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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 affect minority borrowers if those determinations are based on characteristics unrelated to creditworthiness. Using an identification under this rule, we show risk-equivalent Latinx/Black borrowers pay significantly higher interest rates on GSE-securitized and FHA-insured loans, particularly in high-minority-share neighborhoods. We estimate these rate differences cost minority borrowers over $450 million yearly. FinTech lenders' rate disparities were similar to those of non-Fintech lenders for GSE mortgages, but lower for FHA mortgages issued in 2009–2015 and for FHA refi mortgages issued in 2018–2019.

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1. Introduction

A long literature, going back at least to Black et al. (1978), finds 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 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 these variables have a *legitimate business necessity*. Although lenders might view many activities as 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, for example, 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 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 little risk-based pricing. What 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 with the McDash data by Black Knight. Our data set includes never-before-linked loan-level information on income, race, ethnicity, LTVs, 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 et al. (2018).

For the 2009–2015 loan-origination data, we find Latinx and Black 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

[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 et al. (2021) for further discussion.

[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 et al., 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 et al., 2013).

[5] See Van Order and Yezer (2014), Gyourko et al. (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.

rate ≈ 1 point (i.e., 1% of the loan amount), 2 basis points corresponds to 0.1% of the loan amount, that is, 20% of total average profit; 5 basis points corresponds to 50% of total average profit.[7] For the 2018–2019 data, in which we can control for points and total loan costs at origination, the differences are even larger. Latinx and Black 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 is 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 from zero for FHA refinance loans.

We find a strong geographical component to our results. In particular, we find 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 our results contain heterogeneity, 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 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 finding suggests some of our results might be due to differential servicing costs; however, the fact that the relation between the rate differential and either credit score or realized default is minor suggests 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.

[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).

Minority borrowers might 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 LTV, 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 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. Although not as well identified as our interest-rate results, we find 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 these differentials are not driven by differences in unobservable variables, but they are certainly large enough to suggest further study is warranted.

2. Prior literature

Early studies of discrimination in mortgage lending, such as Black et al. (1978), look at the raw HMDA data and find minority loan applicants are rejected much more often than White applicants, even with higher incomes; however, these papers do not control for variables not collected by HMDA, such as credit history. In a widely cited paper, Munnell et al. (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 LTV, 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 et al. (2003) find 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 et al. (2014) examine subprime loans originated in 2005, and find that for 30-year, adjustable-rate mortgages, Black and Latinx borrowers face interest rates that are 12 and 29 basis points, respectively, higher than other borrowers. Bayer et al. (2018) find that after conditioning on credit characteristics, Black and Hispanic borrowers were 103% and 78% more likely, respectively, than other borrowers to be in a high-cost mortgage between 2004 and 2007. Reid et al. (2017) obtain similar results. Ambrose et al. (2021) look at loans approved and funded by a single large lender, New Century Financial Corporation, between 2003 and 2007, and find 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 et al. (2015) use data from the Survey of Consumer Finances to compare mortgage interest rates for minority and non-minority borrowers. They find Black borrowers, on average, pay about 29 basis points more than comparable White borrowers, with the difference being 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 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 et al. (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 et al., 2020 use post-crisis mortgage data from 2009–2019 and show machine-learning techniques to evaluate credit quality may result in a 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 minority borrowers pay significantly higher interest rates. However, unlike us, they conclude 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) the differences are significant for both GSE and FHA loans, even after conditioning on discount points.

Other consumer-debt markets show related results. For example, Dobbie et al. (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 the bias is due primarily to a misalignment of firm and examiner incentives. In a recent working paper, Butler et al., 2020 find that, controlling for credit risk, Black and Hispanic applicants' auto loans are approved at a 1.5-percentage-point-lower rate 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 the GSE and FHA markets

Our research design relies on the unique institutional setting that applies to the underwriting of credit risk in the 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, LTV, property value, etc.) to 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 interest rate 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 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 8×8 matrix of LTVs and credit scores to reflect varying credit risk across the GSE grid.[9] Fig. 1 depicts a typical Fannie Mae LLPA grid for single-family loans with a maturity of 30 years.[10]

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.

Similarly, FHA loans are insured against default by the FHA. Although FHA lenders do not explicitly price using the same LTV $\times$ credit-score grids used in the GSE market, the FHA-loan market has very little risk-based pricing, and what does exist is based on LTV and/or credit

[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.

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

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

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

Fig. 1. 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 December 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.

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 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 responding to this residual liability by making it more difficult to obtain a loan at all, rather than by 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 in which all legitimate-business-necessity variables are observable. Consequently, any interest-rate differentials across race or ethnicity that persist after controlling for these observable variables should be unrelated to creditworthiness and could reflect discrimination.

[11] For example, she notes, "According to CoreLogic servicing data, the share of [FHA] 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."

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. (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, LTV), 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 these 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, LTV, and

[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.

zip code of the mortgaged property) and month-by-month mortgage performance information.
- Equifax data are pre-merged with 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 LTVs and minimal credit scores, among other filters discussed in the Internet Appendix. Our overall merge rate for 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 either Latinx or Black. 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, whereas the mean loan amount is $176,710 for the FHA loans, with a standard deviation of $91,615. The average origination LTV for GSE-securitized loans is 74.0%. The average GSE borrower has a 10% probability of being Latinx or Black and has an average income of $101,981 and an average credit score of 757.6. The average origination LTV for FHA loans is 93.6%. The average FHA borrower has a 24.6% probability of being Latinx or Black, 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 FinTech lenders originated approximately 3.1% of 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, whereas 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 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. The total loan cost is likely to be a better control for cases in which 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 these 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 vs. FHA), and by minority status (Latinx/Black vs. White/Asian) using the AT-

[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, 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 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 comparison is discussed in more detail in the Internet Appendix.

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

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/Black 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-lender identifier from Buchak et al. (2018).

	count	mean	sd	min	max
		(a)GSE loans			
Cash-out refinance	3,376,600	0.0822052	0.2746771	0	1
CRA census tract	3,375,949	0.0926474	0.2899378	0	1
Credit score	2,950,931	757.6442	43.06677	620	850
FinTech	3,376,600	0.0312394	0.1739641	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	0.0442447	0.0054665	0.0275	0.07875
Loan-to-value ratio	3,376,600	0.7397208	0.1488221	0.3	0.95
Minority borrower	3,376,600	0.1001579	0.3002104	0	1
Refinance	3,376,600	0.5309895	0.4990388	0	1
Top-25 lender	3,376,600	0.4095857	0.4917574	0	1
N	3,376,600				
	count	mean	sd	min	max
		(b)FHA loans			
Cash-out refinance	2,273,444	0.0212822	0.1443237	0	1
CRA census tract	2,273,365	0.1781905	0.3826731	0	1
Credit score	1,994,340	697.3241	49.53322	580	850
FinTech	2,273,444	0.0160492	0.1256648	0	1
Income	1,999,753	66.4546	45.83809	20	7424
Loan amount	2,273,444	176.7100	91.61529	40	729
Loan interest rate	2,273,444	0.0440192	0.0068095	0.0275	0.0775
Loan-to-value ratio	2,273,444	0.9358196	0.0674404	0.3	0.9825
Minority borrower	2,273,444	0.2461666	0.4307768	0	1
Refinance	2,273,444	0.2619699	0.4397065	0	1
Top-25 lender	2,273,444	0.2854264	0.4516174	0	1
N	2,273,444				

TOM/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 LTV, income, and loan amount. Similarly, we exclude manufactured housing, investment properties, loans on condos, duplexes, triplexes, and quadraplexes.

