# Consumer-Lending Discrimination in the FinTech Era*

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Abstract

Under U.S. fair-lending law, lenders can discriminate against minorities only for creditworthiness. Using an identification under this rule, afforded by the GSEs' pricing of mortgage credit risk, we estimate discrimination in the largest consumer-lending market for traditional and FinTech lenders. We find that lenders charge otherwise-equivalent Latinx/African-American borrowers 7.9 (3.6) bps higher rates for purchase (refinance) mortgages, costing $765M yearly. FinTechs fail to eliminate impermissible discrimination, possibly because algorithms extract rents in weaker competitive environments and/or profile borrowers on low-shopping behavior. Yet algorithmic lenders do reduce rate disparities by more than a third and show no discrimination in rejection rates.

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

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; however, it is also a question that raises a broader conceptual challenge concerning the very definition of discrimination. As decision-making increasingly moves from humans to machines, what does it mean to say that a decision is "discriminatory" when it is the product of an impersonal classifier? This latter question weighs heavily on organizations considering how to use vast new arrays of data while avoiding impermissible discrimination. It also confronts regulators and courts seeking to identify which proxy variables should give rise to a successful claim of illegal discrimination under U.S. laws. And of course, it is a question that requires a clear answer for economists seeking to examine empirically the extent of discrimination in contexts plagued by omitted variables.

In this paper, we take up these twin conceptual and empirical challenges in the context of consumer lending—a market where the adoption of algorithmic lending has been especially swift and where discriminatory decision-making can have significant implications for the well-being of households.[1] Because of the importance of first defining discrimination in the context of algorithmic decision-making, we begin in this Introduction with that task. In particular, by mapping antidiscrimination law to the economics of statistical discrimination as a solution to a signal-extraction problem, we obtain a workable definition of impermissible discrimination to apply to algorithmic lending (see also Bartlett, Morse, Stanton and Wallace, 2019, for a fuller legal discussion of this topic). We then estimate discrimination in an identified setting and test whether algorithms have reduced biases by removing face-to-face interactions. Whether the shift to algorithmic credit scoring induces more or less discrimination has so far been unknown. The uniqueness of our conceptual and empirical approach thus provides novel insight into the incidence of discrimination both generally and in the context of FinTech lending. Moreover, while the context of our study is consumer lending, the conceptual and empirical approach we

[1] The potential for illegitimate statistical discrimination toward protected classes of borrowers was a key aspect of Congressman Emanuel Cleaver's 2017 investigation into FinTech lending.

take is applicable to other newly algorithmic settings such as wage and hiring decisions, pre-trial release determinations, and the pricing of insurance.

A signal-extraction problem arises in consumer lending because even though economists and lenders can write down a macro-fundamental (life-cycle) model of default risk, some variables are not observable.[2] Lenders' goal in using statistical discrimination is to reconstruct this hidden fundamental information using observable proxies. In the non-algorithmic context, courts have ruled that the law permits lenders to use proxy variables that lead to worse outcomes for minorities, but only if the lender can show that these variables have a *legitimate business necessity*. As we describe in more detail below, the courts have been explicit that in the lending context, legitimate business necessity is the act of scoring credit risk. Furthermore, according to the courts, a lender's use of proxy variables that lead to different outcomes for minority borrowers for other purposes, including lenders' earning of higher profit margins, do not meet this definition of a legitimate business necessity. Lenders cannot make a higher profit, even inadvertently, from a minority- than from a majority-race/ethnicity individual of similar credit risk.

Lenders have used the legitimate-business-necessity defense to argue that any variable that is correlated with default is acceptable. This definition of legitimate business necessity is necessary but not sufficient to comply with the court rulings. An example is illustrative. Surely, the high school that a person attended is an empirically relevant proxy for hidden wealth, where wealth is the endowment variable in a macro-fundamental model of default risk. High school, however, may be correlated with race or ethnicity, even after orthogonalizing with respect to wealth. If so, using high school would punish some minority households for reasons that are unrelated to their credit risk.

Our economic mapping of U.S. antidiscrimination law to the legitimacy of proxy variables in statistical discrimination yields three punchlines: (a) Scoring or pricing loans explicitly on credit-risk macro-fundamental variables is legitimate; (b) Scoring or pricing on a proxy variable that only correlates with race or ethnicity through hidden fundamental variables is legitimate; (c) Scoring or pricing on a proxy variable that has significant residual correlation with

[2] This model would be based on cash-flow variables (income, wealth endowment, the cost of capital, consumption-bundle levels, etc.) rather than behavioral correlates to default, such as conspicuous-consumption predictors, because in the law, the scoring must apply correctly to everyone, not just on average.

race or ethnicity after orthogonalizing with respect to hidden fundamental credit-risk variables is illegitimate.

These punchlines have important implications for the challenge of defining illegitimate discrimination in the era of algorithmic decision-making. For example, for firms seeking to avoid using discriminatory algorithms, they suggest using a firm's proprietary data on otherwise-hidden fundamental variables such as wealth to test whether any given proxy variable has significant residual correlation with race or ethnicity after orthogonalizing with respect to the fundamental variables. A similar approach could be taken by regulators. For instance, fair-lending examinations could include a mandate that lenders provide proof of legitimacy of proxy variables using this type of testing. This arrangement would be akin to putting the burden of value-at-risk modeling on banks, as is done in banking regulation. (We discuss this more in Bartlett, Morse, Stanton and Wallace, 2019). Finally, for researchers, these punchlines imply that in the age of algorithmic decision-making, econometricians require a setting in which all legitimate-business-necessity variables are observable in order to identify discrimination without concern for omitted-variable bias. This last point motivates our empirical study.

Our empirical analysis focuses on interest-rate decisions in the mortgage market. Mortgages are the largest component of household debt, with Latinx and African-Americans (the protected-minority categories for this paper) owing $1.65 trillion in housing debt in 2017.[3] Because of the size of this market, even a single basis point of discrimination becomes material in aggregate. The mortgage market is also important in studies of discrimination because of the government-mandated recording of race and ethnicity under the Home Mortgage Disclosure Act (HMDA) and the public disclosure of HMDA data.

For our purposes, however, the most important advantage of studying discrimination and algorithms in the mortgage context is the role of the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. The GSEs completely determine credit-risk pricing adjustments via a guarantee fee that depends only on the borrower's (observable) credit score and loan-to-value ratio (LTV). In return, lenders are guaranteed against credit risk. Even if this pricing grid is

[3] In 2017, Latinx and African-Americans owed $2.25 trillion in household debt, representing 17.3% of the $13 trillion aggregate household debt. Percent-of-debt estimates are from the 2016 Survey of Consumer Finances, and aggregate debt statistics are from the Federal Reserve.

not the optimal model for predicting default among all application variables,[4] it nevertheless completely determines the price lenders must pay the GSEs to absorb all credit risk. Thus, any mortgage interest rate differences between loans within a given GSE grid cell of credit score and LTV cannot reflect differential credit risk, but must instead reflect strategic pricing decisions on the part of lenders. In other words, the GSE pricing grid provides us with a setting where all legitimate-business-necessity variables are observable. Consequently, within the grid, any additional correlation of loan pricing with race or ethnicity is discrimination.

Our analysis uses a data set that includes never-before-linked information at the loan level on income, race, ethnicity, loan-to-value ratios, debt-to-income ratios, all contract terms (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 restrict our setting to post-2009, after which concerns of put-backs and poor application data were no longer relevant (Goodman, Parrott and Zhu, 2015). For our definition of FinTech firms, we follow the list of platform lenders of Buchak et al. (2017). This is a pure but under-inclusive sample, in that the trend for most mortgage lenders is clearly toward algorithmic decision-making. Of the 2,098 largest mortgage lenders over 2012-2018 in our sample, 45% of them offer complete online or app-based mortgage contracting by 2018. However, because we cannot discern which mortgages are which from lenders that offer both algorithmic and face-to-face loans, we conservatively use the pure-platform sample of Buchak et al. (2017).

Our main results are the following two findings concerning the price of mortgages. First, accepted Latinx and African-American borrowers pay 7.9 and 3.6 basis points more in interest for home-purchase and refinance mortgages, respectively, because of discrimination. These magnitudes represent 11.5% of lenders' average profit per loan.[5] Averaging across the distribution of these products in the U.S., lending discrimination currently costs African-American and Latinx borrowers $765 million in extra interest per year.

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

[5] According to the Mortgage Bankers' Association, the average mortgage profit is 50 basis points (see https://www.mba.org/x73719).

Second, FinTech algorithms discriminate 40% less than face-to-face lenders; Latinx and African-American pay 5.3 basis points more in interest for purchase mortgages and 2.0 basis points for refinance mortgages originated on FinTech platforms. Despite the reduction in discrimination, the finding that even FinTechs discriminate is important. Nor is this simply a mortgage story; one only has to look to the emergence of personal-lending platforms, such as LightStream by SunTrust Bank and Marcus by Goldman Sachs, to see the broader transformation in consumer lending.

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 lower than in purchase mortgages is consistent with an interpretation that monopoly price extraction of rents is easier in purchase-mortgage transactions, where the borrowers have less experience or are acting in a more urgent time frame. Additionally, because lenders may price loans to capture rents in less-competitive areas, prices might be higher in financial-services deserts, which might have higher minority populations. These pricing mechanisms can play out with either human or machine intervention. For instance, one can easily imagine both lending algorithms and human loan officers seeking to detect which types of borrowers are less prone to shopping or which types of geographies have less competitive pricing.

We consider the robustness of our estimates to lingering concerns. Although courts have explicitly held that credit risk is the only legitimate business necessity, the spirit of these decisions may include room for lenders to differentiate loan pricing based on the fixed cost of providing a loan by lender or by geography. We thus additionally include county and lender fixed effects, as well as county-crossed-with-lender fixed effects, with results remaining robust. We also address the robustness of this result to other concerns of servicing rights and the quality of the HMDA race and ethnicity designations. In particular, results are similar when we use naming algorithms to fill in race and ethnicity, compared with dropping observations with missing race and ethnicity. Finally, using the new 2018 HMDA data, which include points paid, we show that our results are robust to concerns about paying points or taking rebates differentially by minority status.

In addition to the ability of FinTech lenders to diminish face-to-face bias in loan pricing, our findings also point to two additional silver linings related to the role of FinTechs and algorithmic decision-making. First, we find that discrimination in loan pricing is declining for all lenders from 2009 to 2015, alongside the advent of FinTech lending. While we cannot prove causation, this finding is consistent with borrowers using online platforms to shop around with greater ease and speed, which should diminish the capacity for lenders to extract rents from minority borrowers.

Second, we find a positive role of FinTech in loan accept/reject decisions. We first note that any discrimination in loan rejection rates—as opposed to discrimination in loan pricing—would appear to be inconsistent with lenders' profit maximization in our setting of the GSE guarantee. Logic suggests that such unprofitable discrimination must reflect a human bias by loan officers. This is what we find.

Face-to-face lenders reject Latinx and African-American applications approximately 6% more often than they reject similarly situated non-minority applicants for both purchase and refinance loans. In aggregate, our findings suggest that from 2009 to 2015, lenders rejected 0.74 to 1.3 million Latinx and African-American applications that would have been accepted except for discrimination. FinTech lenders, on the other hand, do not discriminate at all in the decision to reject or accept a minority loan application in our sample. This is consistent with algorithms acting in a profit-maximizing manner. Because our findings with respect to rejections must rely on proxies for certain variables utilized by the GSEs in approving loans, we note that these results are ground work, requiring further exploration. But they nevertheless point toward the possibility that fully automated underwriting may reduce the incidence of discrimination in loan rejections.

Our paper contributes to a small but growing literature on discrimination in lending. This literature has lagged the wage-discrimination literature, primarily because of the lack of data on ethnicity or race, combined with an identification strategy that handles omitted variables in scoring.

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

Much of the more recent literature focuses on the pre-crisis period, usually looking at subprime lending. Ghent, Hernandez-Murillo, and Owyang (2014) examine subprime loans originated in 2005, and find that for 30-year, adjustable-rate mortgages, African-American and Latinx borrowers face interest rates 12 and 29 basis points, respectively, higher than other borrowers. Bayer, Ferreira, and Ross (2018) find that after conditioning on credit characteristics, African American and Hispanic borrowers were 103% and 78% more likely, respectively, than other borrowers to be in a high-cost mortgage between 2004 and 2007. Similar results were obtained by Reid, Bocian, Li and Quercia (2017).

Cheng, Lin and Liu (2015) use data from the Survey of Consumer Finances to compare mortgage interest rates for minority and non-minority borrowers. They find that black borrowers on average pay about 29 basis points more than comparable white borrowers, with the difference larger for young borrowers with low education, subprime borrowers, and women.

Focusing on the *quality* of consumer credit services, Begley and Purnanandam (2018) study the incidence of consumer complaints about financial institutions to the CFPB. They find that the level of complaints is significantly higher in markets with lower income and educational attainment, and especially in areas with a higher share of minorities, even after controlling for income and education.

In one of the few experimental papers in this area, Hanson, Hawley, Martin, and Liu (2016) show that when potential borrowers (differing only in their name) ask for information about mortgages, loan officers are more likely to respond, and give more information, to white borrowers.

