who has to deal with a delinquent borrower (see Kim, Laufer, Pence, Stanton, and Wallace, 2018), and it is possible that different servicing costs could explain the rate differentials we observe. Kau, Fang, and Munneke (2019) find that minority borrowers have similar default rates to non-minority borrowers but lower prepayment rates; Gerardi, Willen, and Zhang (2020) find that while minority borrowers have higher rates of going 90+ days past due, even after controlling for observables, the conditional differences disappear or even reverse when using foreclosure/REO as the outcome. These results suggest that a servicing cost explanation may be unlikely, but we nevertheless investigate it by looking at how the estimated treatment coefficient varies with ex-post default behavior and with several ex ante default-related variables.

Table 8 repeats the base regressions, this time including as controls three dummy variables for whether each loan subsequently went into foreclosure/REO, 60-days-plus delinquent, or 90-days-plus delinquent. Of course, these ex-post default realizations would not have been available to lenders at the time the loans were initially issued, regardless of how much data they had to analyze, but even conditioning on all three measures makes very little difference to our estimates. We continue to find significant differences between the interest rates paid by minority and non-minority borrowers.

Turning to ex ante measures, Figures 9, 10 and 11 look at how the estimated treatment coefficient varies with credit-score bucket, LTV bucket, and income decile, respectively.[28] We find that it is relatively insensitive to the credit score, though it does increase in LTV, being insignificant or even slightly negative for the lowest LTV bucket, but greater than zero for all other LTV buckets (significantly so for every other bucket for both GSE and FHA purchase loans). The coefficient is also decreasing in income level, though it is significantly greater than zero for all income deciles for GSE loans and FHA purchase loans, and all but four income deciles for FHA refinance loans.

[28]Full regression tables for these regressions are in Internet Appendix I3.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 4.539*** | 1.865*** | 5.583*** | 1.167*** |
| | (0.260) | (0.274) | (0.470) | (0.369) |
| Observations | 690,659 | 374,700 | 544,112 | 111,098 |
| R-squared | 0.675 | 0.683 | 0.577 | 0.629 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) **Post-2012:** Loans issued from 2013 to 2015

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 3.359*** | 1.481*** | 3.715*** | 1.110 |
| | (0.367) | (0.299) | (0.877) | (2.031) |
| Observations | 77,432 | 314,734 | 6,441 | 3,233 |
| R-squared | 0.859 | 0.788 | 0.892 | 0.907 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) **High-quality borrowers:** Credit score $\geq$ 740 (700) and LTV $\leq$ 0.6 (0.75) for GSE (FHA) loans.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Bank × Minority | 4.274*** | 1.516*** | 3.378*** | 1.672*** |
| | (0.192) | (0.320) | (0.483) | (0.599) |
| Nonbank × Minority | 4.954*** | 1.745*** | 5.341*** | 1.509*** |
| | (0.315) | (0.257) | (0.306) | (0.225) |
| Observations | 1,278,029 | 1,466,461 | 1,418,917 | 401,325 |
| R-squared | 0.806 | 0.769 | 0.857 | 0.870 |
| p-value for test of equality | 0.0487 | 0.5762 | 0.0001 | 0.7952 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Nonbank FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(c) **Banks vs. non-banks**

Table 7: **Interest-rate differentials.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 4.619*** | 1.614*** | 4.787*** | 1.510*** |
| | (0.254) | (0.228) | (0.332) | (0.253) |
| Foreclosure/REO | 2.468*** | 1.887*** | 0.588*** | 1.491*** |
| | (0.613) | (0.688) | (0.227) | (0.310) |
| 60+ days delinquent | 5.235*** | 4.297*** | 1.894*** | 0.148 |
| | (0.333) | (0.442) | (0.167) | (0.320) |
| 90+ days delinquent | 1.258*** | 1.864*** | 1.223*** | 1.184*** |
| | (0.463) | (0.443) | (0.171) | (0.352) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: **Interest-rate differentials controlling for ex-post default status.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise; along with controls for whether the loan subsequently went into foreclosure/REO, 60-days-plus delinquent, or 90-days-plus delinquent. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

These patterns suggest that the servicing-cost explanation may have some bite, though it can only explain a fraction of the observed difference in rates between minority and non-minority borrowers. On the other hand, the fact that we see little relation with realized default or credit score suggests that the income and LTV results might instead reflect something else, such as the well-known correlation between income and financial sophistication, which would be consistent with differential shopping behavior across minority and non-minority borrowers.[29]

#### *5.5.3. Measurement of minority status*

The minority designation in our analysis is determined by combining self-reported data from HMDA with — for mortgages in HMDA that lack an indicator of borrower race/ethnicity — the borrower's likely race/ethnicity based on a race and ethnicity name-categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008). It is possible that this algorithm might misclassify a particular borrower's race or ethnicity, and that this misclassification might in some way be correlated with the loan interest rate. To examine this issue, we rerun the regressions in Table 3 and report the results in Tables I8a and I8b in the online Internet Appendix.

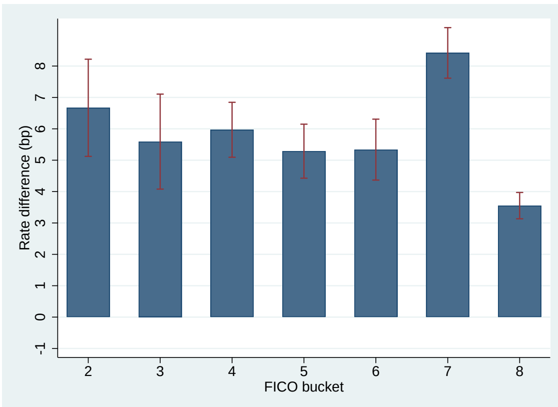
1. Using only observations where race or ethnicity is provided by HMDA; and
2. Setting the treatment variable to 1 if either the borrower *or* the first coborrower is Latinx or African American.

In each case,[30] the estimates are very similar to those in Table 3, confirming that our results are not driven by errors in identifying a borrower's race or ethnicity.

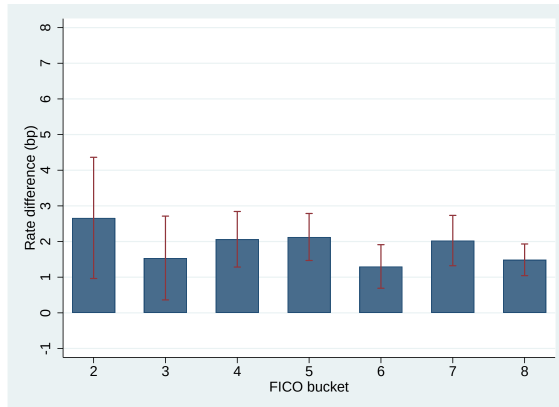
#### *5.5.4. Lender-paid mortgage insurance*

Borrowers taking out GSE loans with an LTV greater than 80% are required to take out private mortgage insurance (PMI) (Goodman and Kaul, 2017). By itself, this does not pose any problem for our results, because both minority and non-minority borrowers face the same requirement. However, PMI can be paid either by the borrower (BPMI) or by the lender (LPMI), sometimes with both occurring for a single lender. With LPMI, the interest rate on the loan is typically higher to compensate the lender for the cost of insurance, so it is in principle possible that the higher rate paid by minority borrowers at least in part reflects their being more likely to take out LPMI than non-minority borrowers. Discussions with McDash suggest that the incidence of LPMI is relatively low (less than 10% of all loans

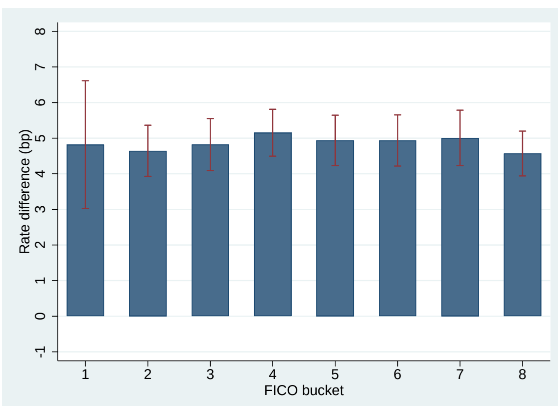
[29] See, for example, Calvet, Campbell, and Sodini (2009).
[30] See Table I8 in the Internet Appendix.



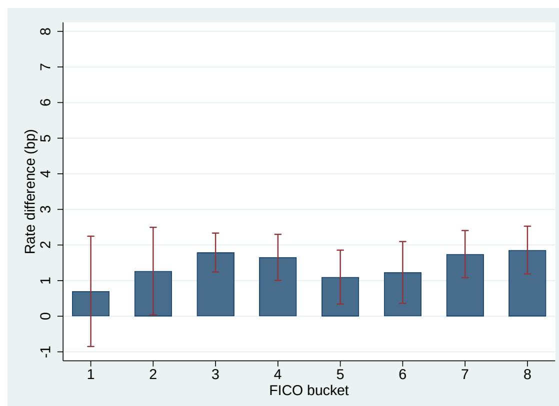

(a) GSE purchase loans




(b) GSE refi loans

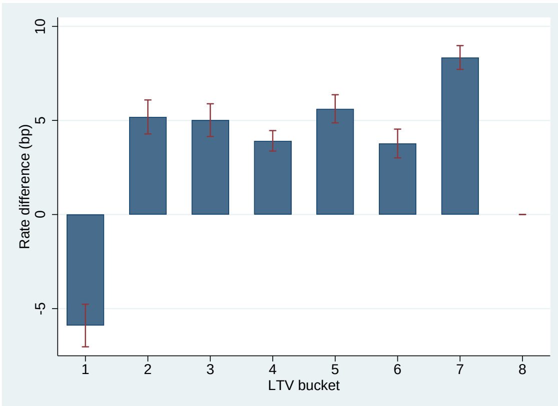



(c) FHA purchase loans

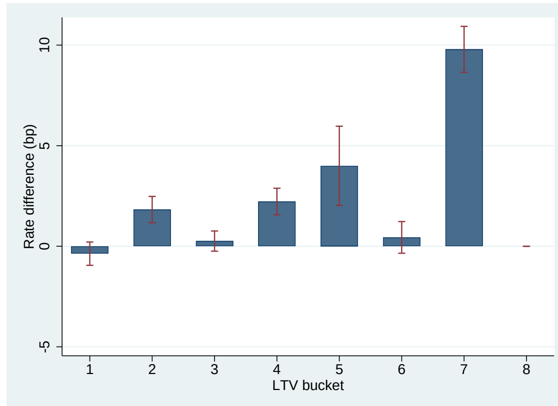



(d) FHA refinance loans

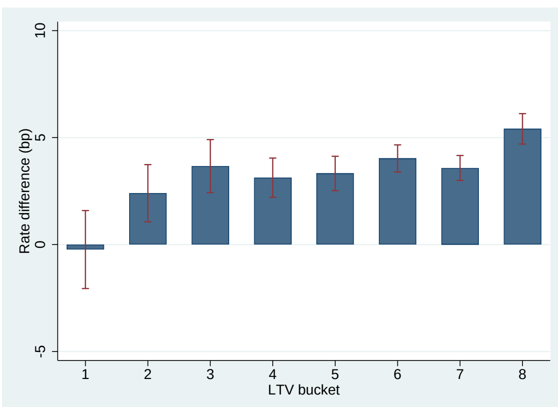
Figure 9: **Interest-rate differentials by GSE-credit-score bucket** (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for credit-score bucket. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level.