As shown in Table 2, the share of refinance mortgages in the 2018–2019 HMDA data is lower for the GSE loans than the share reported in the 2009–2015 data, with 39.1% consisting of 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 an LTV of 76.1%, and the average loan amount for the FHA loans is $232,006, with an LTV of 89.7%. Average borrower income for the GSE loans is $100,707, slightly lower than in 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 which are measured as a fraction of the origination loan balance. For the GSE loans, points represent 0.17% on average of the origination loan balance with a standard deviation of 0.67% 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 represent 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 U.S.) 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

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.

	count	mean	sd	min	max
		(a) GSE loans			
Credit score	2,212,246	747.86608	14.674482	620	829
FinTech	2,212,246	0.13038062	0.33672179	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	0.04441362	0.00538968	0.0275	0.079
Loan-to-value ratio	2,212,246	0.76053186	0.14402249	0.3003096	0.94957983
Minority borrower	2,212,246	0.04495567	0.20720685	0	1
Points	2,164,245	0.00169405	0.0066614	−.01922169	0.02753803
Refinance	2,185,338	0.39142412	0.48806904	0	1
Total loan costs	2,192,384	0.01818049	0.01120778	0	0.07018133
N	2,212,246				
	count	mean	sd	min	max
		(b)FHA loans			
Credit score	953,192	730.0895	18.10742	580.125	826
FinTech	953,192	0.0912523	0.2879678	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	0.0448173	0.006458	0.0275	0.07875
Loan-to-value ratio	953,192	0.8967726	0.0928592	0.300813	0.9823009
Minority borrower	953,192	0.1483636	0.3554602	0	1
Points	920,361	0.0016903	0.0072352	−.0192209	0.0275377
Refinance	943,124	0.3030906	0.4595943	0	1
Total loan costs	901,869	0.0366662	0.0117278	0	0.0701836
N	953,192				

residual that reflects a lender's strategic pricing. Whereas "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 consistency in presentation, we apply this decomposition model to both GSE and FHA loans.

Figs. 2 and 3 illustrate this identification strategy. Fig. 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, Fig. 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 Black 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 approach allows us to capture pricing in the grid, and the fact that a different pricing grid for cash-out refinances, differential pricing by lender, and fluctuations over time exist. 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

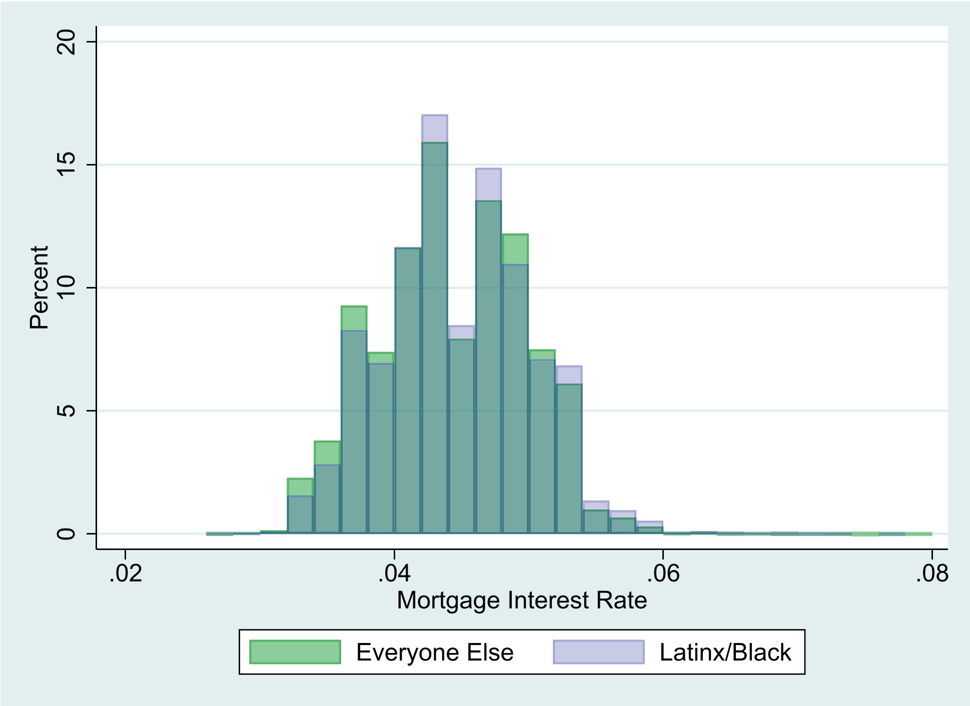
$$\begin{aligned} \text{interest rate}_{it} = {} & \alpha I(\text{Latinx or Black})_i \\ & + \mu_{\text{Cash-out}\times\text{GSE-grid}\times\text{year/month}} \\ & + \mu_{\text{Lender}\times\text{year/month}} + \mu_{\text{Amount decile}} + \epsilon_{it}. \end{aligned} \tag{1}$$

5.1. Baseline estimates

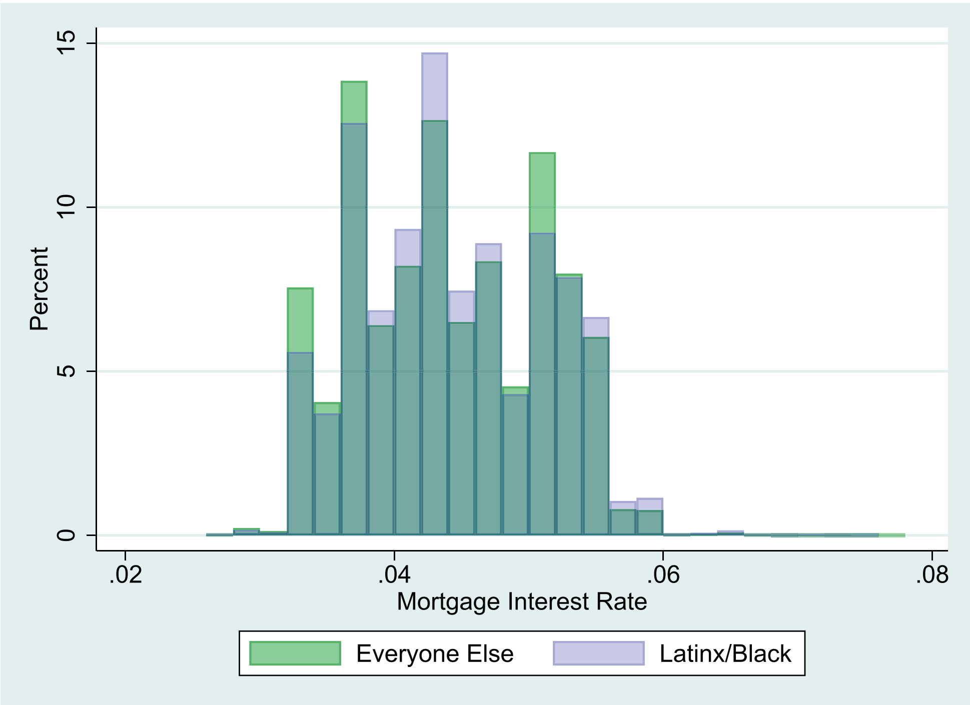
Table 3 presents the results of running Regression (1) for the loans in our sample. The first two columns present estimates for GSE loans, and the second two columns present estimates for FHA loans. Because lenders' pricing strategies may vary by mortgage type, we present estimates for purchase mortgages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