Finally, Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2018) show that the use of machine-learning techniques to evaluate credit quality may result in differential impact on loan provision to minority versus non-minority borrowers. This paper conveys important knowledge in how algorithms are utilized in mortgage markets.

There are also related results from other consumer debt markets. For example, Dobbie, Liberman, Paravisini and Pathania (2018) look at data from a high-cost lender in the UK and find significant bias against immigrant and older loan applicants when measured using long-run profits. However, they find no bias when using the (short-run) measure actually used to evaluate loan examiners, suggesting that the bias is due primarily to a misalignment of firm and examiner incentives.

The rest of the paper is organized as follows. In Section II we discuss our data. We present our methodology for the measurement of mortgage discrimination in Section III, and provide statistics showing the role of the GSE pricing grid in practice. Our empirical results are reported in Section IV. Section V concludes and discusses regulatory implications of our findings.

## II. Data and Statistics

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

- HMDA data include information on applicant income, race, ethnicity, loan amount, and lender name, as well as the census tract of the property.
- ATTOM data provide transaction and assessor information, including lien-holder name, loan-performance data (i.e., prepayment and default), borrower and lender names and exact property location, but very little information on mortgage contract terms other than the loan amount, the origination date, the purpose of the loan, and whether it is a fixed or floating contract.

[6] HMDA reporting is not required for institutions with assets (of the entity and its parent corporation) that are below $10 million on the preceding December 31 (see http://www.ffiec.gov/hmda/pdf/2010guide.pdf).

- McDash data provide loan-level data compiled by Black Night Financial Services and include detailed mortgage terms (including interest rates, loan amount, loan-to-value ratio, and zip code of the mortgaged property) and month-by-month mortgage performance information.
- Equifax data provide information on other consumer financing balances that are held by borrowers in addition to their mortgages and the borrower credit score.
- Freddie Mac Single Family Loan-Level Dataset and Fannie Mae Single Family Loan Performance Data: These data were used to construct estimates of the median and the $25^{th}$ and $75^{th}$ quartiles for the census tract level "back-end" debt-to-income ratio distributions.[7]

We exploit overlapping variables within HMDA, ATTOM, and the McDash/Equifax datasets to construct a merged data set of accepted loans with performance information, contract terms, the mortgage lender, and borrower information. The Appendix describes our merging algorithm, which is governed by compliance with IRB standards and is anonymized.

The HMDA data include information on both ethnicity and race. For our purposes, we define a minority applicant to be one with either Latinx ethnicity or African-American race. We combine to a single minority category in order to keep the minority pool consistent throughout the paper, even when implementing fine-grid geography and lender fixed effects. HMDA has missing values on race and ethnicity (Buchak et al., 2017). 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). In the robustness section, we check for consistency of our results when excluding these fixes.

We trim outliers and unexpected data as follows. We drop the few loans with applicant credit score less than 620, per GSE guidelines. We additionally trim outlier loans with LTV less than 0.30 or greater than 1.3, and we drop loans with HMDA loan amounts of less than $30,000. Finally, we drop applicants who have income recorded as 1 or 9999, HMDA indicators for data top/bottom coding.

[7] The back-end debt-to-income ratio is the sum of a borrower's debt expenses (calculated as all credit report payments plus the payment implied by the current mortgage payment plus taxes and insurance) divided by the borrower's gross monthly income.

We focus on two types of lender origination decisions. Our main evidence concerns loan pricing conditional on acceptance. We also study, in a less precisely identified setting, the decision to accept or reject a loan application.

Panel A of Table 1 reports the summary statistics for the pricing estimations. To standardize our loan pricing analysis, we filter the data to focus on 30-year, fixed-rate, single-family residential loans, securitized by the GSEs over the period 2009 through 2015.[8] We additionally eliminate from our sample any loans made within a census tract covered by the Community Reinvestment Act of 1977 (CRA), given the potential bias these census tracts would introduce into our empirical analysis.[9] The final pricing-analysis sample consists of 3,577,010 loans. The dependent variable, the interest rate on the mortgage, has both a mean and a median of 4.50%. The mean loan amount is $234,000, reflecting an LTV of 0.744, from an applicant who has an 11% probability of being Latinx or African-American. This borrower has $107,200 in income and a high credit score of 755.8.

For our accept/reject analysis, the only loan-level source of data is HMDA, which records application status in the "Action Taken" field. An Action Taken equal to one is a reject ("Application denied by financial institution"). Three weaknesses exist in these data. First, public HMDA data do not indicate whether loan applications are to be securitized through the GSEs, if approved. We mitigate this problem by limiting the accept/reject sample to HMDA mortgages qualifying as being *conventional* (not being backed by the Federal Housing Administration, the Veterans Administration, the Farm Service Agency or the Rural Housing Service) and *conforming* (the loan size falls below the annual conforming loan limit set by the Federal Housing Finance Agency). Second, we are unable to further filter to 30-year loan applications since HMDA does not report the applied-for loan maturity. Therefore, our data pool together 15-, 20-, and 30-year applied-for mortgages for the accept/reject analysis. Third, while we know the precise (observable) variables that the GSEs use to determine loan acceptance/rejection in their automated underwriting systems, we do not have loan-level data on some of these application variables. We therefore augment the rejection data with measures, described in the Appendix, of

[8] We also do a rate analysis on 15 and 20 year mortgages. Statistics and estimation results are included as Appendix Table 1.
[9] Under the CRA Act, financial institutions are required to provide a certain level of lending to CRA districts to counter the lack of financial services in lower-income districts. The pricing of these loans could reflect different economic motives.

credit scores, debt outstanding, debt-to-income ratios, and loan-to-value ratios using medians computed at the census-tract level. A census tract is on average 1,600 households (4,000 inhabitants), designed by the Census Bureau to reflect relatively uniform economic situations. Because our data on rejected applications have these potential weaknesses, we exert more caution in interpreting the accept/reject results (as opposed to the pricing results).

Table 1 reports the summary statistics for the accept (Panel B) and reject (Panel C) applications. Slightly over half of the mortgages are acceptances. The final sample for the accept/reject analysis consists of 6,648,413 accepted loans and 6,535,664 rejected loans. Latinx and African-Americans account for 11.9% of accepted and 18.6% of rejected applications. As expected, accepted applicants have stronger credit-risk profiles than those rejected. Accepted applicants exhibit a higher mean income of $108,300 (versus $97,400 for rejected loans) and a higher mean applied-for loan amount of $213,900 (versus $187,300 for rejected). The summary statistics for the census-tract proxies reflect a similar pattern. Accepted applicants exhibit a higher average credit score of 750.8 (versus 744.2 for rejected loans) and a slightly lower average loan-to-value ratio (LTV) of 0.791 (versus 0.812 for rejected loans). Accepted and rejected applications appear similar with respect to the mean total debt outstanding and mean debt-to-income (DTI) in the census-tract proxies.

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. (2017), we find that FinTech lenders originated approximately 4.3% of accepted loans (Panels A and B) and were responsible for 5.5% of all loan rejections in our sample. 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) both accepted and rejected over 50% of all loans processed.[10]

In all of our analysis, we divide the market between purchase and refinance loans. Purchase loans represent 41.8% of the loans in the pricing analysis, probably because we focus on 30-year maturities rather than 15- or 20-year maturities, which are preferred for refinances. Consistent with this conjecture, for the accept/reject estimations, purchase loans represent 30.8% of accepted loans and 17.3% of rejected loans.

[10] We create a variable of the top 25 mortgage originators per year by matching HMDA lender names with mortgage origination statistics obtained from Inside Mortgage Finance.

## III. Methodology to Identify Price Discrimination

### *III.a. The Lending and Pricing Process in GSE Markets*

GSE involvement in the mortgage process begins with the lender's submission of applicant data (credit score, income, liquid reserves, debt-to-income ratio, loan-to-value ratio, property value, etc.) into one of the two GSEs' automated underwriter systems (Desktop Underwriter for Fannie Mae; Loan Prospector for Freddie Mac). If the GSE underwriter system issues an approval on the application, and the lender decides to make an offer, the applicant gets a price quote and can decide to accept or not. If the mortgage is issued, the lender immediately sells it to the GSE. In return, the GSE compensates the lender with a cash transfer.[11] The GSE then packages the loan with a pool of similar mortgages into a mortgage-backed security (MBS), issues a default-risk guarantee on this product, and sells it to the MBS market.

Within this GSE process, the lender must decide about the price offered to the borrower. This interest rate quote structurally consists of three parts (see Fuster et al., 2013). First, all lenders face the same market price of capital, determined by the base mortgage rate, which reflects the primary market interest rate for loans to be securitized by the GSEs, in essence, the credit-risk-free rate. Second, when the lender sells the mortgage to the GSE, the lender 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 8×9 matrix of LTVs and credit scores to reflect varying credit risk across the GSE grid. Figure 1 depicts a typical GSE grid of Fannie Mae, also called the Loan Level Price Adjustments (LLPAs), for single-family loans with maturity 30 years.[12] 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

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[11] If the originator is a large-volume lender, the lender will transfer loans to the GSE in bulk and, instead of receiving cash for the mortgages, the originator receives back an MBS with a pool of similar-characteristic mortgages produced by that lender. (Sometimes these MBS products have mortgages originated by other lenders to fill out the MBS, but one should think of this pool as primarily being the lender's own issuance.) These MBS products are equally guaranteed by the GSE, but because the lender also retains servicing rights, the lender may be exposed to the extra servicing costs (e.g., additional phone calls and outreach) that happen when loans become delinquent. For this reason, we show all of our results with and without the large-volume lenders.

[12] See FHFA (2000, 2010, 2011, 2012, 2013) and Fuster and Willen (2010).

may reflect simple differences in overhead costs among lenders, but they may also reflect strategic volume positioning or monopoly rent-taking. These pricing strategies may involve human discretion or could be machine-coded.

### *III.b. Discrimination under U.S. Fair Lending Laws*

As discussed in the Introduction, our identification of discrimination relies on the legal setting established by U.S. fair-lending law.[13] A lender accused of discrimination under U.S. fair lending law can assert a defense based on the principle of *legitimate business necessity*. One might imagine that many activities fall under business necessity related to a lender's goal of profit maximizing, but the courts have consistently limited the legitimate-business-necessity defense to a lender's use of variables and practices to ascertain creditworthiness.[14] Thus, the use of variables or practices that induce higher profit-taking (above creditworthiness) from, for example, charging higher rates to applicants in financial deserts or applicants with low shopping characteristics cannot be justified as legitimate business necessity, even though the use of these variables may be profit maximizing. Using strategic pricing variables is not illegal, but any negative impact from using these variables cannot fall disproportionately on minorities or other protected categories.

The legal environment provides guidance for identification of discrimination, but also requires that an econometrician be able to observe all variables determining creditworthiness. However, as described above, the GSEs' role in guaranteeing loans provides a setting (in the largest consumer loan market in the United States) in which we can fully see the price of credit risk by observing a borrower's LTV and credit score.

Figure 2 shows the importance of the GSE grid for loan pricing. Panel A shows histograms of raw mortgage interest rates by minority status. The histograms reveal a wide

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[13] 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.

[14] 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.")

distribution of rates for both minority and non-minority 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 cell mean, Panel B shows a dramatic reduction in the distribution of interest rates for both groups of borrowers, highlighting the central role of the LLPA grid in determining interest rates for GSE mortgages.

We translate the Panel B figure into an empirical model for application *i* occurring in the month-year *t* as follows:

$$interest\ rate_{it} = \alpha\ LatinxAfricanAmerican_i + \mu_{GSEgrid} + \mu_{month\_year} + \varepsilon_{it}, \quad (1)$$

where the mortgage interest rate is regressed on an indicator for the applicant being Latinx- or African- American, 72 GSE-grid fixed effects $\mu_{GSEgrid}$, and month-year fixed effects $\mu_{month\_year}$. Under the GSE identification, any loading of pricing on race/ethnicity is discrimination.

### *III.c. Robustness Identification Concerns*

We address a number of robustness concerns that would threaten the interpretation of the minority coefficient as discrimination.

### *Residual Default Risks: Put-Backs*

Our identification relies on the lender not being exposed to repayment risk. Once a mortgage is placed into the hands of the GSE the only repayment risk faced by the originating lender is put-back risk. Put-backs can occur when the documentation on income (tax returns, pay stubs, etc.), credit score, loan purpose (residential vs. non-occupancy) or property value (the appraisal) is falsified or missing. Put-backs from mortgages issued prior to and through the 2008 mortgage crisis were very material.[15] 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. The magnitudes of put-backs on post-2008 originations have become a trickle compared to the early 2000 issuances. Figure 3, taken from Goodman, Parrott and Zhu (2015), plots put-back rates over the time horizon of the loan, highlighting the different put-back rates across loan-vintage years for loans issued between 2000

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

and 2010. The figure and the analysis in Goodman et al. (2015) support our assumption that put-back risk is immaterial post 2008.