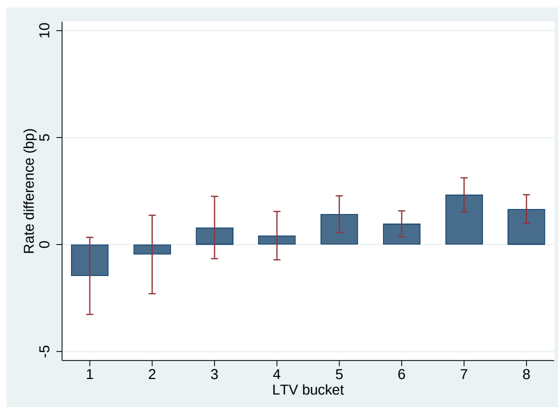

(a) GSE purchase loans




(b) GSE refi loans

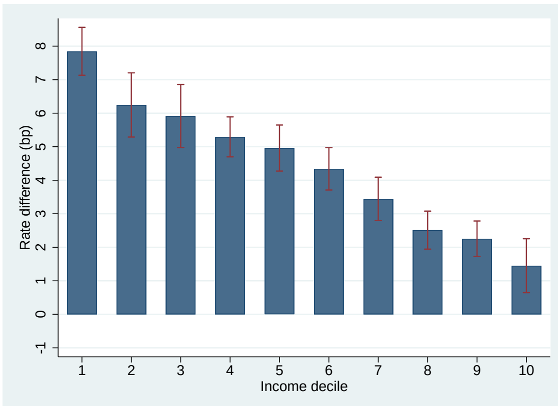



(c) FHA purchase loans

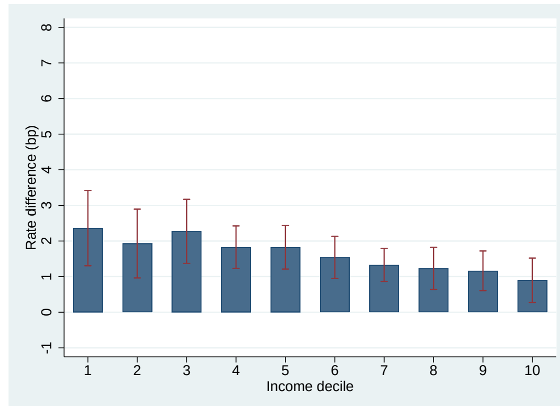



(d) FHA refinance loans

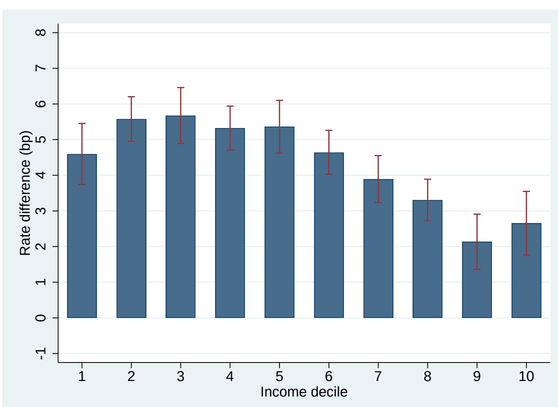
Figure 10: **Interest-rate differentials by GSE-LTV bucket** (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for GSE-LTV bucket. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level.



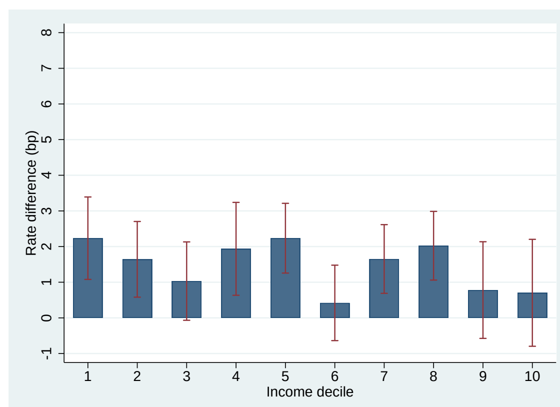

(a) GSE purchase loans




(b) GSE refi loans




(c) FHA purchase loans




(d) FHA refinance loans

Figure 11: **Interest-rate differentials by income decile** (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for income decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, loan-amount decile, and income decile. Standard errors are clustered at the lender level.

with mortgage insurance), and Figure 10 shows that minority GSE borrowers pay more than non-minority borrowers for LTV both below (buckets 1–4) and above (buckets 5–8) 80%. Nevertheless, for completeness, Table 9 shows the results of the baseline regression for GSE loans with LTV $\leq$ 80%. The minority coefficients are similar to those in Table 3, showing that our results are not driven by different propensities to take out LPMI for minority and non-minority borrowers.

| | GSE Loans | |
|---|---|---|
| | Purchase | Refinance |
| | (1) | (2) |
| VARIABLES | Interest rate | Interest rate |
| Minority borrower | 4.215*** | 1.711*** |
| | (0.280) | (0.219) |
| Observations | 844,343 | 1,280,664 |
| R-squared | 0.835 | 0.778 |
| Lender x year/month FE | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y |
| Amount decile FE | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: **Interest-rate differentials for GSE loans with LTV $\leq$ 80%.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

# 6. Discount Points and the 2018–2019 HMDA Data

Borrowers may choose to pay "discount points," an up-front lump sum, to a lender in order to reduce the loan interest rate. Alternatively, they may choose to pay "negative points," i.e., to get a credit from the lender, in return for paying a higher loan interest rate. Even in the complete absence of discrimination, if minority and non-minority borrowers choose to pay different levels of points, they will also pay different interest rates. Bhutta and Hizmo (2021) (BH from now on) analyze a subset of FHA loans originated in 2014 and 2015, including data on points paid. Like us, they find that minority borrowers pay significantly higher interest rates, but they conclude that

> "...these gaps are offset by differences in discount points. We trace out point-rate schedules and show that minorities and whites face identical schedules, but sort to different locations on the schedule."

The 2018–2019 HMDA data allows controls for points and total up-front loan costs in our pricing regressions for both GSE and FHA mortgages. For this purpose, we set the variable "points-paid" to reflect either the amount of discount points paid by a borrower (i.e., points-paid $> 0$) or the amount of negative points paid to receive a lender credit (i.e., points-paid $< 0$).

For direct comparison with our earlier results, Panel (a) of Table 10 includes no controls for points paid or for total loan costs. It reports the results of regressing the loan interest rate against the minority dummy, with fixed effects for lender $\times$ year, cash-out $\times$ LTV decile $\times$ year, cash-out $\times$ census-tract credit-score decile $\times$ year, loan-amount decile $\times$ year, and cash-out $\times$ income $\times$ year.[31] The treatment coefficient is significantly positive in all four loan types, though it is substantially larger for GSE than for FHA loans. Panel (b) of Table 10 runs the same regression, but adding fixed effects for points-paid decile $\times$ year (thus controlling for the level of points). It can be seen that adding this extra control increases the estimated coefficients for GSE purchase loans and GSE and FHA refis. The coefficient is essentially the same for the FHA purchase loans. Panel (c) runs the same analysis as Panel (b), but this time controlling for total-loan-cost decile rather than points-paid decile. This accounts for additional costs and for the possibility that different firms may be reporting/classifying points paid differently. The coefficients are again all significantly greater than zero, and again are of similar magnitudes to those in Panels (a) and (b).[32,33]

Table 11 reports the same regression for FinTech lenders. Interestingly, the 2018–2019 results differ from the results reported in Table 4 for the FinTech lenders. The FinTech results using the 2009–2015 data without controls for origination costs indicated that although the FinTech lenders did charge statistically significant and positive spreads to minority borrowers, the magnitudes of those spreads were comparable to the non-FinTech lenders for the GSE loans, and for both types of lenders the estimated treatment effect was smaller

[31] We include controls for individual income here along with census-tract-level credit scores, because the HMDA data do not include individual credit scores.

[32] Unlike our base analysis, we are unable here to exclude loans with pre-existing or contemporaneous second liens, since these are not reported by HMDA. However, when we repeat the base regressions in Table 3 *without* dropping such loans, the estimated coefficients change by only 0.01–0.05 basis points.

[33] As a robustness check, we also run these regressions with total loan costs on the left hand side and interest-rate deciles on the right. As in Panel (c) of Table 10, the estimated coefficient on the minority indicator is significantly greater than zero in all regressions.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 7.377*** | 5.998*** | 5.529*** | 1.632*** |
| | (0.472) | (0.392) | (0.386) | (0.541) |
| Observations | 1,315,200 | 842,640 | 655,261 | 245,437 |
| R-squared | 0.376 | 0.483 | 0.341 | 0.356 |
| Lender x year FE | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) **No controls for points or costs.**

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 7.820*** | 6.900*** | 5.530*** | 2.172*** |
| | (0.482) | (0.375) | (0.384) | (0.415) |
| Observations | 1,315,200 | 842,640 | 655,261 | 245,437 |
| R-squared | 0.386 | 0.493 | 0.343 | 0.366 |
| Lender x year FE | Y | Y | Y | Y |
| Point decile x year FE | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) **Controlling for points paid.**

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower | 7.709*** | 6.806*** | 5.441*** | 1.926*** |
| | (0.520) | (0.354) | (0.394) | (0.420) |
| Observations | 1,306,553 | 835,769 | 631,631 | 240,015 |
| R-squared | 0.381 | 0.490 | 0.339 | 0.361 |
| Lender x year FE | Y | Y | Y | Y |
| Cost decile x year FE | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(c) **Controlling for total loan costs.**

Table 10: **Interest-rate differentials: 2018/2019 HMDA data controlling for points paid/total loan costs.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for lender $\times$ year, total-cost decile $\times$ year, cash-out $\times$ LTV decile $\times$ year, cash-out $\times$ census-tract credit-score decile $\times$ year, and loan-amount decile $\times$ year. Panel (a) does not control for either points paid or total loan costs, Panel (b) controls for points paid, and Panel (c) controls for total loan costs. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Non-FinTech × Minority | 7.751*** | 6.619*** | 5.466*** | 2.480*** |
| | (0.595) | (0.461) | (0.414) | (0.483) |
| FinTech × Minority | 7.367*** | 7.357*** | 5.000*** | -0.365 |
| | (0.547) | (0.222) | (0.718) | (0.244) |
| Observations | 1,306,553 | 835,769 | 631,631 | 240,015 |
| R-squared | 0.381 | 0.490 | 0.339 | 0.361 |
| Lender x year FE | Y | Y | Y | Y |
| Cost decile x year FE | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |
| FinTech FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: **Interest-rate differentials by FinTech firms: 2018/2019 HMDA data controlling for total loan costs.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for lender × year, total-cost decile × year, cash-out × LTV decile × year, cash-out × census-tract credit-score decile × year, and loan-amount decile × year. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

for refinance loans. The results reported in Table 11 for the FinTech GSE lenders indicate statistically significant spreads charged to minority borrowers of 7.367 basis points for GSE purchase loans and 7.357 basis points for GSE refis. The results for FinTech FHA loans indicate that minority borrowers are charged a statistically significant 5.0 basis points for FHA purchase loans, while FHA refi loans are not charged a statistically significant spread by FinTech lenders. This latter result is more consistent with the lower level of over-pricing for the FHA refinance mortgages that was found in the 2009–2015 data. Thus, in the more recent vintage mortgages, FinTech lenders do appear to charge more for FHA and GSE purchase loans and GSE refinance loans, although they do not for the FHA refinance loans.