The overall mean difference in the purchase-mortgage interest rate between Latinx/Black 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

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

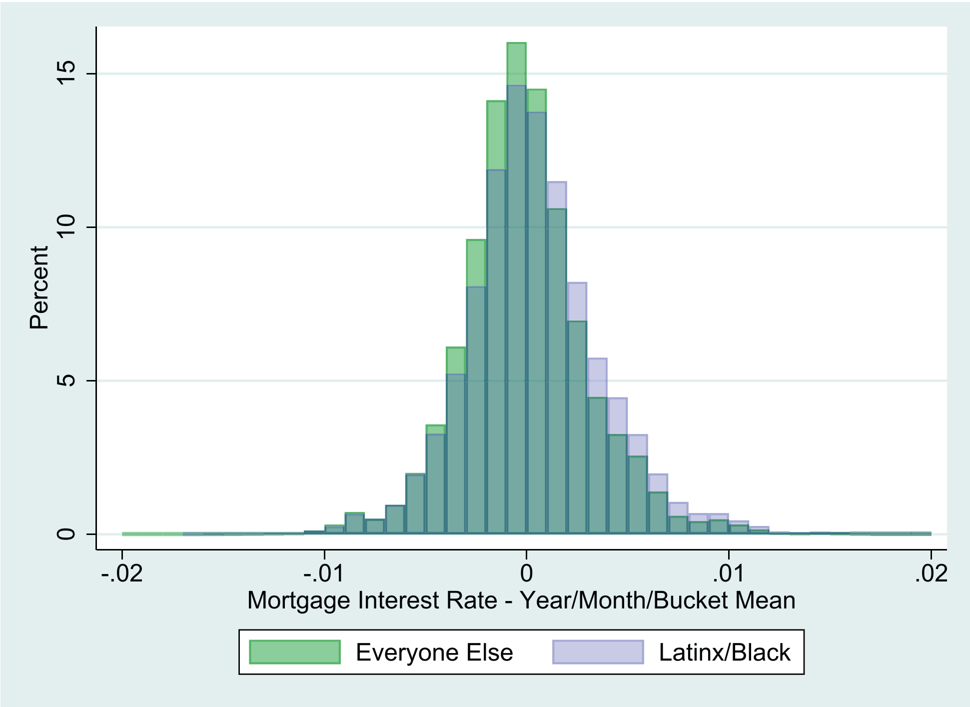


(a) GSE loans

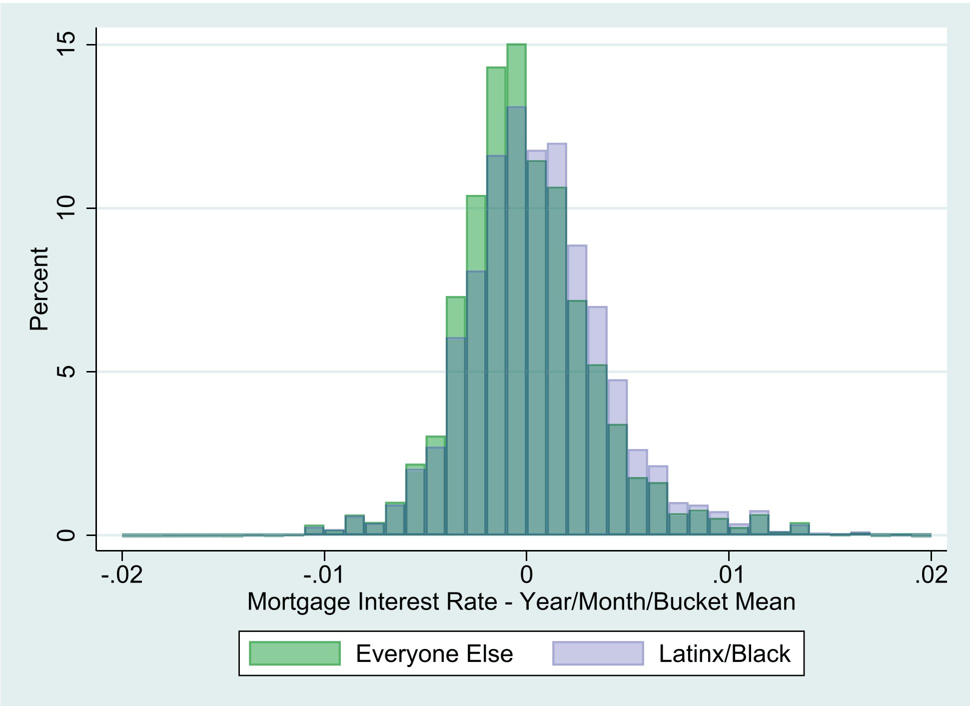


(b) FHA loans

Fig. 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/Black and for everyone else.



(a) GSE loans



(b) FHA loans

Fig. 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/Black borrowers and for everyone else.

points for refis. According to the Mortgage Bankers Association, the average *total* mortgage profit per loan between 2008 and 2019 was 50 basis points of a loan's principal,[17] so using the heuristic that 0.2% in rate ≈ 1 point, 2 basis points 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 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 et al., 2020 find a 54-basis-point gap between the 10th and 90th percentile mortgage rates paid for identical loans with the 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 a given borrower on a given day actually pays.

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 et al. (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." Although they interpret this finding 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 industry participants believe 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 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 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. 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

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

[18] It may also indicate the presence of selection; for example, perhaps the borrowers who seek out FinTech lenders are relatively sophisticated and thus less likely to default. However, Fuster et al. (2019) conclude 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, Forbes Insights, "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 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, note 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 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)).

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 Black 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	4.674***	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 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 Black 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
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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 selection is unlikely to be a major issue.