***Overhead Costs of Issuance***

The interpretation of U.S. fair lending law might evolve such that a court would permit a lender to advance as a legitimate-business-necessity defense the ability to recoup overhead costs that differ by lender or that differ for originating loans in different geographic locations. To address this possibility, we implement a model with lender fixed effects, $\mu_{lender}$, crossed with county fixed effects, $\mu_{county}$:

$$\begin{aligned} & interest\ rate_{it} \qquad (2) \\ & = \alpha\ LatinxAfricanAmerican_i + \mu_{GSEgrid} + \mu_{month_{year}} \\ & + \mu_{lender} * \mu_{county} + \varepsilon_{it}. \end{aligned}$$

This specification forces the appealing interpretation on the discrimination coefficient to be the differences in average interest rate charged to a minority applicant versus that offered to a non-minority applicant by the same lender in that same county within the GSE credit model. This specification has the drawback, however, of removing some of the variation that might be of interest, as lenders may discriminate with geographic pricing because of the competitive environment. Nevertheless, we include it for robustness.

Another possibility is that mortgage-issuance overhead costs are higher in branches with high minority populations, perhaps because minorities are less comfortable with financial-service institutions owing to historical racism and/or ill-treatment based on language. In such a setting, lenders might be forced to expend more time and outreach to build trust. Although we are unaware of any court decisions that examine whether lenders can pass this cost on to borrowers, as economists we would like to know if this cost is driving the loading on the minority variable.

To address this issue, we create a set of lenders who are at least partially algorithmic, looking up which lenders among the 2,098 largest volume issuers have a fully algorithmic mortgage offering (allowing applications to apply fully online without interacting with a person) by 2018. Forty-five percent of the lenders have an algorithmic offering. Because algorithmic offerings have no cost differentials by geography, and because the loans issued by these lenders are a mixture of human-interacted and algorithmic, we would expect the price discrimination coefficient to be smaller for these lenders if the minority cost differential argument were driving our results.

### *Servicing Costs and MBS Holdings*

GSE loans are special in that many lenders do not retain servicing rights in the GSE process nor do they hold the asset on their balance sheets once the loan is put through the GSE system. This is not always true for the very large bank lenders, who provide a GSE with a pool of mortgages and are often repaid in kind (the GSE pays the lender with MBS rather than in cash). These large lenders may hold the MBS on their balance sheets and may be servicers of their own mortgages. In such a situation, the GSE still guarantees the loan. However, servicing costs surely increase with delinquent or defaulting loans. Thus, if the GSE grid does not perfectly model the underlying credit risk (e.g., because it does not incorporate other fundamental variables such as wealth), a large lender might rationally implement a better pricing model using fundamental variables to estimate hidden servicing-cost risk. Likewise, a large lender who plans to hold some balance sheet MBS prepayment risk that is not guaranteed by the GSE may implement a better-than-the-grid model to estimate prepayment risk. Since both of these actions would imply adjustment in prices for credit risk, we assume they would be deemed *legitimate business necessity* by the courts.[16]

To address this concern, we report estimates using a subsample containing only small lenders, filtering out the top 25 lenders by volume each year. This removes approximately half the sample of purchase loans and two-thirds of the sample of refinance loans.

### *Points*

Borrowers may choose to pay "points," an up-front lump sum, to a lender in order to reduce the loan interest rate. A positive minority-variable coefficient would occur, without implying discrimination, if minorities are more fully utilizing their cash for down-payment, leaving no cash to pay points to reduce the rates. Another points story consistent with a positive minority coefficient, again without implying discrimination, would be that Latinx and African-American borrowers may be paying *negative* points (incurring a higher interest rate) to get a

[16] Note that minorities on average prepay less in aggregate statistics, which means our main estimate is probably conservative on this point of large lenders pricing prepayment risk differentially for minorities.

rebate in cash to pay closing costs. In summer 2019, HMDA released its 2018 dataset, which for the first time includes a measure for the magnitude of points paid on the mortgage at origination. The measure includes the level of positive points, negative points (discount rebates) or zero points.

This new information allows for robustness tests on whether the payment of points, either positive or negative, is associated with differential pricing of GSE mortgages, similar to findings for the pre- and post-crisis pricing of FHA/VA mortgages (Woodward, 2008; Bhutta, Fuster and Hizmo, 2019). Using a post-crisis sample of FHA mortgages from Optimal Blue, a firm that provides real-time monitoring for small-volume lenders, Bhutta, Fuster, and Hizmo (2019) found that interest rate discrimination was offset by adjustments in the discount points paid. This result, of course, suggests that not controlling for points could potentially lead to omitted variable bias. However, the pricing of FHA mortgages found in the Optimal Blue sample might not be comparable to that for GSE mortgages, given differences in the underwriting risk of FHA mortgages as well as the need for small FHA lenders to rely on third-party fair-lending compliance monitoring. Potential reasons for pricing differences between FHA and GSE mortgages may include: i) FHA insures higher risk borrowers and does not apply risk-based pricing, thus exposing the FHA to adverse-selection risk and the need for monitoring; ii) FHA lenders are subject to False Claims Act (1863) risk, so lenders must certify that each loan complies with all eligible Housing and Urban Development (HUD) rules for the full term of the loan; iii) the higher cost of servicing nonperforming FHA loans (Kim, Laufer, Pence, Stanton, and Wallace, 2018).

### *HMDA Designation*

A final concern would arise if the coefficient on minority emerges due to errors in identifying borrower race or ethnicity. The minority designation is determined in our analysis by combining self-reported data from HMDA and, for mortgages in HMDA that lack an indicator of borrower race/ethnicity, borrower's likely race/ethnicity based on a race and ethnicity name-categorization algorithm from Kerr and Lincoln (2010) and Kerr (2008). Given the possibility that this algorithm might misclassify a borrower's race or ethnicity, for robustness we also report results where we instead drop these observations.

## IV. Price Discrimination Results

### *IV.a. Interest Rate Discrimination – Main Estimates*

Panel A of Table 2 presents within-GSE-grid estimates of interest rate discrimination for 30-year fixed-rate mortgages that are approved and originated. (Appendix Table 1, Panel B reports an identical table for 15- and 20-year mortgages.) Because lenders' pricing strategies vary by mortgage type, we present estimates for purchase mortgages (columns (1) and (2)) separately from refinance mortgages (columns (3) and (4)). Columns (1) and (3) present simply the overall mean differences in prices paid by Latinx-/African-Americans versus everyone else. Columns (2) and (4) are our full credit-risk model of equation (1), containing the 72 GSE grid fixed effects to capture the pricing in the grid plus month-year fixed effects to capture market-price fluctuations.[17]

The overall mean difference in the purchase-mortgage interest rate between Latinx/African-American and non-minority borrowers is 0.090%, or 9.0 basis points. Of this amount, column (2) shows that 1.1 basis points are explained by the credit-risk model, leaving 7.9 basis points of discrimination. For refinance mortgages (columns (3) and (4)), we identify an economically smaller price discrimination of 3.6 basis points. The interpretation of this main credit-risk-model result is that conditional on being given a loan, African-American and Latinx borrowers pay an average of 7.9 basis points more than other similar borrowers for their purchase mortgages and 3.6 basis points more for refinance mortgages. Given the Mortgage Bankers' Association mean profit of 50 basis points, these discrimination premiums represent 16% and 7% increases, respectively, in profits for lenders, or 11.5% on average.

Also of interest in column (2) is the ability of the credit-risk model to explain 73% of the variation across nearly 1.5 million purchase mortgages and 69% of the variation in 2.1 million refinance mortgages. The unexplained variation (one minus the $R^2$ = 27% – 31%) may reflect strategic pricing either on borrowers' location (perhaps due to collusion or to opportunistic pricing in financial deserts) or on borrowers' behavioral characteristics (perhaps reflecting profiling using variables or soft information that correlate with a lack of shopping). The disparity between purchase and refinance mortgage discrimination suggests that borrower sophistication and hurriedness matter. Refinancing borrowers are, by definition, experienced and may be in less

[17] Our estimates are almost identical if we instead use GSE grid fixed effects interacted with the month-year dummies.

of a hurry to re-contract than the average purchase-mortgage borrower, who may be time constrained to bid on a house on the market.

To put these magnitudes in more context, Panel B shows a back-of-the-envelope calculation of extra interest paid due to discrimination in loan pricing. The total U.S. mortgage market float is $9.5 trillion.[18] Assuming the existing float of mortgages consists of 75% refinance loans and 25% purchase loans, that Latinx- and African-Americans borrowers make up 17.3% of the total float (from the Survey of Consumer Finances (SCF)), and that the average mortgage has a term of 30 years with a 3.5% coupon, our findings imply that discrimination in mortgage interest rates costs Latinx- and African-Americans $765 million extra in interest annually.

### *IV.b. Interest Rate Discrimination – FinTech Lenders*

The twin empirical goals of our paper are to estimate the extent of consumer lending discrimination ($765 million in mortgages alone) and to ask whether FinTech originators perform any better 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 would naturally discover that higher prices could be quoted to profiles of borrowers or geographies associated with low-shopping tendencies. As described earlier, if such pricing induces higher markups 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 system, no residual creditworthiness assessment is needed within the GSE grid to price credit risk; therefore, pricing strategies that cause higher markup for minorities using this strategy would constitute impermissible discrimination. (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.)

[18] Source: Federal Reserve.

Table 3 shows the results for FinTech lenders for purchase mortgages (column (1)) and refinance mortgages (column (2)). Both columns use our full credit-risk model containing the 72 GSE grid fixed effects plus month-year fixed effects. We find, reported in column (1), that FinTech purchase-mortgage discrimination is 5.31 bps, approximately 2/3rds the magnitude of the estimate for the full sample of issuers in Table 2. Column (2) reports that discrimination by FinTech lenders in the pricing of refinance mortgages is 1.97 bps, 55% of the magnitude for the sample of all issuers.

We conclude two things from Table 3. FinTechs do indeed remove some face-to-face biases. In particular, FinTechs discriminate 40% less on average across the two mortgage products. This non-trivial reduction is encouraging with regard to the potential for algorithmic lending to reduce discriminatory lending. Yet the result also clearly tells a flip-side. Both FinTechs and face-to-face lenders may discriminate in mortgages issuance through pricing strategies. We are just scratching the surface in the role of pricing strategy discrimination in the algorithmic era of data use. In short, algorithmic lending may reduce discrimination relative to face-to-face lenders, but algorithmic lending is not alone sufficient to eliminate discrimination in loan pricing.

### *IV.b. Interest Rate Discrimination – Time Pattern*

Woodward and Hall (2012) discuss the importance of shopping behavior for equal treatment in mortgage outcomes. It might be that the existence of FinTech and algorithmic lending creates an environment that is more conducive to shopping for the best rate or more competitive because of FinTech entrants. Figure 4 depicts the price discrimination coefficient by the year of loan issuance. Discrimination has declined between 2009 and 2015. Although we cannot prove causality, this result suggests that competition and/or the ease of shopping matters for outcomes.

### *IV.c. Interest Rate Discrimination - Robustness*

As outlined in the methodology section, this section reports robustness of our minority coefficient estimation and the interpretation of this coefficient as discrimination. We explore the issues of overhead costs, servicing-cost risk and MBS holding risk, HMDA ethnicity and race designations, and points.

First, as discussed in Section III.c, we implement a model that includes lender and geography fixed effects to address concerns that minority borrowers receive pricing based on locational or lender fixed costs. We present the results in Table 4. Across the columns, we introduce county, lender, lender crossed with month-year, and finally lender crossed with county fixed effects. Across all specifications in Table 4, we find discrimination in loan pricing. Even within the same lender originating loans in the same county (column (4)), Latinx- and African-Americans pay 5.2 basis points more for purchase mortgages and 2.0 basis points more for refinance mortgages.

While econometrically interesting, we caution that these specifications may underestimate the incidence of illegal discrimination. In particular, these specifications could fail to capture variation in loan pricing that is indicative of illegal discrimination. Consider, for instance, a lender that establishes a branch office in a county with primarily minority residents for the express purpose of issuing premium-priced loans to the branch's largely minority customers. If the lender uses a branch-wide rate sheet with exorbitant rates (a practice that has been documented in several enforcement actions),[19] the lender crossed with county fixed effect would absorb all variation in loan pricing by this institution. Yet such behavior would almost surely be viewed as conventional red-lining, which is illegal under the disparate treatment theory of discrimination (Gano, 2017). Similar scenarios can be envisioned for the county fixed effect (e.g., all lenders engage in this practice within various counties) and the lender fixed effect (e.g., small lenders establish offices in minority-majority counties and use higher rate sheets for the purpose of placing minority borrowers in higher-priced loans, rather than for cost reasons).