### 6.1. *Comparison with Bhutta and Hizmo (2020)*

There are a number of differences between the data used by BH and in our analysis. In particular, BH look only at FHA loans, while we look at both GSE and FHA loans. Our results are strongest for GSE and FHA purchase loans and for GSE refinance loans, but we also find evidence of small rate differences for FHA refinance loans. In addition to only using FHA loans,

- BH analyze loans originated in 2014 and 2015, while we look at loans originated in 2018 and 2019.
- BH merge the HMDA data with Optimal Blue, while we use the 2018 and 2019 HMDA data directly. Optimal Blue is used primarily by smaller lenders,[34] so the merge with Optimal Blue substantially reduces their sample to only 157,853 loans.[35] Our FHA sample is almost 6 times as large (more than 0.9 million loans) and we analyze 3.2 million loans altogether (including GSE loans), allowing us to estimate more precise coefficients.
- By merging with Optimal Blue, BH are able to use more precise data on loan and borrower characteristics than we are, including, in particular, the borrowers' individual credit scores. We proxy for the unobserved loan-level credit scores in the HMDA 2018–2019 loan-level data using credit score averages by census tract, by loan type (GSE versus FHA), and by minority status (Latinx/African American versus White/Asian) using the ATTOM/HMDA/McDash/Equifax loan-level data from 2009–2015, in addition to income. We, of course, recognize the potential for omitted-variable problems associated with our reliance on a proxy variable, but since we find stability in historical credit score averages using the suitably filtered McDash loan-level data (more than 11 million mortgage originations), we conclude that our solution to the missing-data problem is unlikely to bias our results.[36]

In a recent working paper, Willen and Zhang (2021) revisit the conclusions of Bhutta and Hizmo (2021) using the 2018–2019 HMDA data merged with Optimal Blue. They point out that econometric problems can arise when trying to detect discrimination by regressing interest rate on race and points (or vice versa) if

[34] Bhutta and Ringo (2021, p. 201) note that "Lenders using the Optimal Blue platform tend to be smaller institutions rather than the largest banks;" the January 2019 working-paper version clarifies that the data "do not include loans originated by the largest banks such as Wells Fargo and JPMorgan Chase."

[35] BH estimate that "Optimal Blue covers about one-quarter of the mortgage market." The merge with Optimal Blue reduces the BH sample size from 971,222 to 157,853 loans, a reduction of 84%.

[36] Section I5 in the Internet Appendix performs one additional robustness check, repeating the 2009–2015 analysis using the 2018–2019 specification, i.e., replacing individual credit scores with local average credit scores and individual income, both in- and out-of-sample. The patterns in the results remain unchanged.

1. Borrowers are choosing loans from menus with different points/rate combinations; and
2. Those menus are heterogeneous in level and/or slope across lenders.

Willen and Zhang (2021) derive an alternative testing approach that is robust to heterogeneity in mortgage menus. Like us, they find significant interest-rate discrimination for minority borrowers with conforming loans, but they do not find significant discrimination for FHA mortgages.[37] However, their test is conservative. They note that "While [our methodology] has the advantage of requiring few assumptions to be valid, it has the drawback that a negative result from our metrics does not necessarily imply that there is no discrimination in menus: only that there exists a set of menus which rationalizes the data."

The econometric problems identified by Willen and Zhang (2021) arise when pooling data from lenders with different mortgage menus. Table 12 therefore re-examines differentials in interest rates across minority and non-minority borrowers, controlling for lender-level heterogeneity in both the level and slope.[38] In particular, we regress the loan interest rate against total loan costs and the minority dummy, allowing both the constant term and the coefficient on total loan costs to be different for each lender $\times$ year combination. The coefficient on the minority dummy remains significantly greater than zero in all four cases, and of similar magnitude to those obtained earlier in Table 10.

Overall, we conclude that minorities *do* pay a higher rate than non-minorities, even after conditioning on points/total costs paid. The difference is significant for both GSE and FHA loans, though it is smaller for FHA than for GSE loans.

# 7. Accept/Reject Discrimination

Even though an application might receive a creditworthiness approval in the GSE underwriter system, the lender might still reject an application. Section I6 of the Internet Appendix compares application-rejection rates for minority versus non-minority applicants. While there are some significant caveats with this analysis — in particular, we do not observe the loan-level credit score or loan-to-value ratio of rejected applicants, so we use census-tract-level averages — we do find some significant differences in rejection rates that suggest further study is warranted.

[37] Recall that our analysis looks at GSE rather than conventional loans, because our identification strategy relies on the GSEs' pricing grid.

[38] Figure 5 in Bhutta and Hizmo (2021) also addresses this point, by performing lender-specific regressions.

| VARIABLES | GSE Loans Purchase (1) Interest rate | Refinance (2) Interest rate | FHA Loans Purchase (3) Interest rate | Refinance (4) Interest rate |
|---|---|---|---|---|
| Minority borrower | 7.683*** | 6.781*** | 5.520*** | 1.766*** |
| | (0.534) | (0.338) | (0.390) | (0.446) |
| Observations | 1,303,784 | 834,678 | 620,341 | 231,615 |
| R-squared | 0.386 | 0.496 | 0.350 | 0.386 |
| Lender x year FE | Y | Y | Y | Y |
| Lender x year cost slope | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) Overall difference between minority and non-minority interest rate.

| VARIABLES | GSE Loans Purchase (1) Interest rate | Refinance (2) Interest rate | FHA Loans Purchase (3) Interest rate | Refinance (4) Interest rate |
|---|---|---|---|---|
| Total costs decile 1 × Minority | 7.975*** | 10.23*** | 12.53* | -8.430 |
| | (1.157) | (1.729) | (6.497) | (13.60) |
| Total costs decile 2 × Minority | 9.542*** | 7.173*** | 24.25* | 11.10 |
| | (1.176) | (0.796) | (12.56) | (9.303) |
| Total costs decile 3 × Minority | 9.496*** | 7.408*** | 1.832 | 9.486 |
| | (1.036) | (0.819) | (8.145) | (7.315) |
| Total costs decile 4 × Minority | 8.216*** | 6.606*** | 2.107 | -16.18*** |
| | (0.946) | (0.758) | (5.814) | (5.839) |
| Total costs decile 5 × Minority | 8.833*** | 4.678*** | 4.740 | 6.634* |
| | (0.887) | (0.698) | (4.197) | (3.873) |
| Total costs decile 6 × Minority | 6.493*** | 5.688*** | 6.098*** | 2.097 |
| | (0.703) | (0.714) | (1.916) | (3.070) |
| Total costs decile 7 × Minority | 6.086*** | 6.452*** | 9.885*** | 0.811 |
| | (0.599) | (0.829) | (1.198) | (1.369) |
| Total costs decile 8 × Minority | 5.334*** | 6.761*** | 5.202*** | 1.636** |
| | (0.586) | (1.403) | (0.614) | (0.803) |
| Total costs decile 9 × Minority | 6.945*** | 6.705*** | 5.992*** | 1.982*** |
| | (0.874) | (0.792) | (0.532) | (0.645) |
| Total costs decile 10 × Minority | 9.792*** | 7.703*** | 4.434*** | 1.817*** |
| | (1.260) | (1.736) | (0.524) | (0.595) |
| Observations | 1,303,784 | 834,678 | 620,341 | 231,615 |
| R-squared | 0.386 | 0.496 | 0.350 | 0.386 |
| Lender x year FE | Y | Y | Y | Y |
| Lender x year cost slope | Y | Y | Y | Y |
| Cash-out x LTV decile x year FE | Y | Y | Y | Y |
| Cash-out x credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Difference between minority and non-minority interest rate by total-loan-cost decile.

Table 12: **Interest-rate differentials with firm-specific regression slope: 2018/2019 HMDA data controlling for total loan cost.** The dependent variable is the loan interest rate in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Also on the right is the total loan cost, trimmed at the 1% and 99% levels, with a separate slope for each lender × year combination. Fixed effects are included for lender × year, cash-out × LTV decile × year, cash-out × census-tract credit decile × year, loan-amount decile × year, and income × year. Panel (a) shows the overall coefficient, while panel (b) shows separate coefficients for each loan-cost decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

# 8. Conclusion

The question of whether algorithmic decision-making promotes or inhibits impermissible discrimination is especially relevant in the context of consumer lending, given both the historical challenge of eliminating discrimination in this domain and the importance of consumer lending for the well-being of households. Using a unique data set of mortgage loans that includes never-before-linked information at the loan level on income, race, ethnicity, loan-to-value, and other contract terms, we exploit the unique structure of the GSE and FHA lending markets to identify discrimination in mortgage loan pricing.

Overall, we find that conditional on obtaining a loan, Latinx and African-American borrowers in our base sample of loans issued between 2009 and 2015 (see Table 3) pay on average interest rates that are 4.7–4.9 bps higher for purchase mortgages and almost 2 bps higher for refinance mortgages. Using HMDA data from 2018–2019 with controls for the effect of total loan costs at origination (see Panel (c) of Table 10), we find even larger differences of 7.7 bps for GSE purchase, 6.8 basis points for GSE refinance loans, 5.4 bps for FHA purchase loans, and 1.9 bps for FHA refinance loans. These differences are robust to a wide range of robustness tests. In addition, although FinTech lenders were found to discriminate less than lenders overall in the 2009–2015 vintage loans, we find in the 2018–2019 vintage loans with controls for total loan costs that they charged minority borrowers (see Table 11) additional spreads of 7.4 bps for GSE purchase and refinance loans and 5.0 basis points for FHA purchase loans; however, for FHA refinance loans the spread differentials for minorities were not statistically different from zero. Thus, although the reduced use of face-to-face underwriting among FinTech lenders appears to have reduced discrimination for FHA refinance borrowers, the results for GSE and FHA purchase lending in the 2018–2019 vintage loans is consistent with FinTech lenders using pricing strategies and data analytics that produce discriminatory pricing. These results underscore the fact that even if algorithmic lending can reduce discrimination relative to face-to-face lenders, it is insufficient to eliminate discrimination in loan pricing.

We also find in the 2009–2015 data an important association between minority rate disparities and geography. First, the average level of mortgage rates is higher for *all* borrowers — both minority and non-minority — in high-minority-share census tracts; and second, in those same census tracts, minority borrowers also pay higher rates than non-minority borrowers. Thus, a minority borrower taking out a GSE purchase loan in a decile-10 minority-share census tract pays on average $9.7+4.1 = 13.8$ basis points more than an otherwise-equivalent non-minority borrower in a decile-1 census tract. For FHA purchase loans, the difference is even larger: $14.3 + 1.9 = 16.2$ basis points.

To put these magnitudes in more context, using discrimination estimates for the 2018–2019 HMDA data shown in Table 12; estimates of the total balance outstanding on GSE and FHA mortgages from The Federal Reserve's Z.1 data and HUD, respectively; and assuming the same overall split between purchase and refinance loans that we see in our data, along with the same minority/non-minority split, our findings translate into Latinx/African-American borrowers paying over $450 million extra in interest per year.

How discrimination happens is an important question. We leave a full exploration of this topic to a separate research project, but we can fix ideas here. Lenders may be able to extract monopoly rents from minority borrowers because such borrowers might be prone to less shopping on average (Woodward, 2008; Woodward and Hall, 2012). The fact that the magnitude of discrimination in refinance loans is generally lower than in purchase mortgages is consistent with an interpretation that monopoly price extraction of rents is easier in purchase-mortgage transactions, where the borrowers have less experience or are acting in a more urgent time frame. Additionally, because lenders may price loans to capture rents in less-competitive areas, prices might be higher in financial-services deserts, which might have higher minority populations. These pricing mechanisms can play out with either human or machine intervention. For instance, one can easily imagine both lending algorithms and human loan officers seeking to detect which types of borrowers are less prone to shopping or which types of geographies have less competitive pricing. Alternatively, it is also possible that a lender provides initial quotes that are the same for everybody (conditional on observables), but minority borrowers may be less likely to negotiate for a lower rate (e.g., with a competing offer), perhaps due to how they have been treated in the past (Woodward, 2008). Nevetheless, the courts consistently deem the outcome to be disparate impact, because resulting disparities remain unrelated to creditworthiness.

Finally, our results also speak to ongoing debates concerning the future structure of the GSEs. The GSE underwriting process that informs our identification strategy establishes clear rules for assessing borrower creditworthiness. Accordingly, it is possible that the GSE process itself may be serving to attenuate the incidence of discrimination, given that the incentive to use credit-linked variables that may be correlated with a protected classification is eliminated since the GSEs take on the credit risk of the mortgages. To date, this less-well-understood role of the GSEs has not been considered in GSE reform proposals, nor is it obvious how such a role could be supported within a fully privatized, conventional conforming secondary mortgage market.

# References


Ambrose, B. W., Conklin, J. N., Lopez, L. A., 2021. Does borrower and broker race affect the cost of mortgage credit? Review of Financial Studies 34, 790–826.