5.3. Time pattern

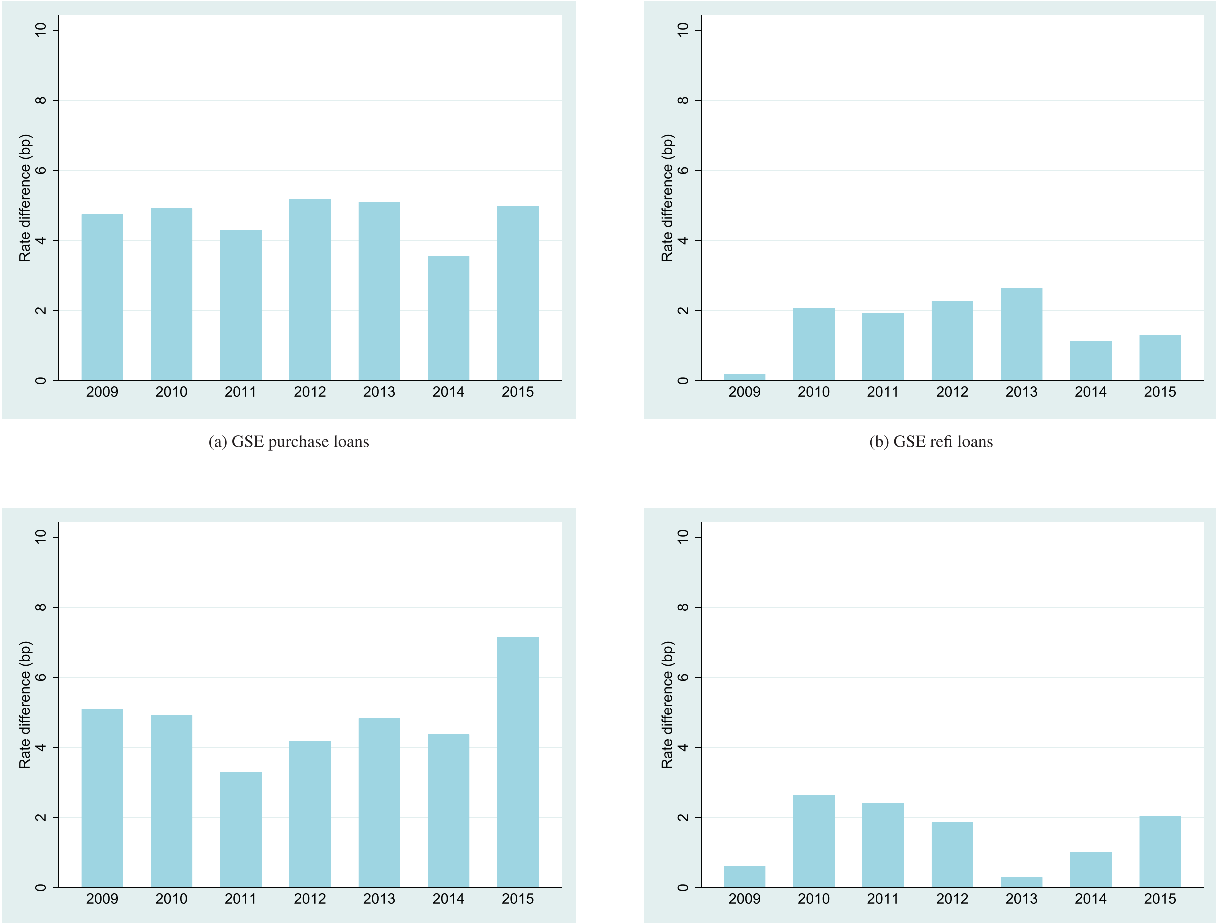
Woodward and Hall (2012) discuss the importance of shopping behavior for equal treatment in mortgage outcomes. The existence of FinTech and algorithmic lending might create an environment that is more conducive to shopping for the best rate or more competitive because of FinTech entrants. Additionally, 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]

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

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

[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 (Regulation Z), 78 Fed. Reg. 11,280 (Feb. 15, 2013).



(a) GSE purchase loans

(b) GSE refi loans

(c) FHA purchase loans

(d) FHA refinance loans

Fig. 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 Black or Latinx, and 0 otherwise. Fixed effects are included for cash-out × GSE-grid bucket × year/month, lender × year/month, and loan-amount decile.

Table 3 with the addition of census-tract × year fixed effects and without firm fixed effects. As before, Latinx and Black 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 0.499 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.

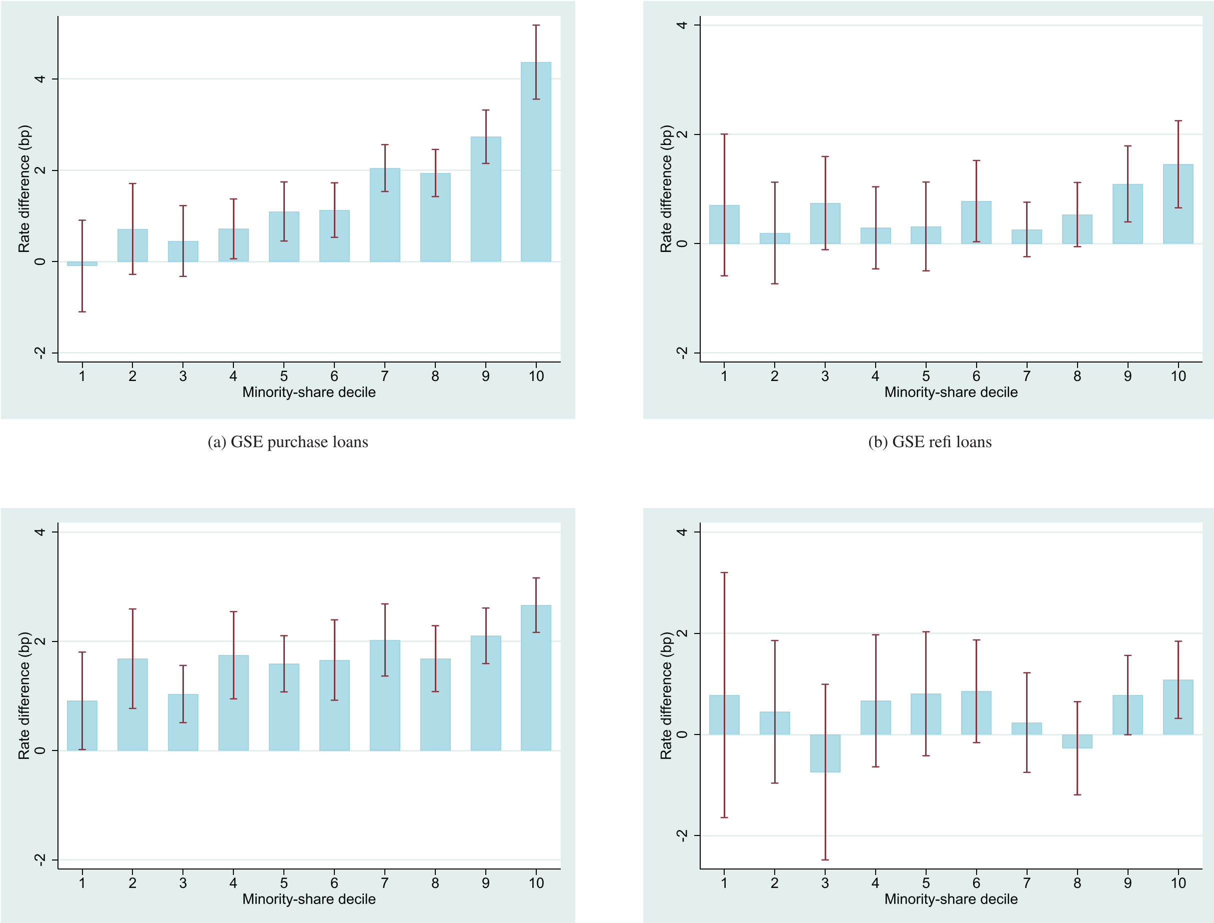
5.4.1. *Census-tract minority share*

Fig. 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 bias might be stronger when the opportunity to encounter minority individuals who could dispel negative stereotypes is lower. 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 basis points (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 finding in more detail, Fig. 6 shows binned scatter plots (see Cattaneo et al., 2019b; 2019a) of the census-tract × year fixed effects from the regression in Fig. 5 plotted against census-tract minority share, with the data in 10 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-