The other overhead-cost concern introduced above is the possibility that the costs of serving minority-intensive areas are higher due to a need to garner trust because of historical exclusion. Table 5, column (1) reports an estimation of the subsample of lenders whose loans come from both traditional face-to-face lending and algorithmic lending. We find similar results as in the baseline. In Panel A, for purchase mortgages, the coefficient is somewhat higher (8.41 bps versus 7.88 in Table 2). The refinance mortgage coefficient for mixture algorithmic lenders

[19] For example, in United States v. Sage Bank, Sage Bank agreed to pay a fine of $1,175,000 and take other remedial action after the United States Department of Justice alleged that Sage bank had assigned a higher "target price" to loan officers who disproportionately served African-American and Hispanic borrowers, resulting in higher priced mortgages for these customers. See United States v. Sage Bank, Sage Bank, Consent Order, November 11, 2015, available at https://www.justice.gov/opa/file/796371/download.

is marginally smaller (3.36 versus 3.56 in Table 2). Overall, this finding is inconsistent with the proposition that lenders are simply pricing in higher overhead costs for procuring a minority loan, given that algorithmic loans could have no such differential in overhead.

The next robustness concern is the role of residual risk for large lenders who hold the GSE-guaranteed MBS or those who service these loans. Column (2), Panels A and B of Table 5 show that when we estimate our full credit-risk specification, but limiting the sample to the non-top-25-volume lenders for every year, the results are not materially different from those in Table 2.

Table 5 also takes up the concern that our filling-in of missing minority variable data in HMDA is biasing the estimation. In column (3), we use only observations where a borrower's race or ethnicity is provided by HMDA. For both purchase mortgages (Panel A) and refinance mortgages (Panel B), our estimates for discrimination in pricing are slightly higher than the estimates obtained in Table 2, confirming that our results are not driven by potential errors in identifying a borrower's race or ethnicity using the name-categorization algorithm.

Last, Table 6 considers robustness to the important concern of points. As previously discussed, borrowers may choose to pay points to a lender in order to reduce the loan interest rate or alternatively they may choose to pay negative points to get a rebate in cash for closing costs, thereby increasing the loan interest rate. Although the HMDA data do not include information on points for our core sample, in October 2015 the Consumer Financial Protection Bureau (CFPB) amended the reporting 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 for the top 100 lenders using recently released HMDA data for 2018, which include a points variable that is either positive, negative, or null. A limitation of the 2018 HMDA data is that it does not include loan-level information on the loan-to-value ratio and FICO score at origination. Nor can we use our merging algorithm to add these data, due to the lack of sufficient post-2018 performance data. We therefore proxy for those variables using the median values of the loan-to-value ratios and FICO scores by census tract for GSE loans using the McDash data set.

Table 6 reports estimates for purchase mortgages (Panel A) and refinance mortgages (Panel B). The dependent variable is now the reported coupon on the mortgage for 30-year fixed rate GSE securitized mortgages plus/minus a points conversion. We apply two industry standards for the conversion of points to coupon: either one point equals an eighth of a percentage point of coupon interest (12.5 basis points); or one point equals one quarter of a percentage point of coupon interest (25 basis points). Column 1 in Panels A and B reports the raw mean differential mortgage pricing for Latinx/African-American purchase mortgages (16.7 basis points) and refinancing mortgages (16.64 basis points) with no further controls. Column 2 in the two panels includes controls for the GSE pricing grid measured using the census tract median to proxy for the loan-level loan-too-value ratio and FICO credit score. As shown, the Latinx/African-American discriminatory pricing differential now falls to 13.4 (13.04) basis points for purchase and refinancing mortgages. Controlling for lender fixed effects further reduces the discriminatory pricing differentials to 10.98 (9.309) basis points for purchase and refinancing mortgages as shown in column 3 in the two panels. The introduction of fixed effects for the GSE grid interacted with twenty buckets of HMDA reported income and twenty buckets of HMDA reported loan amount again modestly reduces (increases) the discriminatory pricing effect to 10.27 (10.06) basis points for the two mortgage types. Columns (5) through (8) in Panels A and B repeat the sequence of regressions using the second industry convention for translating points to coupon and the results are very similar. Overall, these regressions provide a strong robustness check on the possible concern that the omission of controls for positive and negative points might bias our prior results on the levels of Latinx/African-American discriminatory pricing for purchase and refinance mortgages.

## V. Accept/ Rejection Decisions

### *V.a. Identification of Accept/Reject Discrimination*

The other decision that a lender makes is the accept/reject decision. Even though an application might receive a creditworthiness approval in the GSE underwriter system, the lender may still reject an application. If the lender uses the GSE market for securitizing mortgages, no credit risk would remain post-transacting; hence, money would be left on the table.

Why would a lender choose to reject a GSE-accepted applicant? (i) The lender might feel that a particular borrower reflects additional put-back risk. As we have argued, such put-back risk is so small, especially in the latter half of our sample, that even if this put-back risk were residually correlated with race or ethnicity (which is not established), it would not be able to explain any material differences that we find in rejection rates. Thus, this argument would amount to a biased belief affecting loan decisions. (ii) The lender might be directly racist or have other in-group biases. (iii) The lender might prefer to cater to non-minority borrowers in branch banking. None of these explanations falls under legitimate business necessity.[20]

Our linear-probability model of rejection discrimination for application *i* in year *t* is:

$$\begin{aligned} rejection_{it} = {} & \beta\ LatinxAfricanAmerican_i \\ & + f(HMDA\ income_i, HMDA\ loan\ amount_i) \\ & + g(LTV_c, credit\ score_c, debt\ outstanding_c, DTI_c) + \mu_{year} + \varepsilon_{it}. \end{aligned} \tag{3}$$

*Rejection* is an indicator for an application being rejected by the lender. The $f(\cdot)$ function is a non-parametric function of the original HMDA data for income and loan amount. Since we do not know the exact scoring function of lenders on these variables, we use linear splines with 21 knots for income and 47 for loan amount. We control for year fixed effects, $\mu_{year}$, rather than month fixed effects because HMDA does not provide precise dates for the rejections. As mentioned above, we do not have loan-level data on all underwriting variables entering the GSE black box underwriter system. Thus, we proxy using the equivalent variable at the census tract (1,600 households) of the property, *c.* To capture the distribution within the census tract, we include the 25th, 50th, and 75th percentile of *LTV*, *credit score, debt outstanding,* and *DTI* in the census tract, denoted by the function $g(\cdot)$.

Two concerns come to mind that may affect the robustness of our estimation. First is the concern that the lender may keep some loans on its balance sheet after using the GSE accept/reject underwriting. Some large lenders may have their own credit risk model with legitimate-business-necessity variables unseen to the GSE underwriter (and thus to us as econometricians). If these lenders use fundamental models to cherry-pick loans to keep on their balance sheet, our empirical model may load credit risk on our estimation of the Latinx-/African-American variable (assuming this latter variable is correlated with any supplemental, unseen credit risk variables). We address this concern by eliminating large lenders in our robustness tests, since small lenders are unlikely to hold many mortgages on their balance sheet. Removal of large lenders also addresses the concern that servicing-cost risks may affect accept/reject decisions, since only the large lenders obtain servicing contracts for the GSE pools of loans.

[20] Note that a lender that intentionally treated applicants differently based on a protected characteristic would be liable under the *disparate treatment* theory of discrimination, for which there is no legitimate-business-necessity defense. In effect, the disparate treatment theory of liability assumes that intentional discrimination can never constitute a legitimate business necessity.

Second is the concern that a loan officer might deter a potential minority borrower from applying or coach non-minority applicants to increase their likelihood of acceptance. If we had a perfect set of both accepted and rejected applicants' data, we could recreate the GSEs' black-box algorithms and eliminate these possibilities from biasing our results. Without perfect data, this concern creates the possibility for bias in our estimation of discrimination in rejection rates. Importantly, however, this concern is not valid for our FinTech discrimination estimations, given the absence of any loan officer-to-application interaction.

Additionally, even within our non-FinTech results, these two scenarios do not create the same risk of bias, and may very well bias us away from a finding of discrimination. Imagine, for instance, that all lenders coach every non-minority applicant to delay submitting a loan application until the non-minority applicants can increase their credit scores. In such a setting, actual non-minority credit scores will be stronger than the census-tract proxy that we observe. As a result, our specification will estimate discrimination through the fact that non-minority applicants are approved at a greater rate than minority applicants from the same census tract due to the stronger credit scores of the (coached) non-minority applicants. Conversely, imagine all lenders overtly refuse to consider minority applicants except for those applicants having the strongest credit scores. In this setting, among applications that are submitted, actual minority credit scores will likewise be greater than the census-tract proxy that we observe. As a result, our specification will underestimate discrimination due to the fact that minority applicants will be disproportionately accepted within a census tract given the heightened application standard.

Although we cannot fully address this latter possibility, we can again implement a model of lender-crossed-with-county fixed effects, because of the richness of our data. To the extent this latter scenario arises from branch-wide behavior by loan officers, these granular fixed effects models will permit us to estimate discrimination in rejection rates that goes beyond this form of overt bias against minority applicants.

### *V.b. Rejection Discrimination Estimates – Main*

Table 7 reports the main estimation of discrimination in accept/reject decisions across all lenders for purchase (Panel A) and refinance (Panel B) applications. For each panel, we report three columns. Column (1) presents raw mean differences in rejection rates by minority treatment. Column (2) includes the GSE underwriting variables that HMDA provides at the loan level – income, loan amount, and year. Because we do not know the functional form of the underwriter, we include 21 piecewise-linear splines of income and 47 of loan amount, amounting to 136 variables in all. Column (3) adds census-tract-level proxies for the other GSE underwriting variables; namely, an applicant's LTV, credit score, debt-to-income, and total debt. We add three percentiles (the $25^{th}$, $50^{th}$, and $75^{th}$) of these variables to capture the distributional spread in the census tract.

The raw mean difference, reported in the column (1) specifications, indicate that minority applicants are more likely to be rejected by 14.1 percentage points in purchase applications and 12.2 percentage points in refinance applications compared to everyone else. Our estimation covers 3.2 million purchase applications and 10.0 million refinance applications. Of these 13.2 million applications, Table 1 reports that the overall likelihood of rejection is 49.6%. Decomposing these numbers, our minority groups face rejection rates of greater than 60.6%, and everyone else, 47.6%.

Columns (2) and (3) present the main rejection results for all lenders, controlling for the underwriting variables used in the GSE algorithm. Focusing on column (3), lenders reject minority borrowers 9.6 percentage points more often for purchase loans and 7.3 percentage points for refinance loans. Across the sample of 13.2 million applications, applied across the purchase and refinance distribution from Table 1, our result would imply 1.03 million mortgages were rejected from 2009 to 2015 due to discrimination.

### *IV.e. Rejection Discrimination Estimates – FinTech*

Table 8 reports the same rejection rate estimation specifications as Table 7, but only for the sample of FinTech lenders. As before, the overall raw mean rejection rates are higher for Latinx- and African-American applicants among FinTech lenders (5.3 percentage points higher in purchase applications and 5.4 percentage points higher in refinance applications). However, once we implement the models with the underwriting variables, we find that FinTech lenders do not discriminate in mortgage accept/reject decision-making. The evidence points to a story of FinTech lenders implementing little-to-no discrimination in rejection rates, consistent with the idea that algorithms are programmed to not leave money on the table.

### *IV.f. Rejection Discrimination Estimates –Robustness*

Table 9 presents robustness tests addressing the concern that rejection discrimination in Table 7 stems from unobserved creditworthiness among applicants that is of concern to lenders who keep balance sheet or servicing rights risk or from unobserved interactions between lenders and potential applicants ahead of formal application submission. As in the price analysis, we begin our robustness tests by utilizing the richness of our data in lender-crossed-with-county fixed-effects. Column (1) of Table 9 (Panel A for purchase mortgages and Panel B for refinance mortgages) reproduces the main accept/reject result from Table 7, Column (3), including all the underwriting variables. Columns (2), (3) and (4) add in, respectively, lender fixed effects, county fixed effects, and lender-crossed-with-county fixed effects. Interpreting column (4), we find that a given lender rejects Latinx and African-American applicants with a 7% higher probability for purchase applications and a 6.3% higher probability for refinance mortgages compared with the same lender's rejection decision for all other applicants in the same county. These econometrically appealing within-lender-county results are somewhat smaller than those of Column (1), but remain statistically and economically robust in magnitude.

Our other robustness concern involves unobserved creditworthiness, applicable only for lenders who might be holding loans on their balance sheet or for lenders who obtain servicing contracts for the mortgages once issued. As noted previously, large volume lenders may retain servicing rights in arrangements with the GSEs post-securitization (Aldrich et al. 2001). Likewise, it is unlikely that small lenders would be in a position to hold mortgage risk on their balance sheets. Thus, we repeat the analysis for Small-Volume Lenders, where we drop the top 25 originators calculated by year. In Column (5), we implement the most econometrically stringent model, with lender-crossed-with-geography fixed effects. We find results very similar to the results in column (4), which includes the full sample of lenders, despite the sample size being less than half as large.

To be conservative, we update our economic calculations to the most conservative interpretation from our robustness tests in Table 9. In sum, our results imply that between 0.74 million and 1.3 million mortgages were rejected from 2009 to 2015 due to discrimination, with minority applicants in our sample facing a 6% higher rejection rate due to discrimination.

Although we must maintain our caveat that we cannot claim perfect identification in our accept/reject analysis because we do not have access to the exact GSE underwriting model and because we must proxy for certain borrower characteristics, with this granularity of the fixed-effect model, the evidence seems compelling that discrimination exists in accept/reject decisions, but its incidence is diminished among FinTech lenders.