Barocas, S., Selbst, A., 2016. Big Data's disparate impact. California Law Review 104, 671–732.

Bartlett, R., Morse, A., Stanton, R., Wallace, N., 2020. Algorithmic discrimination and input accountability under the Civil Rights Acts. Berkeley Technology Law Journal (forthcoming).

Bayer, P., Ferreira, F., Ross, S. L., 2018. What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders. Review of Financial Studies 31, 175–205.

Begley, T. A., Purnanandam, A. K., 2020. Color and credit: Race, regulation, and the quality of financial services. Journal of Financial Economics (forthcoming).

Bhutta, N., Fuster, A., Hizmo, A., 2020. Paying too much? Price dispersion in the U.S. mortgage market. Working paper, Federal Reserve Board.

Bhutta, N., Hizmo, A., 2021. Do minorities pay more for mortgages? Review of Financial Studies 34, 763–789.

Bhutta, N., Ringo, D., 2021. The effect of interest rates on home buying: Evidence from a shock to mortgage insurance premiums. Journal of Monetary Economics 118, 195–211.

Black, H., Schweitzer, R. L., Mandell, L., 1978. Discrimination in mortgage lending. American Economic Review 68, 186–191.

Black, H. A., Boehm, T. P., DeGennaro, R. P., 2003. Is there discrimination in mortgage pricing? The case of overages. Journal of Banking and Finance 27, 1139–1165.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics 130, 453–483.

Butler, A. W., Mayer, E. J., Weston, J. P., 2020. Racial discrimination in the auto loan market. Working paper, Rice University.

Calvet, L. E., Campbell, J. Y., Sodini, P., 2009. Measuring the financial sophistication of households. American Economic Review 99, 393–398.

Cattaneo, M. D., Crump, R. K., Farrell, M. H., Feng, Y., 2019a. Binscatter regressions. Stata Journal (forthcoming).

Cattaneo, M. D., Crump, R. K., Farrell, M. H., Feng, Y., 2019b. On binscatter. Working paper, University of Michigan.

Cheng, P., Lin, Z., Liu, Y., 2015. Racial discrepancy in mortgage interest rates. Journal of Real Estate Finance and Economics 51, 101–120.

Correia, S., 2017. Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working paper, Duke University.

Courchane, M., Nickerson, D., 1997. Discrimination resulting from overage practices. Journal of Financial Services Research 11, 133–151.

Dobbie, W., Liberman, A., Paravisini, D., Pathania, V., 2020. Measuring bias in consumer lending. Review of Economic Studies (forthcoming).

Elenev, V., Landvoigt, T., van Nieuwerburgh, S., 2016. Phasing out the GSEs. Journal of Monetary Economics 81, 11–132.

Engel, K. C., McCoy, P. A., 2011. The Subprime Virus: Reckless Credit, Regulatory Failure, and Next Steps. Oxford University Press, New York.

Federal Housing Finance Administration, 2009. Fannie Mae and Freddie Mac single-family guarantee fees in 2007 and 2008.

Federal Housing Finance Administration, 2010. Fannie Mae and Freddie Mac single-family guarantee fees in 2008 and 2009.

Federal Housing Finance Administration, 2011. Fannie Mae and Freddie Mac single-family guarantee fees in 2009 and 2010.

Federal Housing Finance Administration, 2012. Fannie Mae and Freddie Mac single-family guarantee fees in 2010 and 2011.

Federal Housing Finance Administration, 2013. Fannie Mae and Freddie Mac single-family guarantee fees in 2012.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., Walther, A., 2020. Predictably unequal? The effects of machine learning on credit markets. Working paper, Federal Reserve Bank of New York.

Fuster, A., Goodman, L., Lucca, D., Madar, L., Molloy, L., Willen, P., 2013. The rising gap between primary and secondary mortgage rates. Federal Reserve Bank of New York Economic Policy Review 19, 17–39.

Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. Review of Financial Studies 32, 1854–1899.

Fuster, A., Willen, P., 2010. $1.25 trillion is still real money: Some facts about the effects of the Federal Reserve's mortgage market investments. Public Policy Discussion Paper 10-4, Federal Reserve Bank of Boston.

Gerardi, K., Willen, P., Zhang, D., 2020. Mortgage prepayment, race, and monetary policy. Working paper, Federal Reserve Bank of Atlanta.

Ghent, A. C., Hernández-Murillo, R., Owyang, M. T., 2014. Differences in subprime loan pricing across races and neighborhoods. Regional Science and Urban Economics 48, 199–215.

Goodman, L., 2015. Wielding a heavy enforcement hammer has unintended consequences for the FHA mortgage market. Research report, Urban Institute, Housing Finance Policy Center.

Goodman, L., Kaul, K., 2017. Sixty years of private mortgage insurance in the United States. Research report, Urban Institute, Housing Finance Policy Center.

Goodman, L., Parrott, J., Zhu, J., 2015. The impact of early efforts to clarify mortgage repurchases: Evidence from Freddie Mac and Fannie Mae's newest data. Research report, Urban Institute.

Gyourko, J., Lee, D., Tracy, J., 2015. First-time homebuyers: The role of thin credit files. Working paper, Wharton.

Hanson, A., Hawley, Z., Martin, H., Liu, B., 2016. Discrimination in mortgage lending: Evidence from a correspondence experiment. Journal of Urban Economics 92, 48–65.

Kau, J. B., Fang, L., Munneke, H. J., 2019. An unintended consequence of mortgage financing regulation — A racial disparity. Journal of Real Estate Finance and Economics 59, 549–588.

Kerr, W. R., 2008. Ethnic scientific communities and international technology diffusion. Review of Economics and Statistics 90, 518–537.

Kerr, W. R., Lincoln, W. F., 2010. The supply side of innovation: H-1B visa reforms and U.S. ethnic invention. Journal of Labor Economics 28, 473–508.

Kim, Y. S., Laufer, S. M., Pence, K., Stanton, R., Wallace, N., 2018. Liquidity crises in the mortgage market. Brookings Papers on Economic Activity (Spring), 347–406.

Munnell, A. H., Browne, L., McEneaney, J., Tootel, G., 1996. Mortgage lending in Boston: Interpreting HMDA data. American Economic Review 86, 25–54.

Reid, C. K., Bocian, D., Li, W., Quercia, R. G., 2017. Revisiting the subprime crisis: The dual mortgage market and mortgage defaults by race and ethnicity. Journal of Urban Affairs 39, 469–487.

Van Order, R., Yezer, A. M., 2014. FHA: Recent history and future prospects. Housing Policy Debate 24, 644–650.

Vickery, J. I., Wright, J., 2013. TBA trading and liquidity in the agency MBS market. Economic Policy Review 19.

Willen, P., Zhang, D. H., 2021. Do lenders still discriminate? A robust approach for assessing differences in menus. Working paper, Federal Reserve Bank of Boston.

Woodward, S. E., 2008. A study of closing costs for FHA mortgages. Report, U.S. Department of Housing and Urban Development.

Woodward, S. E., Hall, R. E., 2012. Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. American Economic Review 102, 3249–3276.

# Internet Appendix

## Contents

# I1. Merging the Mortgage Data

Since there are no unique mortgage loan identifiers in the U.S., we develop algorithms using classifier techniques to match loans found in four independent data sets, as discussed in the main paper: i) the loan-level McDash data compiled by Black Knight Financial Services; ii) property and loan-level data from ATTOM Data Solutions; iii) loan origination data from the HMDA data; and iv) loan performance data from Equifax that we purchased pre-merged to the McDash data.

## *I1.1. McDash/Equifax to ATTOM*

The McDash data is obtained from the largest U.S. mortgage servicers. The data set includes detailed mortgage origination terms such as interest rates, loan amount, loan-to-value ratio, loan purpose, the contract and property type, investor versus owner-occupancy status, and the zip code of the mortgaged property. McDash also includes information on the securitization status of the loans, including indicators for whether the loan was a GSE or GNMA securitization. In addition, the data include month-by-month loan-level mortgage performance information, including indicators for prepayment, delinquency, default, foreclosure, REO and modifications. The McDash data have also been pre-merged by Black Knight with Equifax credit data. The Equifax-enhanced McDash data includes other consumer credit positions of the borrowers such as: the total sum of retail, consumer finance and bank card balances; total student loan debt, total auto loan debt (sum or auto finance and auto bank debt); and Vantage 3.0 score. The McDash data also includes a debt-to-income (DTI) ratio. However, because the DTIs are not standardized as either back-end or front-end by the lenders, the DTI measures across lenders are not comparable and thus we do not use them.[1]

To determine the candidate loans in McDash, we first filter the data for originations between 2009 and 2015, and then apply the following McDash loan-type filters: only residential, single-family properties (including only propertypeid = 1, excluding propertypeid = 2 for condos and townhouses), no HELOCS (mortgagetypeid = 7), no construction, rehabilitation, remodeling loans (purposeofloanid = 3), no transferred loans (duplicate ids). The candidate loan pool in McDash was 20,022,570 loans, of which 41% were purchase mortgages, 53% were refinances, and 6% had a missing loan purpose. We had a 100% merge

[1] The front-end debt-to-income ratio (DTI) is a variation of the DTI that calculates how much of a person's gross income is going toward housing costs. If a homeowner has a mortgage, the front-end DTI is typically calculated as housing expenses (such as mortgage payments, mortgage insurance, and property taxes) divided by gross income. In contrast, a back-end DTI calculates the percentage of gross income going toward other debt types, such as credit cards or car loans in addition to the mortgage, insurance and property taxes.

rate between the filtered McDash data and the Equifax credit data set. The ATTOM data was also filtered to include only residential, single-family loans (use code std = RSFR). The merge rate between the ATTOM and McDash data sets, for high quality merges, was 84%. The merged ATTOM/McDash data set comprises 40% purchase mortgages and 53% refinances. The average merge rate to candidate McDash loans by state was 77.79%, the minimum merge rate was 36.69% (for Vermont, for the 16,845 candidate loans in McDash), and the maximum merge rate was 92.26% (for California, for the 3,137,811 candidate loans in McDash).

The ATTOM data set comprises administrative data obtained from recorder and tax assessor offices in the United State. The data report detailed property-level transaction and ownership information in addition to a time-series history of all recorded mortgage-lien events, including origination indicators for both purchase and refinance mortgages. The recorder data include an indicator for whether liens experienced distress and indicators for REO, foreclosure, short sales events. Finally, although the ATTOM data provide transaction and assessor information, including lien-holder name, loan-performance data (i.e., prepayment and default), borrower and lender names and exact property location, including latitude and longitude, there is little information on mortgage contract terms other than the loan amount, the origination date, the purpose of the loan, and whether it is a fixed or floating contract. We geo-process these data to obtain the census tract for each property.

The first stage of the matching algorithm involves: 1) extracting all transactions related to new mortgage originations for each property in the ATTOM recorder data, 2) identifying their corresponding dates of mortgage payoff when applicable (mortgages might still be active by the time of the ATTOM data snapshot), and 3) flagging associated distress events for the mortgage terminations.

In a second stage, we use a modified k-nearest-neighbor (KNN) classifier for finding, within each zip code, the best matches between between McDash loans and the extracted ATTOM data described above. For each McDash loan, the algorithm scores the quality of matches based on the distance to the 25 nearest ATTOM neighbors in the zip code. For McDash loans competing for the same ATTOM loan, we assign the ATTOM loan to the lowest McDash distance. The other McDash competing loans are then assigned to their next ATTOM nearest neighbor. This process is repeated until all McDash loans have a match or the algorithm has reached the $25^{th}$ nearest neighbor. The few McDash loans that could not find an ATTOM match are eliminated from the crosswalk.