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

[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

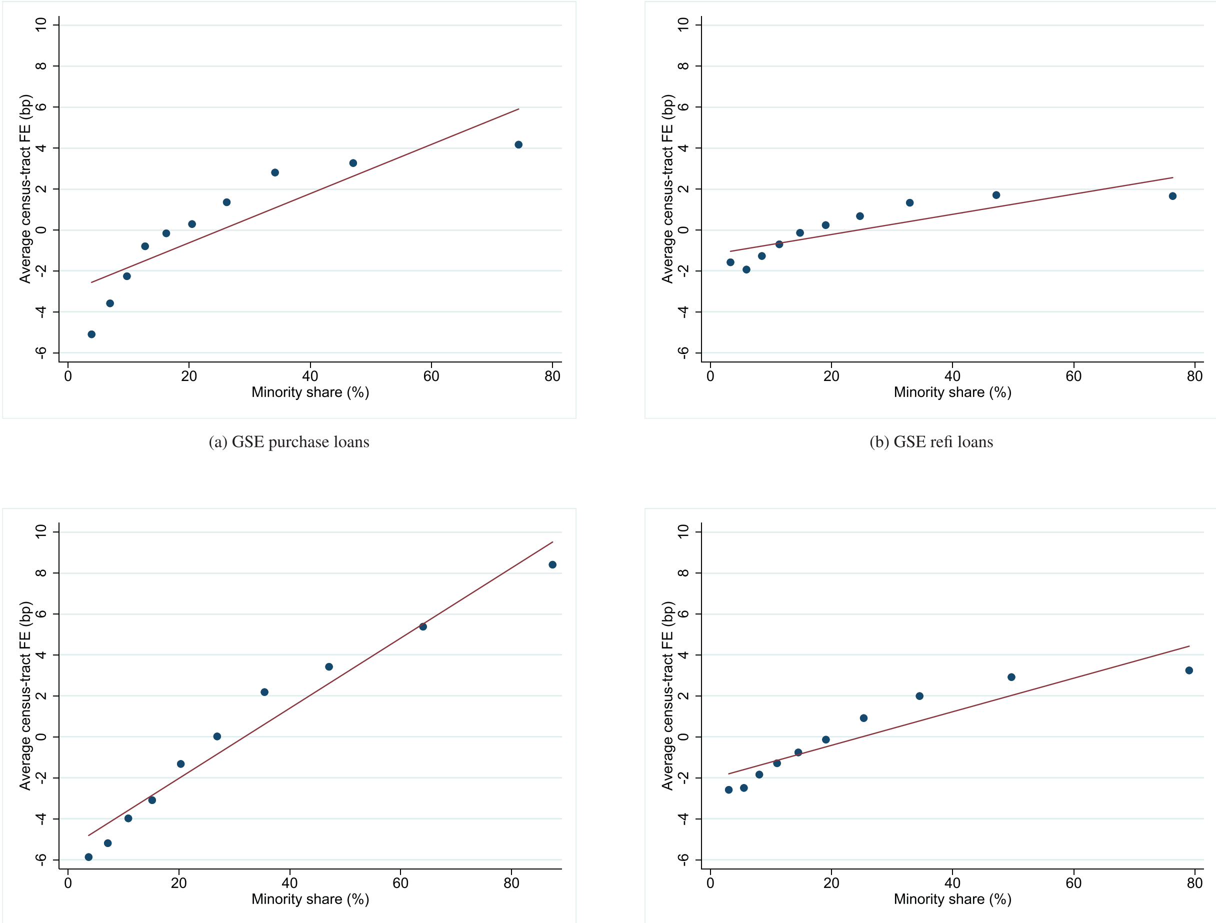
(d) FHA refinance loans

Fig. 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 Black 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.

1 census tracts by 9.7–14.3 basis points for purchase loans (GSE and FHA, respectively) and 3.1–5.8 basis points 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.

Although 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 Fig. 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, other costs are also associated with issuing and servicing loans, for example, prepayment risk, state foreclosure laws (which affect the cost of foreclosure), and rent levels. Looking again at Fig. 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 refinance loans, something that is hard to reconcile with a differential-cost story. Moreover, although 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



(c) FHA purchase loans

(d) FHA refinance loans

Fig. 6. Average interest-rate levels by minority-share decile. The figure shows binned scatter plots of the census-tract × year fixed effects from the regression in Table 5 versus the census-tract minority share, with the data in 10 equal bins.

skewness. Fig. 7 shows binned scatter plots of the absolute residuals from the regressions used for Table 5 against minority share. We see 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.

5.4.2. Firm minority share

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

5.4.3. CRA

Under the Community Reinvestment Act of 1977 (the CRA), banking institutions are evaluated by federal banking agencies to determine if the bank offers credit within low- and moderate-income neighborhoods, generally by reference to the amount of credit extended within low- and moderate-income census tracts. Table 6 shows the treatment coefficient for CRA versus non-CRA census tracts.

We see 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. Refi borrowers pay 1.86 (1.22) basis points more for GSE (FHA) loans.