## V. Conclusion

The question of whether algorithmic decision-making promotes or inhibits impermissible discrimination is especially relevant in the context of consumer lending, given both the historical challenge of eliminating discrimination in this domain and the importance of consumer lending for the well-being of households. Using a unique data set of mortgage loans that includes never-before-linked information at the loan level on income, race, ethnicity, loan-to-value, and other contract terms, we exploit the unique structure of the GSE pricing grid to identify discrimination in mortgage loan pricing. Overall, we find that conditional on obtaining a loan, Latinx and African-American borrowers pay interest rates that are 7.9 bps higher for purchase mortgages and 3.6 bps higher for refinance mortgages. In addition, Latinx and African-American borrowers face higher hurdles in being accepted for a mortgage. Our evidence suggests that at least 6% of Latinx and African-American applications are rejected, but would have been accepted had the applicant not been in these minority groups. This amounts to a rejection of 0.74 to 1.3 million creditworthy minority applications.

Focusing on the effect of FinTech, we find that FinTech lenders discriminate approximately one-third less than lenders overall in terms of pricing. This finding is consistent with FinTech lenders removing discrimination arising from face-to-face interactions between originators and borrowers. Yet, it is also consistent with FinTech lenders using pricing strategies and data analytics that nevertheless 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 supplement these findings regarding discrimination among FinTech lenders with two additional silver linings associated with the emergence of FinTech lending. First, our evidence suggests that over our short time period, discrimination in loan pricing is declining, perhaps due to the ease of applying and shopping around afforded by the growth of FinTech platforms. Second, we also find that algorithmic lenders do not discriminate in accept/reject decisions. Thus, in addition to any efficiency gains of algorithmic innovations in credit scoring, our results suggest that these innovations may also serve to make the mortgage lending markets more accessible to African-American and Latinx applicants.

In this paper, we have also mapped the court's definition of a *legitimate business necessity* defense in lending discrimination cases to the signal extraction problem at the heart of statistical discrimination. In particular, discrimination in loan decisions must be rooted an applicant's creditworthiness and not the ability of a lender to extract rents. This insight points to a workable standard to deploy as lenders turn increasingly to Big Data tools to price and allocate credit. Operationally, in fair lending examinations, we propose a simple test as to whether a particular Big Data variable legitimately proxies for a borrower's creditworthiness and not a protected characteristic: lenders must demonstrate (a) that the Big Data variable (e.g., high school) is correlated with historical data relating to a fundamental lifecycle variable (e.g., income growth),[21] and (b) that this Big Data variable does not predict a protected characteristic after orthogonalizing it to the fundamental lifecycle variable. The use of a Big Data variable that passes such a test could thus be empirically validated as serving a *legitimate business necessity*, given that any negative impact on minority borrowers associated with its use would arise solely through its correlation with the fundamental lifecycle variable of interest.

Finally, our results also speak to ongoing debates concerning the future structure of the GSEs. The GSE underwriting process that informs our identification strategy establishes clear rules for assessing borrower creditworthiness. Accordingly, it is possible that the GSE process itself may be serving to attenuate the incidence of discrimination, given that private lenders' benefit of greater use of variables is eliminated since the GSEs take on the credit risk of the mortgages. To date, this less-well-understood role of the GSEs has not been considered in GSE reform proposals, nor is it obvious how such a role could be supported within a fully privatized, conventional conforming secondary mortgage market. Likewise, outside of mortgage lending, it is possible that our estimates of discrimination are conservative, since these markets lack formal underwriting and pricing standards.

[21] Even if fundamental variables (e.g., income growth) are unobservable for a particular applicant, lending institutions can nevertheless observe how these variables are distributed in the population using historical data. For instance, a bank may have historical fundamental variable data from existing clients, such as historical income growth, but the bank will not have these data for new applicants.

## Appendix: Algorithm for Merging Mortgage Data Sets

Since there are no unique mortgage loan identifiers in the U.S., we develop an algorithm using classifier techniques to match loans found in two independent datasets: the McDash dataset, which contains loan-level data compiled by Black Night Financial Services, and the ATTOM dataset, which provides detailed property transaction and ownership information in addition to a time-series history of all recorded mortgage-lien events such as new mortgage originations, prepayments, REO, foreclosure, short sales, and arms-length sales and loan payoffs.

Our merging process applies a modified k-nearest-neighbor classifier (see Hastie, Tibshirani, and Friedman, 2009; James, Witten, Hastie, and Tibshirani, 2015). The k-nearest-neighbors classifier uses the 25 nearest neighbors in the corresponding zip code in the McDash data. We represent each loan in each data set with a 13-element vector that includes: 1) the original loan balance; 2) the lien position, 3) the origination date of the loan, 4) the ending date of the loan, 5) the foreclosure date of the loan (maybe null), the prepayment date of the loan (maybe null), 6) the appraised market value of the property, 7) the loan purpose (refinance or purchase), 8) loan distress dates (may be null), 9) loan REO date (may be null), 10) loan liquidation date (may be null), 11) short sale indicator variable (may be null), 12) interest rate type (fixed or variable loans), 13) property transaction value if there is a sale. Each of these elements is assigned a category subscore between 0 and 1. Our scoring algorithm takes into account the 13 different elements of each matched pair of loans to calculate a score. The score roughly corresponds to the estimated error for each match, measured in hundredths of a percent. Thus, a match score of 1689 corresponds to a 16.89% chance of an incorrect match, or an 83.11% confidence in the match. We use only matches with scores of 2000 or less. For fixed-rate GSE loans originated between 2009 and 2015, we obtain a 90% merge rate.

Our classifier strategy is less applicable to the merge of the HMDA data to McDash data, because HMDA has a greatly reduced set of loan characteristics at origination and has no loan-level performance strings. For this merge, we instead standardize the lenders' names between ATTOM and HMDA and then merge these data sets using lender names, loan amount, lien type, census tract, and the loan-purpose fields. For the final merge, we unite the ATTOM-to-McDash data to the ATTOM-to-HMDA data using the crosswalk developed with the k-nearest-neighbor algorithm, obtaining a final data set of 6.8 million single-family, fixed-rate GSE loans originated between 2009 and 2015.

**Ethnicity matching using ATTOM data**

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

**The Equifax-enhanced subsample of originations**

To obtain a final data that includes the full spectrum of underwriting characteristics that would have been available to the lender, we again merge the HMDA/ATTOM/McDash data set of fixed rate GSE loans that were originated between 2008 and 2015 to the McDash loans that are merged to Equifax data. The Equifax-enhanced originated loan sample includes other consumer credit positions of the borrowers such as: the total sum of retail, consumer finance and bank card balances; total student loan debt, total auto loan debt (sum or auto finance and auto bank debt); age of the borrower, and Vantage 3.0 score.

## References


Abowd, J., F. Kramarz, and D. Margolis, 1999, High wage workers and high wage firms, Econometrica 67, 251–333.

Aigner, D. J., and G. Cain, 1977, Statistical theories of discrimination in the labor market, Industry and Labor Relations Review 30, 175–187.

Aldrich, S. P. B., W. R. Greenberg, and B. S. Payner, 2001, A capital markets view of mortgage servicing rights, Journal of Fixed Income 11, 37–53.

Arnold, D., W. Dobbie, and C. S. Yang, 2018, Racial bias in bail decisions, Quarterly Journal of Economics (forthcoming).

Arrow, K., 1973, Higher education as a filter, Journal of Public Economics 2, 193–216. Ayres, I., 2002, Outcome tests of racial disparities in police practices, Justice Research and Policy 4, 131–142.

Barocas, S., and A. Selbst, 2016, Big Data's Disparate Impact, California Law Review 104, 671-732.

Bartlett, R. P., A. Morse, R. Stanton and N. Wallace, 2019, Algorithmic Accountability: A Legal and Economic Framework, Working Paper, U.C. Berkeley.

Bayer, P., F. Ferreira, and S. L. Ross, 2016, The vulnerability of minority homeowners in the housing boom and bust, American Economic Review: Economic Policy 8, 1–27.

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

Becker, G. S., 1957, The Economics of Discrimination (University of Chicago Press, Chicago).

Begley, T. A., and A. K. Purnanandam, 2017, Color and credit: Race, regulation, and the quality of financial services, Working paper, University of Michigan.

Black, H., R. L. Schweitzer, and L. Mandell, 1978, Wage discrimination: Reduced form and structural estimates, American Economic Review, Papers and Proceedings 68, 186–191.

Black, H. A., and R. Schweitzer, 1977, A canonical analysis of mortgage lending terms: Testing for lending discrimination at a commercial bank, Urban Studies 22, 13–19.

Blinder, A. S., 1973, Wage discrimination: Reduced form and structural estimates, Journal of Human Resources 8, 436–455.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru, 2017, Fintech, regulatory arbitrage, and the rise of shadow banks, Working Paper 23288, NBER.

Bhutta, N. and A. Fuster, and A. Hizmo, Paying Too Much? Price Dispersion in the US Mortgage Market, 2019, Working paper.

Card, D., A. R. Cardoso, and P. Kline, 2016, Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women, Quarterly Journal of Economics 131, 633–686.

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

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

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

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

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

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

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

Fortin, N., T. Lemieux, and S. Firpo, 2011, Decomposition methods in economics, in O. Ashenfelter, and D. Card, eds., Handbook of Labor Economics, volume 4A, chapter 1 (Elsevier, Amsterdam).

Fulks, M., 2017, Living with the robust causality requirement for disparate impact under the Fair Housing Act, Baker Donelson.

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther, 2018, Predictably unequal? the effects of machine learning on credit markets, Working paper, Federal Reserve Bank of New York.

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

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

Gano, A., 2017, Disparate impact and mortgage lending: A beginner's guide, University of Colorado Law Review 88, 1109–1166.

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

Glassman, A. M., and S. Verna, 2016, Disparate impact one year after Inclusive Communities, Journal of Affordable Housing & Community Development Law 25, 12–24.

Gronau, Reuben, 1998, A useful interpretation of R-squared in binary choice models, Princeton University Working Paper.

Gruenstein Bocian, D., K. Ernst, and W. Li, 2008, Race, ethnicity and subprime home loan pricing, Journal of Urban Economics 60, 110–124.

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

Hastie, T., R. Tibshirani, and J. Friedman, 2009, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, second edition (Springer, New York).

Haughwout, A., C. Mayer, and J. Tracy, 2009, Subprime mortgage pricing: The impact of race, ethnicity, and gender on the cost of borrowing, Staff Report 368, Federal Reserve Bank of New York.

Heckman, J., 1998, Detecting discrimination, Journal of Economic Perspectives 12, 101–116.

Heckman, J., and P. Siegelman, 1993, The Urban Institute audit studies: Their methods and findings, in M. E. Fix, and R. J. Struyk, eds., Clear and Convincing Evidence: Measurement of Discrimination in America, 187–258 (Urban Institute Press, Washington, DC).

James, G., D. Witten, T. Hastie, and R. Tibshirani, 2015, An Introduction to Statistical Learning with Applications in R (Springer, New York).

Kaye, D., 1982, Statistical evidence of discrimination, Journal of the American Statistical Association 77, 773–783.

Y. S. Kim, S. Laufer, K. Pence, R. Stanton, and N. Wallace, 2018, Liquidity Crises in the Mortgage Market,  (Brookings Papers on Economic Activity).

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

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

Maddala, G., and R. P. Trost, 1982, On measuring discrimination in loan markets, Housing Finance Review 1, 693–709.

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

Phelps, E. S., 1972, Money, public expenditure and labor supply, Journal of Economic Theory 5, 69–78.

Rachlis, M., and A. Yezer, 1993, Serious flaws in statistical tests for discrimination in mortgage markets, Journal of Housing Research 4, 315–336.

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

Ross, S., 2002, Paired testing and the 2000 Housing Discrimination Survey, in W. Foster, A. F. Mitchell, and S. E. Fienberg, eds., Measuring Housing Discrimination in a National Study: Report of a Workshop (National Academies Press, Washington DC).

Ross, S. L., M. A. Turner, E. Godfrey, and R. R. Smith, 2008, Mortgage lending in Chicago and Los Angeles: A paired testing study of the pre-application process, Journal of Urban Economics 63, 902–919.

Sandler, A. L., and J. Biran, 1995, The improper use of statistics in mortgage lending discrimination actions, in A. Yezer, ed., Fair Lending Analysis (American Bankers Association, Washington, DC).

Shafer, R., and H. Ladd, 1981, Discrimination in Mortgage Lending (MIT Press, Cambridge, MA).

Smith, R., and M. Delair, 1999, New evidence from lender testing: Discrimination at the pre-application stage, in M. Turner, and F. Skidmore, eds., Mortgage Lending Discrimination: A Review of Existing Evidence (Urban Institute Press, Washington, DC).

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

Woodward, Susan E., 2008. *A Study of Closing Costs for FHA Mortgages*. U.S. Department of Housing and Urban Development Report.

Woodward, Susan E. and Hall, Robert E., 2012, Diagnosing Consumer Confusion and Sub-Optimal Shopping Effort: Theory and Mortgage-Market Evidence, American Economic Review, Vol. 102(7): 3249–3276.