The KNN classifier employs a modified metric for calculating distances between loans, which is based on a weighted sum of absolute differences between elements of an 8-element vector characterizing each McDash and ATTOM loan including: 1) the loan balance at origination, 2) the market value of the property (used for purchase transactions only), 3) the origination date of the loan, 4) interest rate type (fixed or variable rate, null if not available), 5) the lien position (null when not available), 6) the loan purpose (refinance or purchase, null if not available), 7) loan distress indicator (a flag signaling that the loan ended in distress), and 8) the ending date of the loan (null for loans that are still active in the data set). If the loan is flagged as not distressed, then the payoff date. If the loan is flagged as distressed, then the date of the most recent distress event date, such as REO, foreclosure, REO liquidation, or a short sale. Weights for the modified nearest neighbor metric were assigned by manually training a subset of the McDash and ATTOM loans and finding appropriate values that made the algorithm emulate human choices for the best matches.

### *I1.2. HMDA to ATTOM*

The construction of the HMDA-ATTOM crosswalk uses a merging strategy that is similar to the one described above. The first stage consists of building a property specific list of all new mortgage originations for each property identification number in the ATTOM recorder data. The publicly available HMDA data set does not provide information on loan terminations (payoff date, distress status, etc.) nor does it include the month/year of loan origination. The HMDA data does, however, report 1) the census tract of the loan; 2) the purpose of the loan (whether purchase or refinance), and 3) the name of the institution that made the the credit decision for the accepted loan. The geocoded ATTOM data also includes 1) the census tract location of the loan; 2) the purpose of the loan – purchase or refinance – and 3) the originator of record for the loan.

The first stage of our strategy to match the HMDA-ATTOM lender name pairs, is to standardize the lender names in both data sets. This process eliminates non-informative words, such as ‘The’, ‘Credit, ‘Bank’, ‘Company’, etc., from the full names and essentially create buckets of standardized lender names in both data sets. It is important to note that this process allows distinct financial institutions to fall into the same category. For instance, the ATTOM lender names ‘American Mortgage Company’ and ‘American First Lenders Inc.’ in Alameda County, California, would have the same standardized lender names, or fall into the same category for the county. By classifying HMDA and ATTOM loans into categories, we are simply creating another matching dimension for assessing the quality of matches between HMDA and ATTOM loans. The algorithm thus learns the best HMDA-ATTOM lender names that produce good loan matches. Another advantage of the approach is that it allows lender names with null values in ATTOM to be grouped in a ‘NULL’ category that can also be included in the loan-matching process.

To assess the likelihood of matches by standard lender names within a census tract, we construct a matching score for HMDA-ATTOM standard lender name pairs based on frequencies of unique matches between loans based solely on the following parameters: 1) census tract, 2) loan amount (ATTOM loans are rounded to the thousands), 3) year of loan origination, 4) the purpose of the loan (purchase or refinance). The higher the frequency, measured in percentage, the lower the score for the standard lender HMDA-ATTOM pair. More formally, the pair matching score is defined as $1 - PairFrequency$.

The next stage in the algorithm is to establish for each HMDA loan within the census tract up to 15 nearest neighbors (i.e. candidate ATTOM loans) based on a distance metric. The distance metric is computed with respect to: 1) loan amount rounded to thousands with penalties for ATTOM loans differing by $\pm 1000$, 2) year of the loan origination with penalties for HMDA loan applications on a year prior to the year of an ATTOM loan recorded in January. This captures the fact the there might be a time lag between the loan application and the recording of the lien at the county. 3) the purpose of the loan (purchase or refinance) with penalties for mismatches, and 4) the HMDA-ATTOM standard lender name pair matching score.

Finally, for each HMDA loan, the matching algorithm selects the best ATTOM match based on its distance to the 15 nearest ATTOM neighbors. For HMDA loans competing for the same ATTOM loan, we assign the ATTOM loan to the lowest HMDA distance. The other HMDA competing loans are then assigned to their next ATTOM nearest neighbor. This process is repeated until all HMDA loans have a match or the algorithm reaches the $15^{th}$ nearest neighbor. Those few HMDA loans that could not find an ATTOM match are eliminated from the crosswalk.

We also apply filters to the raw HMDA data before applying our algorithms. Our candidate HMDA loans include only approved loans (action type = 1), having a property-type flag for 1–4 family homes (property type = 1 or NULL), and a loan purpose flag for purchase or refinance loans (loan purpose = 1 or 3). Additionally, we also required a HMDA loan to have a property with a valid census-tract number and an origination year between 2009 and 2015. These filters leave us with 51,482,961 loans originated. The filtered HMDA data comprise 38% purchase loans and 62% refinance loans. The ATTOM data were also filtered to include only residential, single-family loans (use code std = RSFR), valid census tracts, a loan purpose of either purchase or refinance loans, and an origination date between 2009 and 2015. This gave a total of 58,540,894 candidate loans in the ATTOM data. The merge rate between the ATTOM data and the candidate HMDA loans was 76.83% including only loans with low distance metric scores. The ATTOM to HMDA candidate merge comprised 37% purchase loans and 63% refinance loans. Again, the state with the highest merge rate was California at 89% and the worst merge rates were for the states of Mississippi, 33.5%, Vermont, 16.7%, and West Virginia, 33.29%.

### *I1.3. ATTOM, McDash/Equifax and HMDA*

The final stage of the data construction process is a four-way data merge between ATTOM, McDash/Equifax, and HMDA using the two crosswalks. Before further filtering, the four-way merged data set comprises 11,493,172 fixed-rate mortgages originated between 2009 and 2015. We obtain our final sample of 5,650,044 mortgages, as reported in Table 1, by applying the following filters: i) filtering out credit scores less than 620 for GSE loans[2] and 580 for FHA loans (loss of 98,931 observations);[3] ii) filtering out loan-to-value ratios less than .3 (loss of 105,108 observations); iii) filtering out FHA loan-to-value ratios greater than 98.25% (loss of 1,024,599 observations);[4] iv) filtering out GSE loan-to-value ratios greater than 95% (loss of 385,442 observations);[5] v) filtering out loan contract rates less than 2.75% or greater 8% (loss of 426 observations); vi) filtering out loan amounts less than $40,000 (loss of 17,009 observations); vii) filtering out all mortgages with terms that were either less than 358 months or greater than 362 months (loss of 1,609,469 observations); viii) filtering out loans with second liens, either closed end second liens or outstanding balances on home equity lines of credit (loss of 1,220,477 observations); ix) filtering out income less than $20,000 (loss of 75,950 observations); x) filtering out HMDA-defined non-owner occupied loans (loss of 663,930 observations); and finally, xi) filtering out missing values for the enhanced HMDA treatment variable based on the race and ethnicity of the borrower of record reported in the ATTOM data if the borrower1 record for race and ethnicity in HMDA is missing (loss of 641,832 observations), as discussed below in Section I1.4.1.

As reported in Table 1, 59.76% (3,376,600) of the mortgages are GSE loans and 40.24% (2,273,444) are FHA-insured. As shown in Table 3, filtering for observations with missing credit scores and missing income, as well as dropping census tracts with only one observation, leaves an analysis data set of GSE and FHA loans consisting of 59.5% (2,905,161) purchase mortgages and 41.5% (1,977,359) refis.

[2]See `https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/Subpart-B3-Underwriting-Borrowers/Chapter-B3-5-Credit-Assessment/Section-B3-5-1-Credit-Scores/1032996841/B3-5-1-01-General-Requirements-for-Credit-Scores-08-05-2020.htm`.

[3]See `https://www.fha.com/fha_credit_requirements`.

[4]See Gyourko et al. (2015).

[5]The maximum loan-to-value ratio for GSE-securitized loans is 97% (see `https://www.fdic.gov/consumers/community/mortgagelending/guide/part-1-docs/fannie-standard-97-percent-loan-to-value-mortgage.pdf`). However, Federal Reserve Board economists advised us to exclude loan-to-value ratios above 95%, because these loans exhibit large swings in underwriting and pricing, possibly due to sourcing through specialty loan programs.

### *I1.4. Credit Score proxy for HMDA 2018–2019*

The 2018–2019 HMDA data does not report a credit score for each loan.[6] Fortunately, the mean GSE and Ginnie Mae credit scores were quite stable over this period, so our use of the 2009–2015 credit score averages by census by loan type by race and ethnicity as a proxies for the loan-level 2018–2019 credit scores is supported by the historical data.[7] As discussed above, the 2009–2015 data is a merge of ATTOM/McDash/Equifax/HMDA data sets. To construct our loan-level proxies for credit score, we first determine the average credit score by census tract by loan type (GSE versus FHA) and minority status (Latinx/African American versus White/Asian) for all of the census tracts in the data set. We then assign this average to the loan-level HMDA 2018–2019 data by each loan's census tract, loan-type and minority status. We, of course, recognize the potential for omitted-variable problems that may be associated with our reliance on a proxy variable due to the missing "true" loan-level credit score information in HMDA 2018–2019. However, the historical stability of the credit-score averages reduces these concerns.

#### *I1.4.1. Ethnicity matching using the ATTOM data*

Because there are missing ethnicity data for some HMDA loans, we augment the HMDA ethnicity variable. We first apply the race and ethnicity name-categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008) to assign an ethnicity to all the lien-holder names that are found in ATTOM. We then create an analysis subset of the ATTOM data that includes only the ATTOM crosswalk identification number and the ethnicity matches with no lien-holder name information. This data subset is then merged with the ATTOM-McDash-Equifax-HMDA merged data. We report our pricing results with both the HMDA only race/ethnicity indicators and with the enhanced HMDA race/ethnicity indicators using our ethnicity matches for the originated loans. The 2018/2019 HMDA estimations and the accept/reject estimations use only the HMDA race/ethnicity indicators.

There are 9.0 million total loans in the merged and filtered ATTOM data. Excluding

[6] We also cannot update the 2018–2019 data through a new three-way merge due to the lack of sufficient post-2018 ATTOM/McDash/Equifax performance data

[7] Although the mean GSE and the Ginnie Mae credit scores fell slightly in 2013, over the period between 2009 and 2019, the absolute value of the average annual percentage change in mean credit scores was .82% for Ginnie Mae loans and .87% for GSE loans. The percentage change in the mean Ginnie Mae credit score was 0.0% measured from year-end 2009 to year-end 2019 and the percentage change for the same eleven-year change in the mean GSE credit score was 1% (See `https://www.urban.org/sites/default/files/publication/101611/january_chartbook_2020.pdf` and `https://www.urban.org/sites/default/files/publication/64761/2000311-The-Credit-Box-Shows-Early-Signs-of-Loosening.pdf`). In addition, we see exactly the same pattern of relative credit score time-series stability for FHA only and GSE loans in the 2009–2018 McDash data for 11.9 million mortgages suitably filtered for first liens, 30-year fixed rate mortgages, and residential single family mortgages.

1.1 million of these loans for which a synthetic allocation, based on the name-categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008), cannot be performed (e.g., if the loan is taken out in the name of a trust), here is a comparison of HMDA race/ethnicity with the synthetic allocation:

| | Updated HMDA race/ethnicity | | |
|---|---|---|---|
| HMDA race/ethnicity | Black/Hispanic | White/Asian | Total |
| Black/Hispanic | 590,785 | 491,277 | 1,082,062 |
| Unknown | 86,435 | 672,104 | 758,539 |
| White/Asian | 255,063 | 5,828,979 | 6,084,042 |
| Total | 932,283 | 6,992,360 | 7,924,643 |

From the numbers above, we can see that the name-categorization algorithm

- classifies 54.6% of known Black/Hispanic borrowers as Black/Hispanic; and
- classifies 4.2% of known White/Asian borrowers as Black/Hispanic.

The first rate is over 13× the second, and both are very different from the unconditional 15.1% that we would expect from random assignment.[8]

### *I1.4.2. Summary of data*

Table I1 presents a summary of all of the variables used in our analysis including their definitions and data sources. As shown in the table, the data for the pricing regressions are sourced from the merged HMDA, ATTOM, McDash/Equifax data from 2009 through 2015.