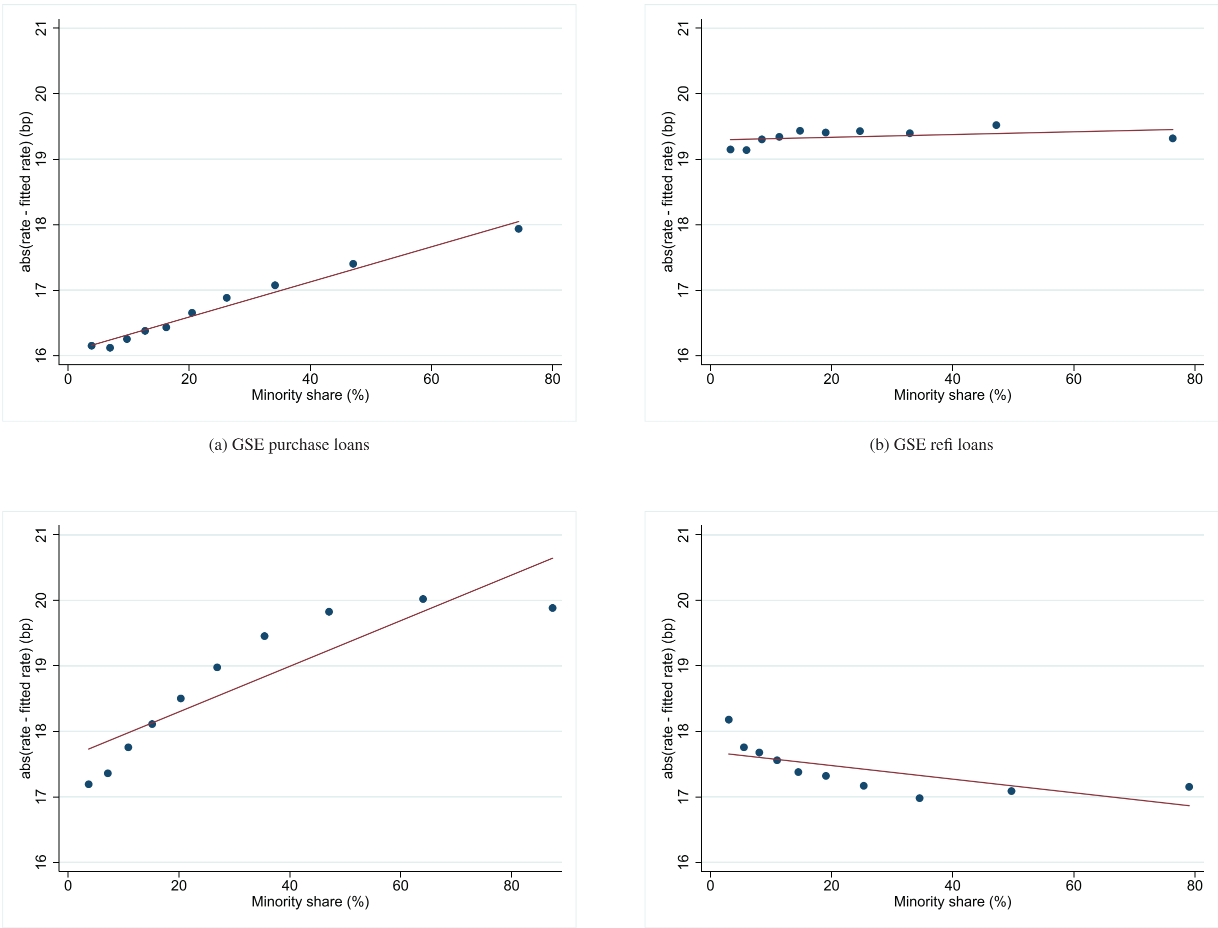
5.5. Additional robustness tests

This section performs some additional robustness tests, exploring the issues of put-back risk, servicing-cost risk, and HMDA ethnicity/race designations. Section 4.2 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 the originating lender faces is put-back risk. Put-backs can occur when

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



(a) GSE purchase loans

(b) GSE refi loans

(c) FHA purchase loans

(d) FHA refinance loans

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

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, e.g., Goodman et al., 2015).

Of course, realized put-backs being low does not necessarily imply 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 these loans as ones with a borrower credit score of at least 740 and an LTV of 0.6 or below; for FHA loans, we define them 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

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

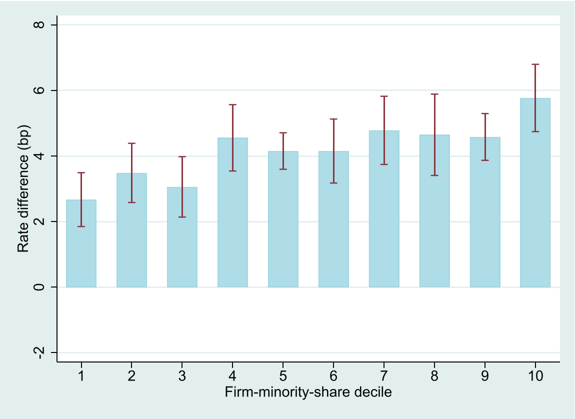
[26] Indeed, as late as November 2012, lenders' fear of put-backs was cited in a speech by Ben Bernanke as a reason for tight lending standards (see https://www.federalreserve.gov/newsevents/speech/bernanke20121115a.htm).

[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.

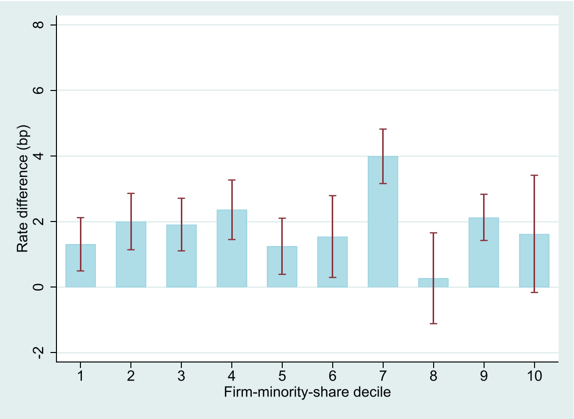
Table 5
Interest-rate differentials with census-tract controls. The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is Black or Latinx, and 0 otherwise. Fixed effects are included for cash-out × GSE-grid bucket × year/month, loan-amount decile, and census-tract × year/month. 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	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 × year FE	Y	Y	Y	Y

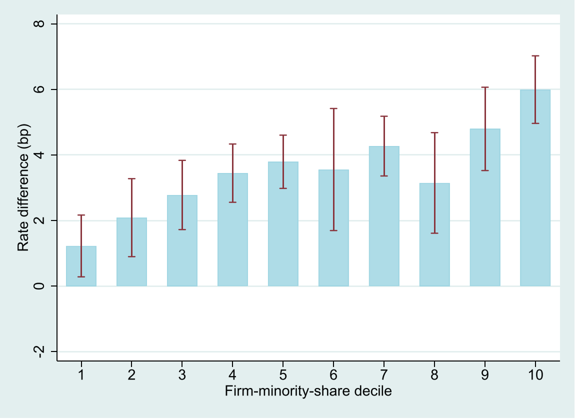
Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.



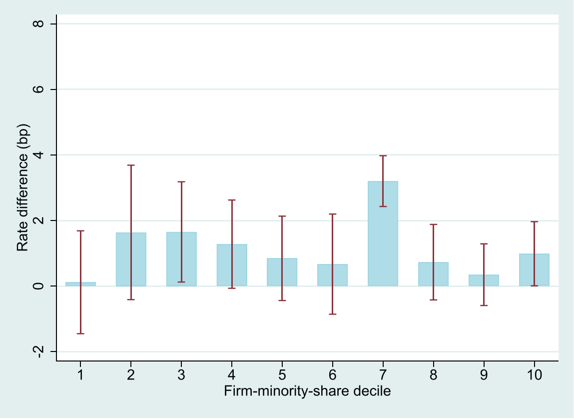
(a) GSE purchase loans



(b) GSE refi loans



(c) FHA purchase loans



(d) FHA refinance loans

Fig. 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 Black 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.

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 Black 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.

	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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 should be less relevant for nonbank lenders than for banks, who have more franchise value at stake. Panel (c) of 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.)

Together, these results imply 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. Significant costs are also borne by the servicer who has to deal with a delinquent borrower (see Kim et al., 2018), and different servicing costs could explain the rate differentials we observe. Kau et al. (2019) find minority borrowers have similar default rates to non-minority borrowers but lower prepayment rates; Gerardi et al. (2020) find that although 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 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. As noted above, 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, Figs. 9, 10, and 11 look at how the estimated treatment coefficient varies with the credit-score bucket, LTV bucket, and income decile, respectively.[28] We find 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.

These patterns suggest 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 to realized default or credit score suggests 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 for borrower race/ethnicity — the borrower's likely race/ethnicity based

[28] Full regression tables for these regressions are in Internet Appendix I3.
[29] See, for example, Calvet et al., 2009.

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 Black 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	4.539***	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	6441	3233
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 ≥ 740 (700) and LTV ≤ 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**

on a race and ethnicity name-categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008). This algorithm might misclassify a particular borrower's race or ethnicity, and 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 Internet Appendix:

1. Using only observations for which 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 Black.

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

[30] See Table I8 in the Internet Appendix.