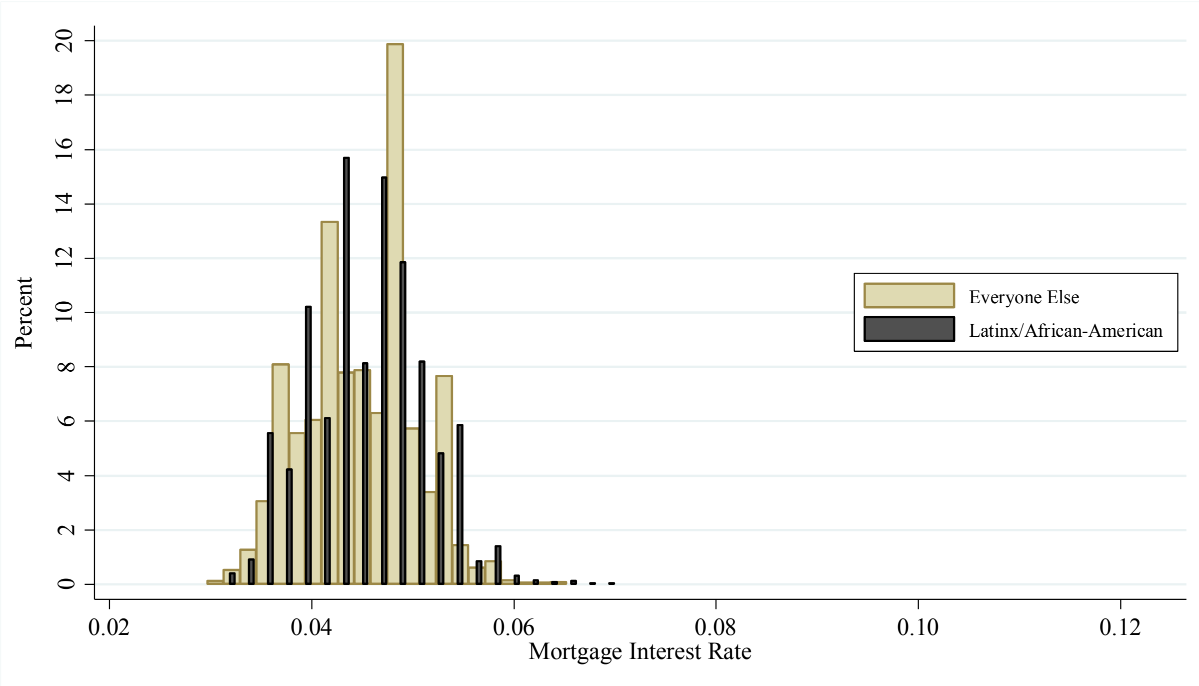
**Table 2: All Eligible Mortgages (Excluding MCM): LLPA by Credit Score/LTV**

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

**Figure 1: An Example of the GSE Grid**

Presented is the LLPA (Loan-Level Price Adjustment) Grid of Fannie Mae for 2011. The figure is from the Fannie Mae Selling Guide, dated 12/23/2010. (MCMs, now retired, refers to "My Community Mortgages", a program of subsidized loans for low-income target areas.) The LLPA Grid has a parallel grid at Freddie Mac called the Credit Fees in Price chart. These grids provide the additional g-fee (guarantee fee) that lenders must pay the GSE for guaranteeing the mortgage, varying by LTV and credit score. In practice, these lump-sum fees are translated to flows concepts to be added to the interest rate passed on to borrowers to pay for credit risk.

***Panel A: Raw Interest Rates by Race/Ethnicity***




***Panel B: Excess Interest Rates over Month-Year GSE Grid Rate by Race/Ethnicity***

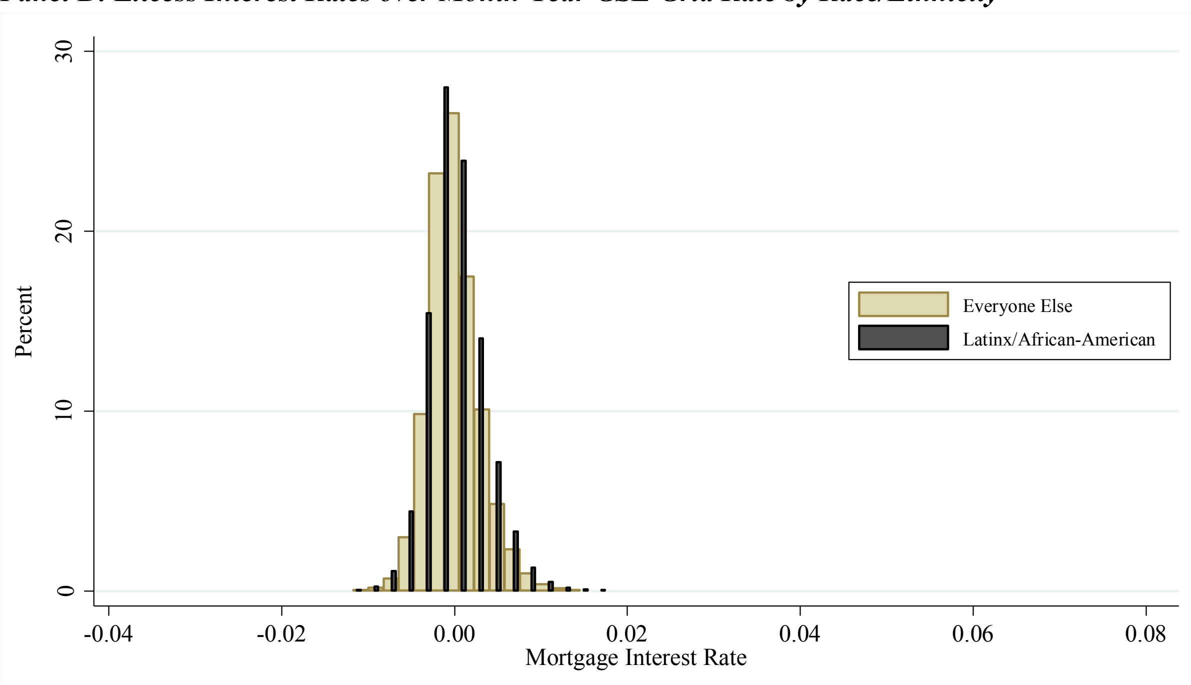
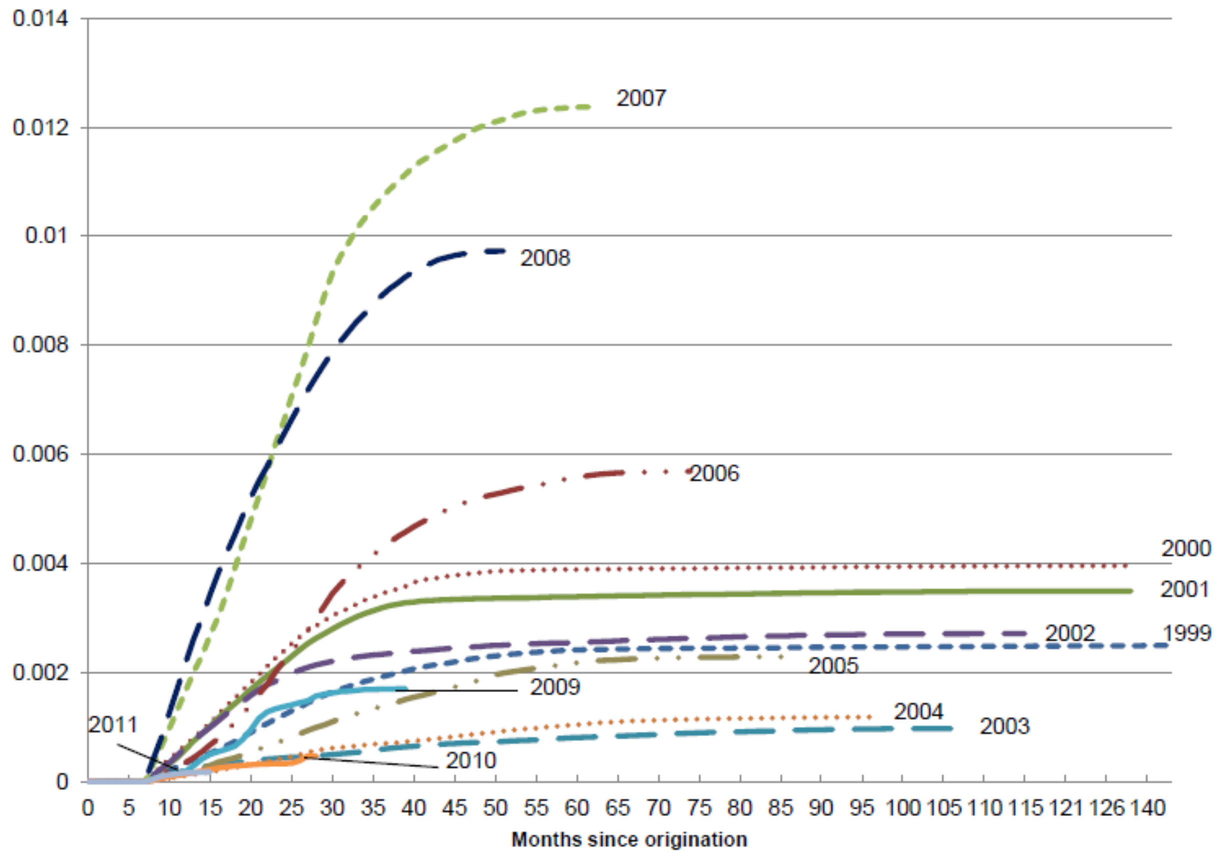



**Figure 2: Interest Rate Histograms by Race/Ethnicity: The Role of the GSE Grid**

Presented are two histograms of interest rates originated on 30-year fixed-rate mortgages, 2009-2015, that are processed in the GSE system. Panel A shows the raw data histogram of interest rates. Panel B de-means the histogram to the GSE grid for the month and year. The histograms are plotted for Latinx and African-Americans and for everyone else.




*Sources:* Fannie Mae and Freddie Mac credit database and Urban Institute calculations.

**Figure 3: Put-Backs for Issuances 2000 - 2010**

> *Source: Goodman, Laurie S., and Jun Zhu, 2013. "Reps and Warrants: Lessons from the GSEs Experience". Urban Institute: Housing Policy Center White Paper.*

Presented is a copy of Figure 2 from the aforementioned Urban Institute White Paper (permission granted in copyright.). The Figure shows the dollars put back on Freddie Mac loans by issuance vintage. The take-away of the figure for our purposes are twofold. First is the small value of put-backs after 2008. Second is the low volume of put-backs in the first 30 days of loan life, when lenders remain exposed to credit-risk for originated loans.

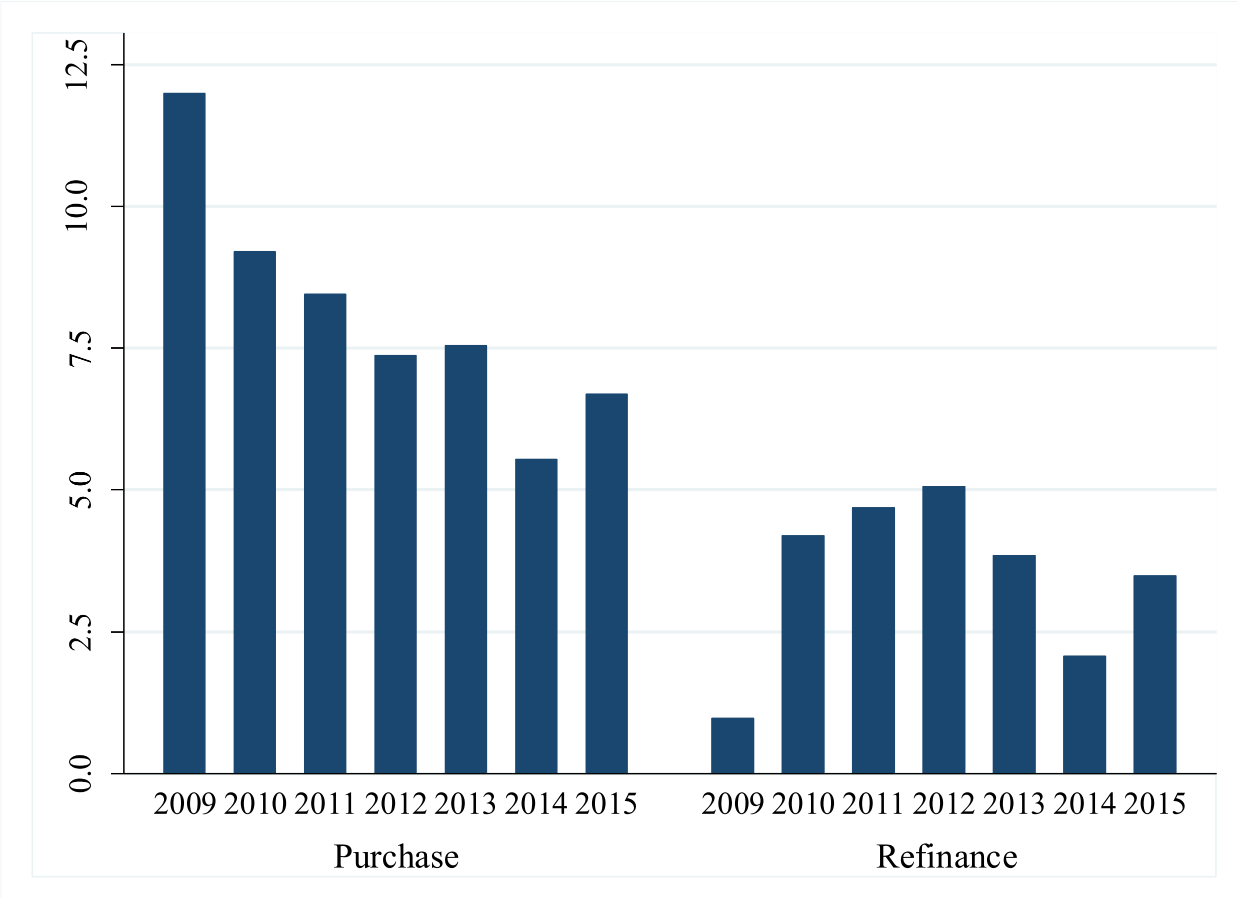



**Figure 4: Interest Rate Discrimination Estimates by Year**

Plotted are the purchase and mortgage discrimination estimates (the beta coefficient on Latinx/African-American) by year for the credit risk model of interest rate discrimination (akin to Table 2, columns 2 and 4, but by year). The sample is all loans for 30-year fixed-rate mortgages, securitized through the GSE system, 2009-2015. The estimation regresses interest rates on the GSE grid fixed effects and month-year fixed effects. Estimates are converted to basis points (1 basis point =0.01%) for ease of conveyance.