As discussed in Section 6, we extend our analysis of GSE and FHA mortgage pricing by including controls for the effects of loan points, total loan costs, and lender credits that are available in the recently released 2018 and 2019 HMDA data. As shown in the table, we are now able to control for both positive points and negative points (lender credits) that are payable or received at loan origination. In addition, as a robustness check we also use total loan costs which is measured in HMDA as the total dollar costs of the loan at origination. As discussed above, a limitation of the 2018 and 2019 HMDA data is that it does not include loan-level information on the credit score at origination, and we cannot use our merging algorithm to add this variable due to the lack of sufficient post-2018 performance data in

[8]The overall proportion of HMDA-identified Black/Hispanic borrowers is

$$\frac{1{,}082{,}062}{1{,}082{,}062 + 6{,}084{,}042} = 15.1\%.$$

ATTOM. We therefore proxy for this variable using the mean values of the credit scores by census tract by loan type by minority status (from the McDash/Equifax data set).

For the accept/reject analysis we restricted to HMDA data only, since HMDA was the only source of information for rejected loans. A significant limitation with the 2009 through 2015 vintage of HMDA data was that neither the loan-to-value nor the credit score of the loans were reported. We therefore constructed proxies for both the loan-to-value ratio and the credit score for each loan in the HMDA data set using census tract annual deciles for the loan-to-value ratio and the credit scores for originated loans found in the merged ATTOM/McDash data. The merged ATTOM data provided the needed information for the census tracts and the McDash data provided the needed information to compute the decile ranges for the loan-to-value ratios and the credit scores by census tract for each loan.

| Variable | Definition |
|---|---|
| **HMDA** | |
| **HMDA LARS 2009–2019** | |
| Loan Amount ($000) | Dollar amount of loan |
| Applicant Income ($000) | Gross annual income of the Borrower |
| HMDA Minority (1 = Yes, 0 = No) | Based on first response by primary borrower: $\begin{cases} 1 \text{ if ethnicity} = 1 \text{ or race} = \text{Latinx/African American;} \\ 0 \text{ if ethnicity} = 0 \text{ and race} = \text{Asian/White.} \end{cases}$ |
| Enhanced HMDA Minority | Same as above, where missing HMDA values are updated via ATTOM borrower name-categorization. |
| Conventional loan (1 = Yes, 0 = No) | Any loan other than FHA, VA, FSA, or RHS loans. |
| Owner occupied (1 = Yes, 0 = No) | If Owner-Occupied as a principal dwelling |
| Loan rejected (1 = Yes, 0 = No) | $\begin{cases} 1 \text{ if HMDA action type} = 3 \text{ or } 5; \\ 0 \text{ if HMDA action type} = 1 \text{ or } 2. \end{cases}$ |
| Reason for loan rejection | Reason for rejection (1–9): $\begin{cases} \text{“Hard” rejection} = 1, 2, 3, 4 \text{ or } 5; \\ \text{“Soft” rejection} = 6, 7, 9 \text{ or action type} = 5. \end{cases}$ |
| CRA census tract (1 = Yes, 0 = No) | CRA identifier: $\begin{cases} 1 \text{ if percentage of tract median family income compared to} \\ \text{MSA/MD median family income} < 80\%; \\ 0 \text{ if percentage is} >= 80\%. \end{cases}$ |
| Top 25 lender | Matched to **Inside Mortgage Finance** by volume |
| Fintech lender (1= Yes, 0 = No) | Fintech firms in Buchak et al. (2018) |
| **HMDA Institutional 2009–2015** | |
| Respondent ID | Institution identifier |
| Respondent (Lender) name | Institution name |
| **HMDA LARS 2018–2019** | |
| Discount points ($000) | Points paid, in dollars, to reduce the interest rate |
| Lender credits ($000) | Amount, in dollars, of lender credits |
| Total loan costs ($000) | Total loan costs at origination |
| Loan interest rate | Origination interest rate |
| Loan to value ratio | Loan amount to property value |
| Legal Enterprise Identifier | Unique institution identifier |
| Proxy credit score | Census tract average by loan type and minority status. |
| **McDash/Equifax 2009–2015** | |
| Loan interest rate | Origination interest rate |
| Loan credit score | Equifax credit score |
| Loan maturity (Months) | Maturity of the loan |
| Loan-to-value ratio | Ratio of loan amount to the property value |
| Refinance (1 = Yes, 0 = No) | Purpose of the loan was to refinance another loan |
| Cash-out refinance (1 = Yes, 0 = No) | Purpose of the loan was to refinance and extract cash |
| Purchase loan (1 = Yes, 0 = No) | Purpose of the loan was to purchase a home |
| GSE securitized loan (1 = Yes, 0 = No) | Loan was securitized by a GSE. |
| FHA loan (1 = Yes, 0 = No) | Loan was insured by FHA |
| Single family residential (1 = Yes, 0 = No) | Single family detached, excluding condo and 2–4 family |
| Second liens (1=Yes, 0=No) | 1 if positive balance on closed-end seconds or HELOCs |
| Put-back loan (1=Yes, 0=No) | Forced originator buy-back of loan |
| **ATTOM (2009–2015)** | |
| First lien mortgage | Loan recorded as a first lien |
| Loan origination date (mm/yy) | Month and year of origination |
| Lender of recorder | Assessor office recorded lender name |
| ATTOM minority | See Section I1.4.1 |
| Census tract | Geo-processed using ARC-GIS |
| Default (1 = Yes, 0 = No) | Loan foreclosed or REO through 2017 |

Table I1: Summary of data sources and variable definitions

## I2. Regression Tables for Figures in Section 5.4

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority-share decile 1 × Minority | -0.0956 | 0.709 | 0.912** | 0.780 |
| | (0.512) | (0.662) | (0.455) | (1.235) |
| Minority-share decile 2 × Minority | 0.715 | 0.196 | 1.682*** | 0.448 |
| | (0.508) | (0.474) | (0.465) | (0.719) |
| Minority-share decile 3 × Minority | 0.451 | 0.743* | 1.036*** | -0.743 |
| | (0.395) | (0.435) | (0.267) | (0.885) |
| Minority-share decile 4 × Minority | 0.717** | 0.290 | 1.746*** | 0.666 |
| | (0.334) | (0.383) | (0.407) | (0.666) |
| Minority-share decile 5 × Minority | 1.098*** | 0.316 | 1.589*** | 0.805 |
| | (0.330) | (0.415) | (0.263) | (0.625) |
| Minority-share decile 6 × Minority | 1.128*** | 0.780** | 1.658*** | 0.854* |
| | (0.304) | (0.379) | (0.375) | (0.518) |
| Minority-share decile 7 × Minority | 2.049*** | 0.261 | 2.025*** | 0.236 |
| | (0.262) | (0.254) | (0.337) | (0.502) |
| Minority-share decile 8 × Minority | 1.940*** | 0.533* | 1.683*** | -0.272 |
| | (0.263) | (0.300) | (0.308) | (0.469) |
| Minority-share decile 9 × Minority | 2.734*** | 1.094*** | 2.101*** | 0.779* |
| | (0.299) | (0.355) | (0.259) | (0.400) |
| Minority-share decile 10 × Minority | 4.368*** | 1.453*** | 2.662*** | 1.081*** |
| | (0.414) | (0.407) | (0.254) | (0.389) |
| Observations | 1,320,489 | 1,489,679 | 1,476,836 | 367,372 |
| R-squared | 0.827 | 0.788 | 0.870 | 0.894 |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Census tract × year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I2: **Interest-rate differentials by minority-share decile (see Figure 5).** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for minority-share decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, loan-amount decile, and census-tract × year. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| VARIABLES | GSE Loans<br>Purchase<br>(1)<br>Interest rate | <br>Refinance<br>(2)<br>Interest rate | FHA Loans<br>Purchase<br>(3)<br>Interest rate | <br>Refinance<br>(4)<br>Interest rate |
|---|---|---|---|---|
| Foreclosure/REO | 2.541*** | 1.987*** | 1.589*** | 0.722* |
| | (0.747) | (0.632) | (0.256) | (0.419) |
| 60+ days delinquent | 5.390*** | 4.221*** | 1.901*** | 0.172 |
| | (0.385) | (0.447) | (0.206) | (0.395) |
| 90+ days delinquent | 0.889 | 2.415*** | 1.118*** | 1.205*** |
| | (0.543) | (0.568) | (0.198) | (0.404) |
| Minority-share decile 1 × Minority | -0.0896 | 0.721 | 0.764* | 0.744 |
| | (0.507) | (0.665) | (0.455) | (1.231) |
| Minority-share decile 2 × Minority | 0.669 | 0.158 | 1.571*** | 0.422 |
| | (0.509) | (0.480) | (0.463) | (0.717) |
| Minority-share decile 3 × Minority | 0.446 | 0.701 | 0.949*** | -0.787 |
| | (0.393) | (0.433) | (0.268) | (0.874) |
| Minority-share decile 4 × Minority | 0.681** | 0.273 | 1.652*** | 0.651 |
| | (0.333) | (0.384) | (0.406) | (0.666) |
| Minority-share decile 5 × Minority | 1.076*** | 0.312 | 1.493*** | 0.802 |
| | (0.332) | (0.410) | (0.263) | (0.623) |
| Minority-share decile 6 × Minority | 1.093*** | 0.769** | 1.599*** | 0.844 |
| | (0.305) | (0.379) | (0.376) | (0.518) |
| Minority-share decile 7 × Minority | 2.024*** | 0.257 | 1.960*** | 0.238 |
| | (0.263) | (0.257) | (0.340) | (0.501) |
| Minority-share decile 8 × Minority | 1.913*** | 0.527* | 1.627*** | -0.270 |
| | (0.263) | (0.295) | (0.307) | (0.470) |
| Minority-share decile 9 × Minority | 2.705*** | 1.073*** | 2.066*** | 0.777* |
| | (0.296) | (0.351) | (0.259) | (0.400) |
| Minority-share decile 10 × Minority | 4.326*** | 1.451*** | 2.633*** | 1.088*** |
| | (0.415) | (0.407) | (0.254) | (0.390) |
| Observations | 1,320,489 | 1,489,679 | 1,476,836 | 367,372 |
| R-squared | 0.828 | 0.788 | 0.870 | 0.894 |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Census tract × year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I3: **Interest-rate differentials by minority-share decile, including ex-post performance.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variables are three ex-post performance indicators plus an indicator that equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for minority-share decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, loan-amount decile, and census-tract × year. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