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 Black 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 × 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 requirement 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, in principle, it is possible that the higher rate paid by minority borrowers could in part reflect their being more likely than non-minority borrowers to take out LPMI. Discussions with McDash suggest the incidence of LPMI is relatively low (less than 10% of all loans with mortgage insurance), and Fig. 10 shows 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 ≤ 80%. The minority coefficients are similar to those in Table 3, showing our results are not driven by different propensities to take out LPMI for minority and non-minority borrowers.

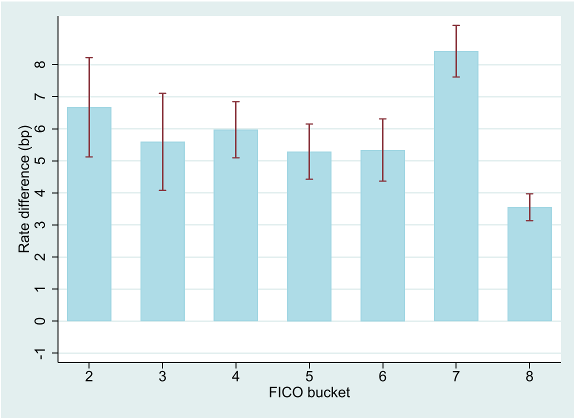
6. Discount points and the 2018–2019 HMDA data

Borrowers may choose to pay "discount points," an up-front lump sum, to a lender to reduce the loan interest rate. Alternatively, they may choose to pay "negative points," that is, to get a credit from the lender, in return for paying a higher loan interest rate. Even in the 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) analyze a subset of FHA loans originated in 2014 and 2015, including data on points paid. Like us, they find 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."

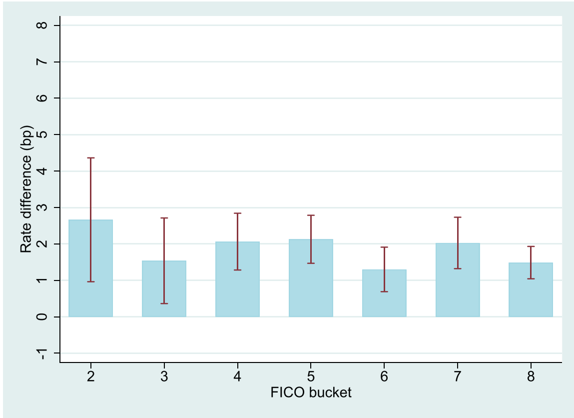
The 2018–2019 HMDA data allow controls for points and total up-front loan costs in our pricing regressions for both GSE and FHA mortgages. For this purpose, we set the variable "points-paid" to reflect either the amount of discount points paid by a borrower (i.e., points-paid > 0) or the amount of negative 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 × year, cash-out × LTV decile × year, cash-out × census-tract credit-score decile × year, loan-amount decile × year, and cash-out × income × 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 × year (thus controlling for the level of points). The table shows 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 to account for additional costs and for the possibility that

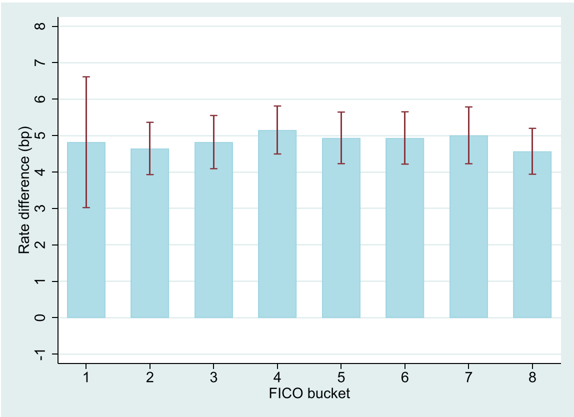
[31] We include controls for individual income here along with census-tract-level credit scores, because the HMDA data do not include individual credit scores.



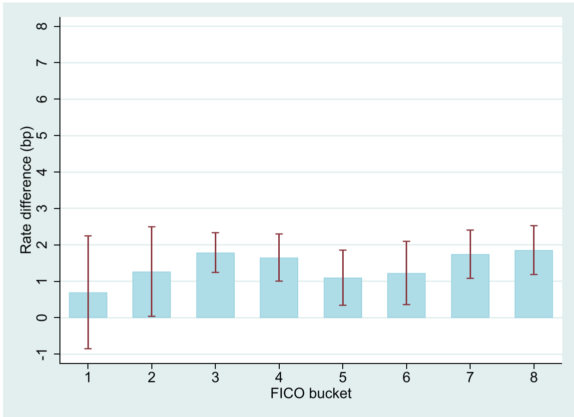
(a) GSE purchase loans



(b) GSE refi loans



(c) FHA purchase loans



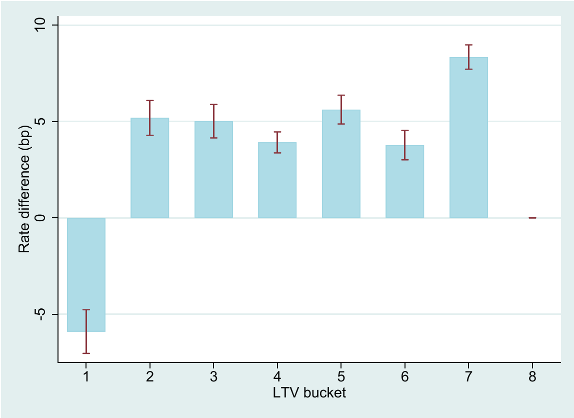
(d) FHA refinance loans

Fig. 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 Black 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.

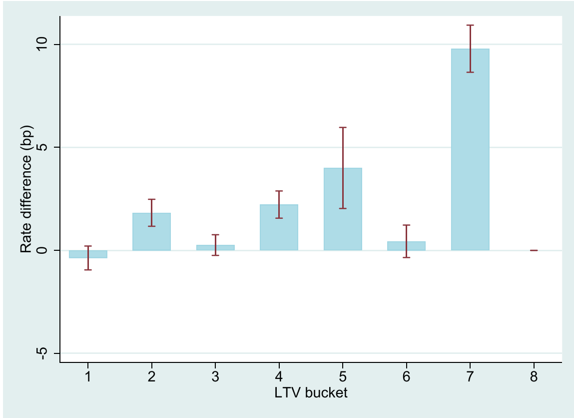
Table 9
Interest-rate differentials for GSE loans with LTV ≤80%. The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is Black or Latinx, and 0 otherwise. Fixed effects are included for cash-out × GSE-grid bucket × 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	
	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

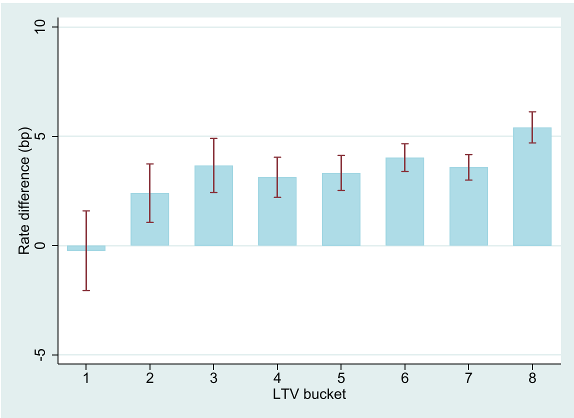
Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.