**Table 1: Summary Statistics**

Panel A reports summary statistics for the pricing estimations. Data are GSE, 30-year fixed rate mortgage originations obtained from a loan-level merge of HMDA, ATTOM, McDash, and Equifax data. Loan amount, applicant income and Latinx-/African-American are from HMDA. Interest rate, LTV, and credit score are from McDash-Equifax. Top 25 Volume Lender is calculated annually from volume of loans by lender. FinTech is a platform identifier from Buchak et al (2017). Panels B and C report statistics for accept/reject analyses. Because we only have HMDA data for rejections, we proxy for LTV, credit score, debt outstanding, and debt-to-income ratio using census tract medians. For all panels, Top 25 Volume Lender is calculated annually from the volume of loans by lender. FinTech is a platform identifier from Buchak et al (2017).

| **Panel A: For Pricing Analysis: GSE, 30-Year Fixed Rate Mortgage Acceptances (N = 3,577,010)** | | | | | |
|---|---|---|---|---|---|
| | Mean | St. Deviation | Minimum | Median | Maximum |
| Interest Rate % (McDash) | 4.50% | 0.56% | 2.00% | 4.50% | 12.50% |
| Loan Amount $,000 | $234.0 | $122.6 | $30.0 | $210.0 | $729.0 |
| Applicant Income $,000 | $107.2 | $92.0 | $19 | $89 | $9,980 |
| Credit Score (McDash-Equifax) | 755.8 | 43.4 | 620 | 766 | 850 |
| Loan-to-Value(McDash-Equifax) | 0.744 | 0.165 | 0.300 | 0.774 | 1.300 |
| FinTech | 0.043 | 0.203 | | | |
| Top 25 Lender | 0.523 | 0.499 | | | |
| Latinx/African-American | 0.110 | 0.313 | | | |
| Purchase=1; Refinance=0 | 0.418 | 0.493 | | | |
| **Panel B: For Accept/Reject Analysis: Conventional Mortgage Acceptances (N = 6,648,413)** | | | | | |
| | Mean | St. Deviation | Minimum | Median | Maximum |
| Loan Amount $,000 | $213.9 | $114.7 | $30.0 | $191.0 | $729.0 |
| Applicant Income $,000 | $108.3 | $103.2 | $19 | $89 | $9,999 |
| Credit Score (census tract) | 750.8 | 24.1 | 620 | 756 | 832 |
| Loan-to-Value (census tract) | 0.791 | 0.101 | 0.300 | 0.799 | 1.283 |
| Debt Outstanding (census tract) | 18,180 | 8,145 | 0 | 17,739 | 529,506 |
| Debt-to-Income% (census tract) | 32.7 | 3.6 | 1.0 | 32.5 | 63.0 |
| FinTech | 0.042 | | | | |
| Top 25 Lender | 0.522 | | | | |
| Latinx/African-American | 0.119 | | | | |
| Purchase=1; Refinance=0 | 0.308 | | | | |
| **Panel C: For Accept/Reject Analysis: Conventional Mortgage Rejections (N = 6,535,664)** | | | | | |
| | Mean | St. Deviation | Minimum | Median | Maximum |
| Loan Amount $,000 | $187.3 | $101.2 | $30.0 | $166.0 | $428.0 |
| Applicant Income $,000 | $97.4 | $129.7 | $19 | $75 | $9,999 |
| Credit Score (census tract) | 744.2 | 26.9 | 620.0 | 749.0 | 830.0 |
| Loan-to-Value (census tract) | 0.812 | 0.099 | 0.300 | 0.800 | 1.283 |
| Debt Outstanding (census tract) | 18,322 | 9,290 | 0 | 17,715 | 513,857 |
| Debt-to-Income% (census tract) | 32.9 | 3.9 | 1.0 | 33.0 | 61.0 |
| FinTech | 0.055 | | | | |
| Top 25 Volume Lender | 0.515 | | | | |
| Latinx/African-American | 0.186 | | | | |
| Purchase=1; Refinance=0 | 0.173 | | | | |

## Table 2: Interest Rate Discrimination

Panel A reports discrimination results using the GSE grid for identification. The dependent variable is the interest rate on originated GSE 30-year fixed-rate mortgages expressed in basis points (i.e., 100 basis points = 1%). Estimates for purchase mortgages are in Columns (1) and (2); estimates for refinances are in Columns (3) and (4). Columns (1) and (3) report raw differences in means, as a starting point for understanding the role of the credit risk model. Columns (2) and (4) report discrimination estimates for the full credit risk model, including the GSE grid and month-year fixed effects. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels. Panel B presents economic magnitude calculations, aggregating the findings in Panel A to the mortgage market outstanding as of the end of 2018. Latinx-/African-American percentage representation in the mortgage market float (17.3%) is from the Survey of Consumer Finances. The aggregate housing debt is from the Federal Reserve Bank of New York.

**Panel A: Estimates**

| | *Dependent Variable: Mortgage Interest Rate (Basis Points)* | | | |
|---|---|---|---|---|
| | *Purchase Mortgages* | | *Refinance Mortgages* | |
| | (1) | (2) | (3) | (4) |
| Latinx/African-American | 9.035*** | 7.882*** | 2.978*** | 3.556*** |
| | [1.024] | [0.311] | [0.798] | [0.292] |
| Observations | 1,495,021 | 1,495,021 | 2,081,989 | 2,081,807 |
| R-squared | -- | 0.729 | -- | 0.694 |
| Month-Year FE | N | Y | N | Y |
| GSE Grid FE | N | Y | N | Y |

**Panel B: Economic Magnitude Calculation**

| | |
|---|---|
| *A* . Market Size of Housing Debt (Federal Reserve of New York) ($M) | $9,536,000 |
| *B* . Latinx/African-American % of the Float in Mortgage Market (SCF data) | 0.173 |
| *C* . Extra Interest Payments per Basis Point of Discrimination ($M) | $165.0 |
| Discrimination Estimates from Panel (A): | |
| *D* . Extra Interest Rate (bps): Purchase Mortgages (estimate from column 2) | 7.882 |
| *E* . Extra Interest Rate (bps): Refinance Mortgages (estimate from column 4) | 3.556 |
| *F* . Share of refinance loans in stock of float | 0.75 |
| *G* . Weighted average extra interest rate ( $= D*(1-F) + E*F$ ) | 4.6 |
| Annual Aggregate Extra Interest Paid by Latinx-/African-Americans (= $C*G$) ($M) | $765.1 |

**Table 3: Interest Rate Discrimination - FinTech Results**

This table replicates our main credit risk specification, but only for the subsample of FinTech lenders. The columns reproduce the specification of column (2) and (4) of Table 2, regressing interest rates (in basis points) on the GSE grid dummy variables, month-year effects, and an indicator for whether the borrower is Latinx- or African-American. The sample is the list of FinTech platforms from Buchak et al (2017). Column (1) reports purchase-mortgage estimates, and column (2) reports refinance mortgages. Standard errors clustered at the lender level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | *Dependent Variable: Mortgage Interest Rate (Basis Points)* | |
|---|---|---|
| | *Purchase* | *Refinance* |
| *Sample:* | *FinTech Lender* | *FinTech Lender* |
| | (1) | (2) |
| Latinx/African-American | 5.306*** | 1.970** |
| | [0.422] | [0.620] |
| Observations | 42,318 | 111,912 |
| R-squared | 0.729 | 0.707 |
| Year FE | Y | Y |
| GSE Grid FE | Y | Y |

**Table 4: Interest Rate Discrimination - Robustness to Lender and Geography Fixed Effects**

This table mitigates the concern that our Table 2 estimates are picking up differential costs of delivering a mortgage by lender or by geography. Panels A and B report estimates for interest rate discrimination (in basis points) for purchase and refinance mortgages, respectively. Column (1) repeats the OLS estimate of Table 2, regressing interest rates expressed in basis points (i.e. 100 basis points = 1%) on the GSE grid-dummy variables, month-year fixed effects, and an indicator for whether the borrower is ethnically Latinx or African-American. This is the main credit risk model. Column (2) adds county fixed effects; column (3) adds lender fixed effects; column (4) adds lender crossed with month-year fixed effects; and column (5) includes lender crossed with county fixed effects. Standard errors in brackets are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

**Panel A: Purchases**

| | *Dependent Variable: Mortgage Interest Rate (Basis Points)* | | | | |
|---|---|---|---|---|---|
| | *Varying Fixed Effects* | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Latinx/African-American | 7.882*** | 6.953*** | 5.448*** | 5.573*** | 5.157*** |
| | [0.311] | [0.241] | [0.267] | [0.306] | [0.326] |
| Observations | 1,495,021 | 1,495,005 | 1,493,797 | 1,458,657 | 1,468,357 |
| R-squared | 0.729 | 0.733 | 0.748 | 0.766 | 0.759 |
| Month-Year FE | Y | Y | Y | Y | Y |
| GSE Grid FE | Y | Y | Y | Y | Y |
| County FE | N | Y | Y | Y | Y |
| Lender FE | N | N | Y | Y | Y |
| Month-Year x Lender FE | N | N | N | Y | N |
| County x Lender FE | N | N | N | N | Y |

**Panel B: Refinances**

| | *Dependent Variable: Mortgage Interest Rate (Basis Points)* | | | | |
|---|---|---|---|---|---|
| | *Varying Fixed Effects* | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Latinx/African-American | 3.556*** | 3.643*** | 2.227*** | 1.797*** | 2.019*** |
| | [0.292] | [0.280] | [0.219] | [0.206] | [0.178] |
| Observations | 2,081,807 | 2,081,798 | 2,080,699 | 2,036,215 | 2,052,246 |
| R-squared | 0.694 | 0.697 | 0.712 | 0.737 | 0.721 |
| Month-Year FE | Y | Y | Y | Y | Y |
| GSE Grid FE | Y | Y | Y | Y | Y |
| County FE | N | Y | Y | Y | Y |
| Lender FE | N | N | Y | Y | Y |
| Month-Year x Lender FE | N | N | N | Y | N |
| County x Lender FE | N | N | N | N | Y |

**Table 5: Interest Rate Discrimination - Robustness**

This table addresses robustness concerns for interpreting discrimination in pricing results. All specifications use the formulation of the main credit risk model of Table 2, columns (2) and (4), which include GSE-grid dummies and month-year fixed effects. Panels A and B present results for purchase and refinance mortgages, respectively. Column (1) restricts the analysis to lenders who offer a mixture of fully algorithmic and face-to-face loans, addressing robustness concern that procuring minority borrowers involve more overhead cost. Column (2) restricts the analysis to only non-top-25-volume lenders, addressing robustness of our results to the concern that large lenders retain the MBS and servicing rights after securitizing through the GSEs. Small lenders do not service GSE loans. Column (3) drops borrowers who do not designate their race or ethnicity directly in HMDA; i.e. those replace by a designation using names algorithms. Standard errors clustered at the lender level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| | *Dependent Variable: Mortgage Interest Rate (Basis Points)* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| *Robustness Concern:* | *Procuring Minority Borrowers Requires More Overhead Costs* | *Residual Risk due to Servicing Costs or MBS Holding* | *Ethnicity Designation* |
| *Sub-Sample:* | *Lenders with Some Algorithmic Mortgages* | *Small Lenders* | *Only use HMDA-Classified Ethnicity Observations* |
| *Reasoning:* | *Algorithmic Loans cannot have Varying Overhead Costs by Race* | *Unlikely to service the loans or hold as MBS on balance sheet* | *Eliminate software errors in race/ethnicity classification* |
| **Panel A: Purchases** | | | |
| Latinx/African-American | 8.418*** | 8.654*** | 8.095*** |
| | [0.479] | [0.350] | [0.326] |
| Observations | 704,149 | 846,547 | 1,370,384 |
| R-squared | 0.728 | 0.729 | 0.729 |
| Month-Year FE | Y | Y | Y |
| GSE Grid FE | Y | Y | Y |
| **Panel B: Refinances** | | | |
| Latinx/African-American | 3.361*** | 3.842*** | 3.837*** |
| | [0.275] | [0.221] | [0.319] |
| Observations | 1,023,049 | 859,715 | 1,857,191 |
| R-squared | 0.7 | 0.732 | 0.695 |
| Month-Year FE | Y | Y | Y |
| GSE Grid FE | Y | Y | Y |