## I3. Regression Tables for Figures in Section 5.5

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Credit-score bucket 1 × Minority | | | 4.819*** | 0.698 |
| | | | (0.916) | (0.790) |
| Credit-score bucket 2 × Minority | 6.670*** | 2.663*** | 4.647*** | 1.268** |
| | (0.790) | (0.867) | (0.366) | (0.627) |
| Credit-score bucket 3 × Minority | 5.592*** | 1.538** | 4.821*** | 1.789*** |
| | (0.772) | (0.599) | (0.373) | (0.278) |
| Credit-score bucket 4 × Minority | 5.969*** | 2.064*** | 5.154*** | 1.653*** |
| | (0.447) | (0.398) | (0.336) | (0.330) |
| Credit-score bucket 5 × Minority | 5.287*** | 2.127*** | 4.938*** | 1.099*** |
| | (0.439) | (0.336) | (0.361) | (0.386) |
| Credit-score bucket 6 × Minority | 5.337*** | 1.301*** | 4.935*** | 1.229*** |
| | (0.495) | (0.312) | (0.366) | (0.443) |
| Credit-score bucket 7 × Minority | 8.420*** | 2.027*** | 5.007*** | 1.744*** |
| | (0.411) | (0.360) | (0.398) | (0.338) |
| Credit-score bucket 8 × Minority | 3.552*** | 1.487*** | 4.569*** | 1.857*** |
| | (0.214) | (0.226) | (0.321) | (0.342) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I4: **Interest-rate differentials by GSE-credit-score bucket (see Figure 9).** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for credit-score bucket. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| VARIABLES | GSE Loans Purchase (1) Interest rate | GSE Loans Refinance (2) Interest rate | FHA Loans Purchase (3) Interest rate | FHA Loans Refinance (4) Interest rate |
|---|---|---|---|---|
| LTV bucket 1 × Minority | -5.897*** | -0.368 | -0.233 | -1.466 |
| | (0.578) | (0.295) | (0.930) | (0.919) |
| LTV bucket 2 × Minority | 5.186*** | 1.825*** | 2.400*** | -0.465 |
| | (0.461) | (0.334) | (0.682) | (0.936) |
| LTV bucket 3 × Minority | 5.017*** | 0.258 | 3.668*** | 0.796 |
| | (0.443) | (0.256) | (0.632) | (0.742) |
| LTV bucket 4 × Minority | 3.917*** | 2.224*** | 3.126*** | 0.418 |
| | (0.278) | (0.337) | (0.468) | (0.576) |
| LTV bucket 5 × Minority | 5.619*** | 4.001*** | 3.325*** | 1.424*** |
| | (0.381) | (1.004) | (0.409) | (0.436) |
| LTV bucket 6 × Minority | 3.775*** | 0.441 | 4.026*** | 0.969*** |
| | (0.389) | (0.402) | (0.324) | (0.309) |
| LTV bucket 7 × Minority | 8.345*** | 9.790*** | 3.581*** | 2.326*** |
| | (0.322) | (0.584) | (0.298) | (0.405) |
| LTV bucket 8 × Minority | - | - | 5.409*** | 1.660*** |
| | | | (0.363) | (0.342) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I5: **Interest-rate differentials by GSE-LTV bucket (see Figure 10).** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for LTV bucket. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Income decile 1 × Minority | 7.847*** | 2.361*** | 4.598*** | 2.235*** |
| | (0.365) | (0.539) | (0.437) | (0.590) |
| Income decile 2 × Minority | 6.246*** | 1.930*** | 5.579*** | 1.642*** |
| | (0.489) | (0.493) | (0.318) | (0.541) |
| Income decile 3 × Minority | 5.917*** | 2.273*** | 5.676*** | 1.031* |
| | (0.480) | (0.459) | (0.400) | (0.561) |
| Income decile 4 × Minority | 5.293*** | 1.826*** | 5.321*** | 1.936*** |
| | (0.304) | (0.305) | (0.315) | (0.665) |
| Income decile 5 × Minority | 4.960*** | 1.826*** | 5.360*** | 2.235*** |
| | (0.350) | (0.313) | (0.377) | (0.499) |
| Income decile 6 × Minority | 4.342*** | 1.539*** | 4.641*** | 0.420 |
| | (0.323) | (0.303) | (0.315) | (0.540) |
| Income decile 7 × Minority | 3.444*** | 1.327*** | 3.894*** | 1.652*** |
| | (0.330) | (0.238) | (0.336) | (0.492) |
| Income decile 8 × Minority | 2.512*** | 1.230*** | 3.308*** | 2.023*** |
| | (0.289) | (0.303) | (0.296) | (0.491) |
| Income decile 9 × Minority | 2.255*** | 1.163*** | 2.136*** | 0.780 |
| | (0.270) | (0.285) | (0.394) | (0.692) |
| Income decile 10 × Minority | 1.450*** | 0.896*** | 2.656*** | 0.703 |
| | (0.410) | (0.319) | (0.455) | (0.765) |
| Observations | 1,357,721 | 1,439,333 | 1,521,775 | 273,087 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.864 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Income decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I6: **Interest-rate differentials by income decile (see Figure 11).** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for income decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, loan-amount decile, and income decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Firm-minority-share decile 1 × Minority | 2.671*** | 1.308*** | 1.225** | 0.118 |
| | (0.419) | (0.415) | (0.481) | (0.800) |
| Firm-minority-share decile 2 × Minority | 3.484*** | 2.001*** | 2.087*** | 1.638 |
| | (0.461) | (0.438) | (0.607) | (1.046) |
| Firm-minority-share decile 3 × Minority | 3.058*** | 1.909*** | 2.779*** | 1.653** |
| | (0.470) | (0.409) | (0.539) | (0.780) |
| Firm-minority-share decile 4 × Minority | 4.555*** | 2.361*** | 3.445*** | 1.280* |
| | (0.516) | (0.463) | (0.454) | (0.687) |
| Firm-minority-share decile 5 × Minority | 4.152*** | 1.247*** | 3.792*** | 0.847 |
| | (0.284) | (0.437) | (0.414) | (0.656) |
| Firm-minority-share decile 6 × Minority | 4.152*** | 1.544** | 3.556*** | 0.670 |
| | (0.498) | (0.636) | (0.950) | (0.779) |
| Firm-minority-share decile 7 × Minority | 4.782*** | 3.991*** | 4.270*** | 3.202*** |
| | (0.531) | (0.424) | (0.465) | (0.395) |
| Firm-minority-share decile 8 × Minority | 4.648*** | 0.272 | 3.147*** | 0.730 |
| | (0.633) | (0.707) | (0.783) | (0.587) |
| Firm-minority-share decile 9 × Minority | 4.581*** | 2.128*** | 4.795*** | 0.348 |
| | (0.364) | (0.359) | (0.648) | (0.480) |
| Firm-minority-share decile 10 × Minority | 5.771*** | 1.625* | 5.993*** | 0.987** |
| | (0.524) | (0.912) | (0.526) | (0.499) |
| Observations | 1,388,718 | 1,562,071 | 1,543,799 | 450,154 |
| R-squared | 0.782 | 0.746 | 0.830 | 0.844 |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Firm-minority-share decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I7: **Interest-rate differentials by firm-minority-share decile (see Figure 8).** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise, interacted with indicator variables for firm-minority-share decile. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, loan-amount decile, and firm-minority-share decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

## I4. Base analysis using alternative definitions of race

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower (HMDA) | 4.878*** | 1.692*** | 4.977*** | 1.666*** |
| | (0.268) | (0.234) | (0.348) | (0.262) |
| Observations | 1,265,196 | 1,385,476 | 1,440,492 | 398,894 |
| R-squared | 0.803 | 0.770 | 0.854 | 0.870 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) HMDA definition

| | GSE Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Interest rate | Interest rate | Interest rate | Interest rate |
| Minority borrower or coborrower | 4.299*** | 1.491*** | 4.746*** | 1.463*** |
| | (0.240) | (0.209) | (0.322) | (0.234) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Expanded definition

Table I8: **Interest rate differentials using alternative definitions of minority.** The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Panel (a) uses only race or ethnicity provided by HMDA; Panel (b) sets the treatment variable to 1 if either the borrower *or* first coborrower is Latinx or African American. Fixed effects are included for cash-out $\times$ GSE-grid bucket $\times$ year/month, lender $\times$ year/month, and loan-amount decile. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

## I5. Imputed credit scores

To get a sense for whether using imputed credit scores significantly affects the results of the 2018–2019 analysis in Section 6, we here re-estimate the 2009–2015 results using the 2018–2019 specification, i.e., replacing the individual credit scores with local average credit scores and individual income.

Panel (a) of Table I9 is a copy of the baseline results in Table 3; Panel (b) runs the same regressions, but replaces the fixed effects based on GSE bucket (in turn based on the observed, loan-specific credit score) with fixed effects based on the census-tract average credit score for each loan, calculated using data over the full period 2009–2015. Table I10 performs the same analysis but out of sample: the census-tract average credit scores are calculated using loans originated from 2009–2011, while the regression is run using only loans originated from 2013–2015. In both cases, though the levels of the estimated coefficients differ somewhat between the two panels, the patterns in the results remain unchanged.

## I6. Accept/Reject Discrimination

In addition to setting the loan interest rate, the lender also decides whether to accept or reject a loan application at all. After the 2008 mortgage crisis, many lenders have imposed their own, stricter, approval requirements on top of those of the GSEs or FHA, called "overlays."[9] Thus, even though an application might receive a creditworthiness approval in the GSE underwriter system, the lender might still reject the application. In this section we look at whether loan rejection rates differ between minority and non-minority borrowers, regressing loan rejection status (0 or 1) on the minority indicator variable plus controls.

An important caveat is that because rejected loans were never issued, we do not know their exact terms, or even their maturities. Similarly, because they do not appear in the ATTOM or McDash data sets, we lack loan-level data on some important underwriting variables. In particular, we do not observe the borrower's credit score or loan-to-value ratio. We proxy for these in our analysis using the census-tract 25th, 50th, and 75th percentile credit score, which we estimate using the ATTOM/McDash merged data. However, these data limitations mean that unlike the interest-rate analysis in the main paper, any analysis of rejection rates is necessarily subject to the omitted-variable problem discussed in the Introduction; we cannot be completely sure that any differences in rejection rates are caused by discrimination rather than differences in unobservable variables. However, the HMDA

[9] See, for example, Michele Lerner, "Navigating the Wide World of Mortgage Overlays," Washington Post, Oct. 17, 2014).

| VARIABLES | GSE Loans Purchase (1) Interest rate | GSE Loans Refinance (2) Interest rate | FHA Loans Purchase (3) Interest rate | FHA Loans Refinance (4) Interest rate |
|---|---|---|---|---|
| Minority borrower | 4.674*** | 1.632*** | 4.866*** | 1.527*** |
| | (0.255) | (0.227) | (0.333) | (0.253) |
| Observations | 1,371,629 | 1,540,939 | 1,533,532 | 436,420 |
| R-squared | 0.803 | 0.769 | 0.854 | 0.869 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) Using loan-specific credit score

| VARIABLES | GSE Loans Purchase (1) Interest rate | GSE Loans Refinance (2) Interest rate | FHA Loans Purchase (3) Interest rate | FHA Loans Refinance (4) Interest rate |
|---|---|---|---|---|
| Minority borrower | 5.501*** | 2.486*** | 5.433*** | 2.051*** |
| | (0.271) | (0.263) | (0.360) | (0.376) |
| Observations | 1,550,104 | 1,660,739 | 1,653,627 | 317,292 |
| R-squared | 0.773 | 0.752 | 0.845 | 0.854 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x LTV bucket x credit decile x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Using census-tract mean credit score

Table I9: **In-sample comparison of results using loan-specific versus census-tract mean credit scores.** The dependent variable is the interest rate on fixed-rate mortgages originated from 2009 to 2015 in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Both panels include fixed effects for lender $\times$ year/month and loan-amount decile. Panel (a) (a copy of Table 3) also includes fixed effects for cash-out $\times$ GSE-grid bucket $\times$ year/month. Panel (b) instead includes fixed effects for cash-out $\times$ LTV bucket $\times$ census-tract credit-score decile $\times$ year/month, calculated using all data from 2009–2015. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| VARIABLES | GSE Loans<br>Purchase<br>(1)<br>Interest rate | <br>Refinance<br>(2)<br>Interest rate | FHA Loans<br>Purchase<br>(3)<br>Interest rate | <br>Refinance<br>(4)<br>Interest rate |
|---|---|---|---|---|
| Minority borrower | 4.539*** | 1.865*** | 5.583*** | 1.167*** |
| | (0.260) | (0.274) | (0.470) | (0.369) |
| Observations | 690,659 | 374,700 | 544,112 | 111,098 |
| R-squared | 0.675 | 0.683 | 0.577 | 0.629 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x bucket x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) Using loan-specific credit score

| VARIABLES | GSE Loans<br>Purchase<br>(1)<br>Interest rate | <br>Refinance<br>(2)<br>Interest rate | FHA Loans<br>Purchase<br>(3)<br>Interest rate | <br>Refinance<br>(4)<br>Interest rate |
|---|---|---|---|---|
| Minority borrower | 5.767*** | 3.397*** | 6.193*** | 1.608** |
| | (0.305) | (0.306) | (0.439) | (0.716) |
| Observations | 541,555 | 308,371 | 414,734 | 52,283 |
| R-squared | 0.626 | 0.638 | 0.557 | 0.613 |
| Lender x year/month FE | Y | Y | Y | Y |
| Cash-out x LTV bucket x credit decile x year/month FE | Y | Y | Y | Y |
| Amount decile FE | Y | Y | Y | Y |
| Cash-out x income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Using census-tract mean credit score