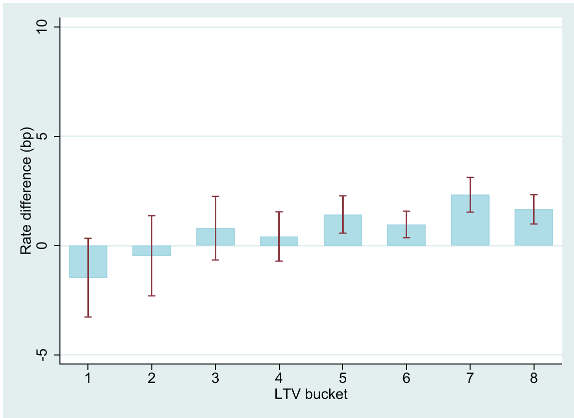
(a) GSE purchase loans



(b) GSE refi loans



(c) FHA purchase loans



(d) FHA refinance loans

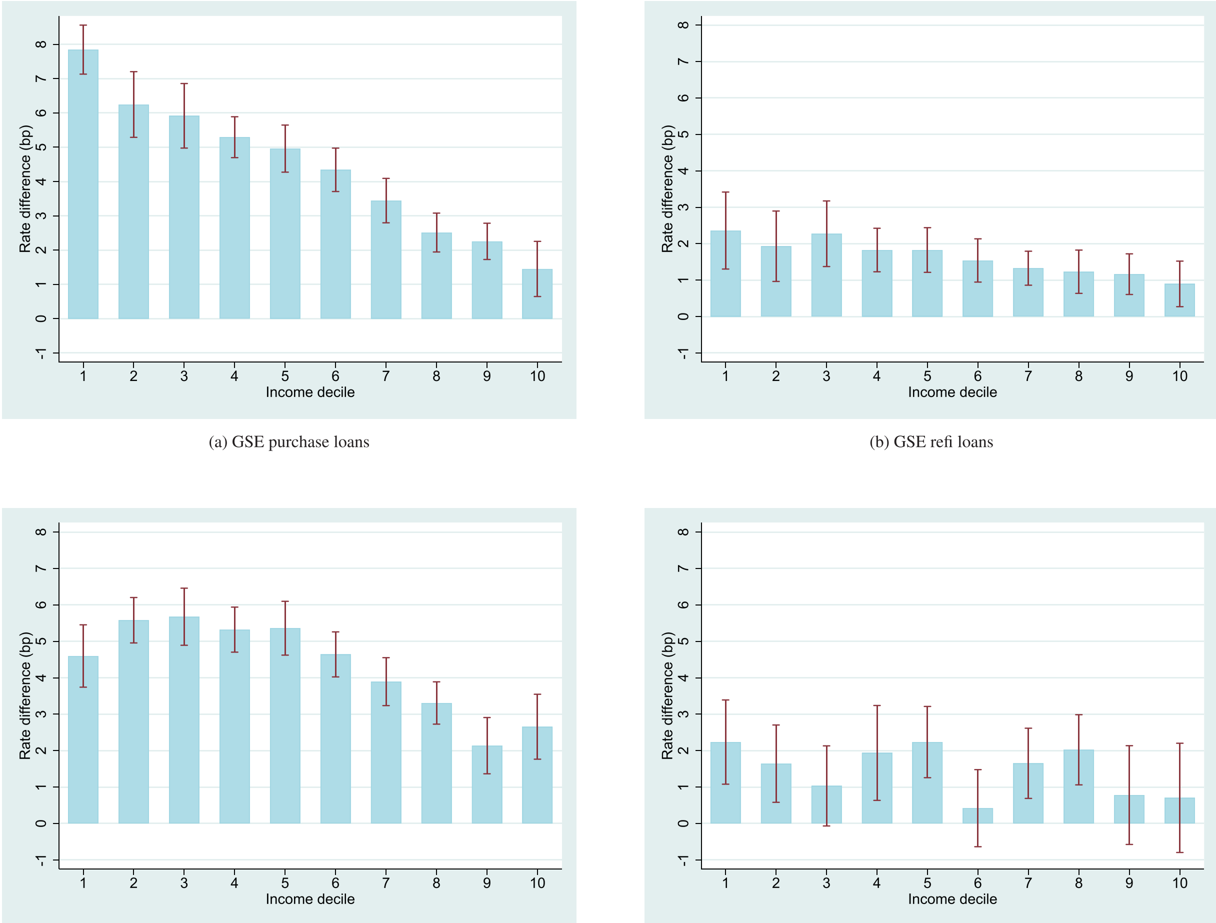
Fig. 10. Interest-rate differentials by GSE-LTV bucket (point estimates and 95% confidence intervals). The dependent variable is the interest rate on originated fixed-rate mortgages in basis points. The independent variable equals 1 if the borrower is Black or Latinx, and 0 otherwise, interacted with indicator variables for GSE-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.

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 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 minority borrowers are charged a statistically significant 5 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 Black and Latinx borrowers more for FHA and GSE purchase loans and GSE refinance loans, though not for FHA refinance loans.

[32] Unlike our base analysis, we are unable here to exclude loans with pre-existing or contemporaneous second liens, because 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.



(a) GSE purchase loans

(b) GSE refi loans

(c) FHA purchase loans

(d) FHA refinance loans

Fig. 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 Black 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.

6.1. Comparison with Bhutta and Hizmo (2020)

A number of differences exist between the data used by BH and the data we used in our analysis. In particular, BH look only at FHA loans, whereas 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, whereas we look at loans originated in 2018 and 2019.
- BH merge the HMDA data with Optimal Blue, whereas 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 six 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 vs. FHA), and by minority

[34] Bhutta and Ringo (2021, p. 201) note, "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 JP-Morgan 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%.

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 Black 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. 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
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.**

status (Latinx/Black 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 because we find stability in historical credit-score averages using the suitably filtered McDash loan-level data (more than 11 million mortgage originations), we

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 Black 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.

	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 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 Black 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. 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	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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

conclude 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

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, “While [our methodology] has the advantage of requiring few assumptions to be valid, it has the drawback that a

[36] Section I5 in the Internet Appendix performs one additional robustness check, repeating the 2009–2015 analysis using the 2018–2019 specification, that is, 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.

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

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 × 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 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. Although this analysis has some significant caveats — in particular, we do not observe the loan-level credit score or LTV 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.

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, LTV, 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 Black 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 basis points higher for purchase mortgages and almost 2 basis points 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 basis points for GSE purchase, 6.8 basis points for GSE refinance loans, 5.4 basis points for FHA purchase loans, and 1.9 basis points for FHA refinance loans. These differences are robust to a wide range of robustness tests. In addition, we find that for loans issued between 2009 and 2015, rate disparities were comparable across both FinTech and non-FinTech lenders for GSE mortgages but were slightly lower for FinTech FHA purchase and refi mortgages. However, we find in the 2018–2019 vintage loans with controls for total loan costs that rate disparities were roughly the same for FinTech and non-FinTech lenders for all loans types except FinTech FHA refinance loans, where spread differentials for Black and Latinx borrowers 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/Black 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 seek-

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

ing to detect which types of borrowers are less prone to shopping or which types of geographies have less competitive pricing. Alternatively, a lender might provide 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). Nevertheless, 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, the GSE process itself could 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 because 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.

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