## Table 6: HMDA 2018 Analysis with Points-Adjusted Interest Rate

The sample is the issued GSE mortgages for 2018. The dependent variable is the interest rate on originated GSE 30-year fixed-rate mortgages expressed in basis points (i.e., 100 basis points = 1%). Estimates for purchase and refinance mortgages are in Panel (a) and Panel (b) respectively. Columns (1) to (4) differ from columns (5) to (8) in the mapping of a point to effective interest rate, using the industry norm (applied differentially by lenders) that paying (or inversely rebating) a point decreases (increases) the coupon by an eighth to a fourth of a percentage point. Columns (1) and (5) report raw differences in means, as a starting point. Columns (2) and (6) add in the approximate GSE grid fixed effects, where the LTV data and FICO score used in constructing the grid buckets is at the census tract level. Columns (3) and (7) add lender fixed effects to columns (2) and (6) specifications. The only loan-level variables in HMDA are income and loan amount; thus in Columns (4) and (8), we interact 20 buckets of income and 20 buckets of loan amount with the census tract-level GSE grid buckets. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

| **Panel A: Purchase Mortgages** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dependent Var.:* | Effective Interest Rate = Coupon +/- Points Conversion | | | | | | | |
| *Points Conversion:* | 1 point = 1/8th of 1% coupon impact | | | | 1 point = 1/4th of 1% coupon impact | | | |
| Latinx/African American | 16.73*** | 13.41*** | 10.98*** | 10.27*** | 17.45*** | 14.26*** | 11.62*** | 10.90*** |
| | [1.264] | [1.157] | [0.784] | [0.916] | [1.323] | [1.238] | [0.793] | [0.954] |
| Observations | 1,140,686 | 913,573 | 913,573 | 895,150 | 1,140,686 | 913,573 | 913,573 | 895,150 |
| R-squared | 0.011 | 0.046 | 0.196 | 0.292 | 0.011 | 0.044 | 0.205 | 0.297 |
| GSE Grid FE | N | Y | Y | N | N | Y | Y | N |
| Lender FE | N | N | Y | Y | N | N | Y | Y |
| GSE Grid FE * 20 Buckets of HMDA-Reported Income * 20 Buckets of HMDA-Reported Loan Amount | N | N | N | Y | N | N | N | Y |

| **Panel B: Refinance Mortgages** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Dependent Var.:* | Effective Interest Rate = Coupon +/- Points Conversion | | | | | | | |
| *Points Conversion:* | 1 point = 1/8th of 1% coupon impact | | | | 1 point = 1/4th of 1% coupon impact | | | |
| Latinx/African American | 16.64*** | 13.04*** | 9.309*** | 10.06*** | 18.01*** | 14.06*** | 9.935*** | 10.57*** |
| | [3.646] | [3.195] | [2.744] | [1.526] | [3.666] | [3.262] | [2.802] | [1.589] |
| Observations | 587,796 | 485,285 | 485,285 | 472,961 | 587,796 | 485,285 | 485,285 | 472,961 |
| R-squared | 0.006 | 0.094 | 0.290 | 0.400 | 0.007 | 0.096 | 0.294 | 0.403 |
| GSE Grid FE | N | Y | Y | N | N | Y | Y | N |
| Lender FE | N | N | Y | Y | N | N | Y | Y |
| GSE Grid FE * 20 Buckets of HMDA-Reported Income * 20 Buckets of HMDA-Reported Loan Amount | N | N | N | Y | N | N | N | Y |

## Table 7: Application Rejection Discrimination

This table reports discrimination in rejection rates for mortgages. The dependent variable is an indicator for an application being rejected by the lender. The sample is the set of all HMDA 30-year, fixed-rate mortgage applications run through GSE underwriting. The credit-risk model controls consist of three sets of variables, with the inclusion noted beneath the estimation. The first column presents raw mean differences. Column (2) presents the full set of HMDA data publicly available, which includes the year, applicant income, and applicant loan amount, including 21 piecewise-linear functions of income and 47 of loan amount. Column (3) includes the full set of variables used in the black box of the GSE underwriter system that determines GSE acceptability of applications, which adds in census tract proxies for LTV, credit score, debt-to-income (DTI), and total debt. We include quartiles (25th, 50th and 75th percentiles) of each variable to capture within-tract dispersion. We construct these census tract variables from McDash (for LTV, total debt, and credit score) and from the GSE data (for DTI). Standard errors clustered at the lender level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

**Panel A: Purchase Mortgages**

| | *Dependent Variable: Application Rejection* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Latinx/African-American | 0.141*** | 0.109*** | 0.0957*** |
| | [0.00510] | [0.00508] | [0.00448] |
| Observations | 3,179,813 | 3,179,813 | 3,179,273 |
| R-squared | -- | 0.055 | 0.063 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | N | Y | Y |
| Year FE | N | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | N | N | Y |

**Panel B: Refinance Mortgages**

| | *Dependent Variable: Application Rejection* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Latinx/African-American | 0.122*** | 0.0896*** | 0.0728*** |
| | [0.00867] | [0.00577] | [0.00505] |
| Observations | 10,004,264 | 10,004,264 | 10,002,727 |
| R-squared | -- | 0.049 | 0.055 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | N | Y | Y |
| Year FE | N | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | N | N | Y |

**Table 8: Application Rejection Discrimination - FinTech Lenders**

The dependent variable is an indicator for an application being rejected by the lender. The sample is the set of stand-alone FinTech platforms from Buchak et al (2017). The credit risk model controls consists of three potential sets of variables, with the inclusion noted beneath the estimation. The first column presents raw mean differences. Column (2) presents the full set of HMDA data publicly available, which includes the year, applicant income, and applicant loan amount, including 21 piecewise-linear functions of income and 47 of loan amount. Column (3) includes the full set of variables used in the black box of the GSE underwriter system that determines GSE acceptability of applications, adding in census tract proxies for LTV, credit score, debt-to-income (DTI), and total debt. We include quartiles (25th, 50th and 75th percentiles) of each variable to capture within-tract dispersion. We construct these census-tract variables from McDash (for LTV, total debt, and credit score) and from the GSE data (for DTI). Standard errors clustered at the lender lever are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

**Panel A: Purchase Mortgages**

| | *Dependent Variable: Application Rejection* | | |
|---|---|---|---|
| | *Sample: FinTech Lenders* | | |
| | (1) | (2) | (3) |
| Latinx/African-American | 0.0527* | 0.0411 | 0.0328 |
| | [0.0281] | [0.0224] | [0.0220] |
| Observations | 70,813 | 70,813 | 70,791 |
| R-squared | -- | 0.043 | 0.048 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | N | Y | Y |
| Year FE | N | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | N | N | Y |

**Panel B: Refinance Mortgages**

| | *Dependent Variable: Application Rejection* | | |
|---|---|---|---|
| | *Sample: FinTech Lenders* | | |
| | (1) | (2) | (3) |
| Latinx/African-American | 0.0540** | 0.0288* | 0.0233 |
| | [0.0213] | [0.0154] | [0.0132] |
| Observations | 337,582 | 337,582 | 337,508 |
| R-squared | -- | 0.052 | 0.058 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | N | Y | Y |
| Year FE | N | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | N | N | Y |

## Table 9: Application Rejection Discrimination - Lender & Location Fixed Effects

This table reports robustness tests for our analysis of discrimination in rejection rates. The dependent variable is an indicator for an application being rejected by the lender. Column (1) repeats the specification from the third column of Table 7. Column (2) adds in lender fixed effects. Column (3) includes county and lender fixed effects. Column (4) includes lender crossed with county fixed effects. Column (5) repeats the column (4) specification but limits the sample to only small lenders. Panel (A) presents purchase mortgage application results, and Panel (B) presents results for refinance applications. Standard errors clustered at the lender level are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

**Panel A: Purchase Mortgages**

| | *Dependent Variable: Application Rejection* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Sample Restriction:* | | | | | Small Lenders |
| Latinx/African-American | 0.0957*** | 0.0745*** | 0.0714*** | 0.0698*** | 0.0657*** |
| | [0.00448] | [0.00342] | [0.00319] | [0.00311] | [0.00223] |
| Observations | 3,179,273 | 3,178,331 | 3,178,324 | 3,137,844 | 1,838,121 |
| R-squared | 0.063 | 0.224 | 0.227 | 0.264 | 0.337 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | Y | Y | Y | Y | Y |
| Lender FE | N | Y | Y | N | N |
| County FE | N | N | Y | N | N |
| Lender # County FE | N | N | N | Y | Y |

**Panel B: Refinance Mortgages**

| | *Dependent Variable: Application Rejection* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Sample Restriction:* | | | | | Small Lenders |
| Latinx/African-American | 0.0728*** | 0.0617*** | 0.0628*** | 0.0633*** | 0.0527*** |
| | [0.00505] | [0.00484] | [0.00477] | [0.00476] | [0.00285] |
| Observations | 10,002,727 | 10,001,968 | 10,001,964 | 9,954,232 | 4,415,763 |
| R-squared | 0.055 | 0.164 | 0.167 | 0.188 | 0.327 |
| Application Income & Application Loan Amount: 68 piecewise-linear splines | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |
| LTV, Credit Score, Debt-to-Income, and Total Debt: Quartile Variables by Census Tract | Y | Y | Y | Y | Y |
| Lender FE | N | Y | Y | N | N |
| County FE | N | N | Y | N | N |
| Lender # County FE | N | N | N | Y | Y |

## Appendix Table 1: Statistics & Estimation of Interest Rate Discrimination for Shorter Maturities

This table reports statistics and analysis on GSE-issued conforming mortgages, with maturities of less than 30 years. Panel A reports statistics akin to Table 1, panel A except for the shorter maturity sampling. Data are from a loan-level merge of HMDA, ATTOM, McDash, and Equifax data. Loan amount, applicant income and Latinx-/African-American are from HMDA. Interest rate, LTV, and credit score are from McDash-Equifax. Top 25 Volume Lender is calculated annually from volume of loans by lender. FinTech is a platform identifier from Buchak et al (2017). Panel B reports discrimination results using the GSE grid for identification. The dependent variable is the interest rate. Columns (1) and (3) report raw differences in means, as a starting point for understanding the role of the credit risk model. Columns (2) and (4) report discrimination estimates for the full credit risk model. We regress the rate on the GSE grid fixed effects and the month-year effects, identifying discrimination as the estimate on an Latinx/African-American indicator variable. Standard errors are clustered at the lender level. ***, **, and * indicate significance at the 1%, 5%, and 10% conventional levels.

**Panel A: Statistics for Accepted GSE <30 Year Fixed Rate Mortgages (N = 1,390,286)**

| | Mean | Standard Deviation | Minimum | Median | Maximum |
|---|---|---|---|---|---|
| Interest Rate % (McDash) | 3.94% | 0.64% | 2.00% | 3.88% | 7.63% |
| Loan Amount $,000 | $185.4 | $100.1 | $30.0 | $163.0 | $729.0 |
| Applicant Income $,000 | $111.4 | $101.5 | $19 | $91 | $9,600 |
| Credit Score (McDash-Equifax) | 758.6 | 45.6 | 620 | 772 | 850 |
| Loan-to-Value(McDash-Equifax) | 0.669 | 0.177 | 0.300 | 0.685 | 1.300 |
| FinTech | 0.050 | | | | |
| Top 25 Lender | 0.591 | | | | |
| Latinx/African-American | 0.113 | | | | |
| Purchase=1; Refinance=0 | 0.101 | | | | |

**Panel B: Estimates of Interest Rate Discrimination for Shorter Maturity Originations**

| | *Dependent Variable: Mortgage Interest Rate (in basis points)* | | | |
|---|---|---|---|---|
| | *Purchase Mortgages* | | *Refinance Mortgages* | |
| | (1) | (2) | (3) | (4) |
| Latinx/African-American | 13.35*** | 11.70*** | 2.916** | 5.548*** |
| | [2.485] | [1.625] | [1.375] | [0.685] |
| Observations | 140,613 | 140,613 | 1,249,673 | 1,249,634 |
| R-squared | -- | 0.674 | -- | 0.600 |
| Month-Year FE | N | Y | N | Y |
| GSE Grid FE | N | Y | N | Y |