Table I10: **Out-of-sample comparison of results using loan-specific versus census-tract mean credit scores.** The dependent variable is the interest rate on fixed-rate mortgages originated from 2013 to 2015 in basis points. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Both panels include fixed effects for lender $\times$ year/month and loan-amount decile. Panel (a) also includes fixed effects for cash-out $\times$ GSE-grid bucket $\times$ year/month. Panel (b) instead includes fixed effects for cash-out $\times$ LTV bucket $\times$ census-tract credit-score decile $\times$ year/month, calculated using data from 2009–2011. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

data do allow us to control for loan-level lender, year, borrower income and the loan amount. We apply the same filter for borrower income and loan amount that were applied to the variables in Table 1.[10]

Table I11 reports summary statistics for the data, with Panels (a) and (b) showing results for GSE and FHA loan applications, respectively. The sample contains over 14 million loan applications, of which 9.67 million are for GSE and 4.45 million are for FHA loans. Since the available information in HMDA for rejected applications is much more limited, especially for the key variables such as the loan-level loan-to-value ratios and credit scores, we proxy for these variables using year-by-census-tract averages for single-family residential mortgages in the McDash data from 2009 through 2015. As shown in Table I11, the mean proxy credit score for the overall sample of accepted and rejected conventional loan applications is 755 for conventional loan applications versus 734 for FHA loan applications. The mean proxy loan-to-value ratio for the conventional loan applications is .76 whereas it is .85 for the FHA loan applications. About 75% of the conventional applications are for refinance loans, compared with 35% of the FHA applications. We use the HMDA designation for ethnicity and race to construct the minority indicator variable and, as shown, 12.5% of the conventional loan applications are submitted by minorities, compared with 27.4% of the FHA loan applications. The average income for the accepted/rejected conventional loan applications is $110,467 and the average loan amount requested is $221,873. The average income for accepted/rejected FHA loan applications is $70,052 and the average loan amount requested is $184,362. Finally, 46% of the conventional loan applications were rejected, compared with 41% of the FHA loan applications.

Panel (a) of Table I12 reports the main estimation, regressing a loan rejection indicator on a minority indicator, with fixed effects for year interacted with deciles of census-tract LTV (1st quartile, median and 3rd quartile), credit score (1st quartile, median and 3rd quartile), loan amount, and borrower income, along with lender $\times$ year. The discrimination coefficient is significantly positive and of similar magnitude for both GSE and FHA loan applications and for both purchase and refinance applications. Holding the control variables fixed, these estimates suggest that minority applicants for conventional purchase loans are 6.73 percentage points more likely to be rejected than non-minority applicants, while for refinance loans the difference is 5.96 percentage points. These numbers are roughly 1/7 of the unconditional rejection rate for conventional loan applications of 46.1%, indicating that minority borrowers are approximately 14% more likely to be rejected than are non-minority

[10] In our analysis, we treat a loan as accepted if the HMDA "action type" is 1 (loan originated) or 2 (application approved but not accepted). We treat a loan as rejected if the HMDA "action type" is 3 (application denied) or 5 (file closed for incompleteness).

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Income | 9,664,550 | 110.46699 | 115.88721 | 20 | 9996 |
| Loan amount | 9,664,550 | 221.87324 | 111.90696 | 40 | 729 |
| Minority | 9,664,550 | .12480519 | .33049791 | 0 | 1 |
| Refinance | 9,664,550 | .74541184 | .43562949 | 0 | 1 |
| Reject | 9,664,550 | .46139562 | .4985075 | 0 | 1 |
| 25% census-tract credit score | 9,663,911 | 712.11633 | 26.532284 | 630 | 832 |
| Median census-tract credit score | 9,663,911 | 755.09137 | 21.598272 | 630 | 832 |
| 75% census-tract credit score | 9,663,911 | 785.31096 | 13.803307 | 630 | 840 |
| 25% census-tract LTV | 9,664,550 | .62663992 | .10922252 | .3 | .97 |
| Median census-tract LTV | 9,664,550 | .76305101 | .08666704 | .3 | .97 |
| 75% census-tract LTV | 9,664,550 | .87595723 | .08147638 | .3 | .97 |
| $N$ | 9,664,550 | | | | |

(a) Conventional loans

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| Income | 4,451,104 | 70.05239 | 54.03933 | 20 | 9000 |
| Loan amount | 4,451,104 | 184.3625 | 92.73324 | 40 | 729 |
| Minority | 4,451,104 | .2737831 | .445899 | 0 | 1 |
| Refinance | 4,451,104 | .35426 | .4782885 | 0 | 1 |
| Reject | 4,451,104 | .4124184 | .4922698 | 0 | 1 |
| 25% census-tract credit score | 4,450,986 | 688.87 | 26.31922 | 630 | 832 |
| Median census-tract credit score | 4,450,986 | 734.3627 | 27.07211 | 630 | 832 |
| 75% census-tract credit score | 4,450,986 | 774.0142 | 20.54524 | 630 | 844 |
| 25% census-tract LTV | 4,451,104 | .7159381 | .0982594 | .3 | 1 |
| Median census-tract LTV | 4,451,104 | .8503841 | .0817061 | .3 | 1 |
| 75% census-tract LTV | 4,451,104 | .9438698 | .0564498 | .3 | 1 |
| $N$ | 4,451,104 | | | | |

(b) FHA loans

Table I11: **Summary Statistics: accept/reject sample.** Data are fixed-rate mortgage applications obtained from HMDA, with supplemental data obtained from McDash and Equifax. Loan amount, applicant income, LTV, and Latinx-/African-American are from HMDA. Census-tract quartiles for income and credit score are computed using the HMDA/ATTOM/McDash/Equifax merged data.

applicants. Across FHA loan applications, Table I12 reports similar differences in rejection rates between minority and non-minority loan applicants. In particular, minority applicants for FHA purchase loans are approximately 9 percentage points more likely to be rejected than non-minority applicants, while applicants for FHA refinance loans are 6.8 percentage points more likely to be rejected.

Panel (b) of Table I12 reports the same results, but only for loan applications to FinTech lenders. The difference between minority and non-minority applicants is still significant, but substantially smaller than for the sample overall for conventional loan applications. In particular, the coefficients for conventional loan applications (both purchase and refinance) are less than 50% of their values in the sample overall. For FHA loan applications, our FinTech results also show a decline in the difference in rejection rates across minority and non-minority loan applicants. However, the decline for FinTech lenders is more modest, with the estimated coefficient for purchase applications falling by just 16% and the estimate for refi applications falling by about 10%.

Finally, Table I13 runs the same regression separately for "hard" rejections (denial reasons 1–5: debt-to-income ratio, employment history, credit history, collateral, and insufficient cash) and "soft" rejections (denial reasons 6, 7 and 9: unverifiable information, credit application incomplete, and "other;" plus all applications with action type 5, "file closed for incompleteness"), since it is possible that soft reasons for rejection may be more likely to be subject to bias than hard reasons. The discrimination coefficient is significantly greater than zero in all cases, for both rejection types. Apparently counter to the intuition that discrimination should show up more for soft rejections, the coefficient is larger for "hard" rejections. In interpreting this coefficient, however, it is again important to take account of the unconditional probability of each outcome. As a back-of-the-envelope adjustment, 13.3% of the loan applications in our sample receive a hard rejection, while 10.5% receive a soft rejection. Thus the average minority coefficient of approximately 4.4% in Panel (a) means that minority borrowers have a roughly 33% higher chance of a hard rejection than do non-minority borrowers; the average minority coefficient of 1.4% in Panel (b) translates into minority borrowers having a 14% higher chance of a soft rejection. Thus, the effect is somewhat larger for hard rejections, but it is sizeable for both.

While we stress again that we cannot be sure that these differences are not just a result of differences in unobservable variables, they are certainly large enough to suggest that further study is warranted.

| | Conventional Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Reject | Reject | Reject | Reject |
| Minority | 0.0673*** | 0.0596*** | 0.0916*** | 0.0681*** |
| | (0.00300) | (0.00468) | (0.00356) | (0.00716) |
| Observations | 2,454,895 | 7,199,070 | 2,870,285 | 1,573,343 |
| R-squared | 0.241 | 0.188 | 0.213 | 0.309 |
| Lender x year FE | Y | Y | Y | Y |
| LTV decile x year FE | Y | Y | Y | Y |
| Credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) **All lenders**

| | Conventional Loans | | FHA Loans | |
|---|---|---|---|---|
| | Purchase | Refinance | Purchase | Refinance |
| | (1) | (2) | (3) | (4) |
| VARIABLES | Reject | Reject | Reject | Reject |
| Non-FinTech × Minority | 0.0685*** | 0.0612*** | 0.0920*** | 0.0687*** |
| | (0.00302) | (0.00467) | (0.00362) | (0.00774) |
| FinTech × Minority | 0.0329*** | 0.0280*** | 0.0772*** | 0.0614*** |
| | (0.00751) | (0.00606) | (0.0118) | (0.00336) |
| Observations | 2,454,895 | 7,199,070 | 2,870,285 | 1,573,343 |
| R-squared | 0.241 | 0.188 | 0.213 | 0.309 |
| Lender x year FE | Y | Y | Y | Y |
| LTV decile x year FE | Y | Y | Y | Y |
| Credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Income decile x year FE | Y | Y | Y | Y |
| FinTech FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) **FinTech vs. non-FinTech lenders**

Table I12: **Application-rejection differentials.** The dependent variable is an indicator for an application being rejected by the lender. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for year interacted with deciles of census-tract LTV (1st quartile, median and 3rd quartile), credit score (1st quartile, median and 3rd quartile), loan amount, and borrower income, along with lender × year. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| VARIABLES | Conventional Loans<br>Purchase<br>(1)<br>Hard | <br>Refinance<br>(2)<br>Hard | FHA Loans<br>Purchase<br>(3)<br>Hard | <br>Refinance<br>(4)<br>Hard |
|---|---|---|---|---|
| Minority | 0.0464*** | 0.0428*** | 0.0477*** | 0.0394*** |
| | (0.00254) | (0.00421) | (0.00355) | (0.00517) |
| Observations | 2,454,895 | 7,199,070 | 2,870,285 | 1,573,343 |
| R-squared | 0.179 | 0.173 | 0.163 | 0.291 |
| Lender x year FE | Y | Y | Y | Y |
| LTV decile x year FE | Y | Y | Y | Y |
| Credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) **Hard Rejection**

| VARIABLES | Conventional Loans<br>Purchase<br>(1)<br>Soft | <br>Refinance<br>(2)<br>Soft | FHA Loans<br>Purchase<br>(3)<br>Soft | <br>Refinance<br>(4)<br>Soft |
|---|---|---|---|---|
| Minority | 0.00989*** | 0.00930** | 0.0268*** | 0.0112 |
| | (0.00182) | (0.00364) | (0.00194) | (0.00925) |
| Observations | 2,454,895 | 7,199,070 | 2,870,285 | 1,573,343 |
| R-squared | 0.159 | 0.141 | 0.130 | 0.193 |
| Lender x year FE | Y | Y | Y | Y |
| LTV decile x year FE | Y | Y | Y | Y |
| Credit decile x year FE | Y | Y | Y | Y |
| Amount decile x year FE | Y | Y | Y | Y |
| Income decile x year FE | Y | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) **Soft Rejection**

Table I13: **Hard- versus soft-rejection differentials.** The dependent variable is an indicator for an application being rejected (for "hard" reasons in Panel (a) and for "soft" reasons in Panel (b)) by the lender. The independent variable equals 1 if the borrower is African-American or Latinx, and 0 otherwise. Fixed effects are included for year interacted with deciles of census-tract LTV (1st quartile, median and 3rd quartile), credit score (1st quartile, median and 3rd quartile), loan amount, and borrower income, along with lender $\times$ year. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.